THE EFFECTS OF ICT USE AND MOBILE PHONE BANS AT SCHOOL ON EDUCATIONAL OUTCOMES AMONG 15-YEAR-OLDS IN UKRAINE

by

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Abstract

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The widespread use of digital devices by children has been suggested as a possible contributing factor to the downward trend in adolescents' educational outcomes which has led to ongoing policy debate regarding restrictions on their use in schools. This study examines the association between different types of ICT use at school and educational outcomes in Ukraine, as well as the role of mobile phone bans in shaping these relationships among 15-year-olds. The research applies multilevel modelling and is based on microdata from the Programme for International Student Assessment (PISA) 2022 for Ukrainian regions. The analysis finds that ICT use at school for learning and leisure is negatively associated with educational outcomes in Ukraine, and the magnitude of this association is practically meaningful. No statistically significant association is found between mobile phone bans and students' educational outcomes. Additional analysis indicates that mobile phone bans are not effectively enforced in schools. Policy implications include the need for a nationwide policy in Ukraine on digital device restrictions for in-person schooling, with particular attention to enforcement mechanisms and the security considerations under wartime circumstances.

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AI USE DECLARATION

During the preparation of this thesis, ChatGPT and Claude AI were used for grammar correction, improving language clarity, and as an advanced search tool. ChatGPT and Claude AI were also used for coding assistance.

Any suggestions produced by the AI tools were critically evaluated and substantially modified by the author before being incorporated into the thesis. All analyses and interpretations are the author's own.

LIST OF ABBREVIATIONS

BRR. Balanced repeated replication

DiD. Difference-in-differences

ESCS. PISA index of economic, social, and cultural status

HLM. Hierarchical linear model

ICC. Intraclass correlation coefficient

ICT. Information and communication technology

MG-SEM. Multigroup structural equation modelling

ML. Maximum likelihood

MLM. Multilevel linear model

MSA. Measure of sampling adequacy

OECD. Organisation for Economic Co-operation and Development

OLS. Ordinary least squares

PCA. Principal component analysis

PISA. Programme for International Student Assessment

SCM. Synthetic control method

SEM. Structural equation modelling

UCEQA. Ukrainian Center for Educational Quality Assessment

Chapter 1

INTRODUCTION

Human capital plays a significant role in economic development, and education is one of its fundamental components (Aghion et al. 2025). Societies benefit from individuals with stronger skills and competencies, as this contributes to faster economic growth and quicker adaptation to technological change. Therefore, any decline in students' skills and performance becomes a major concern for a country's future development.

A downward trend for educational outcomes among 15-year-olds has been observed across several Programme for International Students Assessments (PISA) cycles, particularly for reading (see Figure 1).

The widespread use of digital devices by children has been suggested as a possible contributing factor. In recent years, there has been an ongoing policy debate in many countries about restricting the use of digital devices among schoolchildren. Some countries have ban for mobile phones at school level like the UK, some nation-wide legal bans like France (Euronews 2024). The scope of mobile phone restrictions varies, ranging from prohibiting phone use during lessons, as in Finland (Euronews 2025) and Italy, to not using it on school premises altogether as in France. Concerns about students' well-being and negative impact on educational outcomes are among the main reasons for these measures.

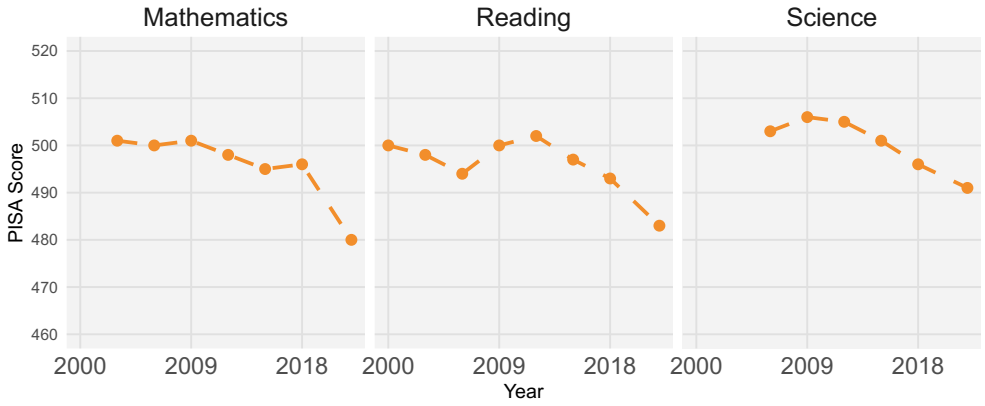


Figure 1. Trends in performance in mathematics, reading, and science since the first PISA assessment for OECD average-23[1]

Source: Adapted from OECD (2023b), author's own visualization

In Ukraine, according to OECD (2023b), the decline in student achievement in mathematics among 15-year-olds was broadly comparable to the OECD average, whereas reading performance deteriorated significantly more than the OECD average between 2018 and 2022 (see Figure 2).

In addition to the effects of COVID-19, these declines were influenced by full-scale Russian invasion in 2022 that led to loss of school infrastructure, wartime school closures, air raid alert disruptions, power outages, loss of teacher's stuff and overall instability and stress among the whole population. Still, the ICT use contribution to the declines cannot be excluded, as Ukrainian 15-year-olds rank among the highest in the average time spent using digital devices for learning at

[1] OECD average-23 refers to the arithmetic mean across all OECD member countries excluding Austria, Chile, Colombia, Costa Rica, Estonia, Israel, Lithuania, Luxembourg, the Netherlands, the Slovak Republic, Slovenia, Spain, Türkiye, the United Kingdom, and the United States (OECD 2023b).

school (OECD 2023c). Therefore, policies related to ICT use within the school could be especially relevant. Among the major drawbacks of intensive ICT use at school may be distractions during classes and the crowding out of time needed for learning due to extensive ICT-related leisure time.

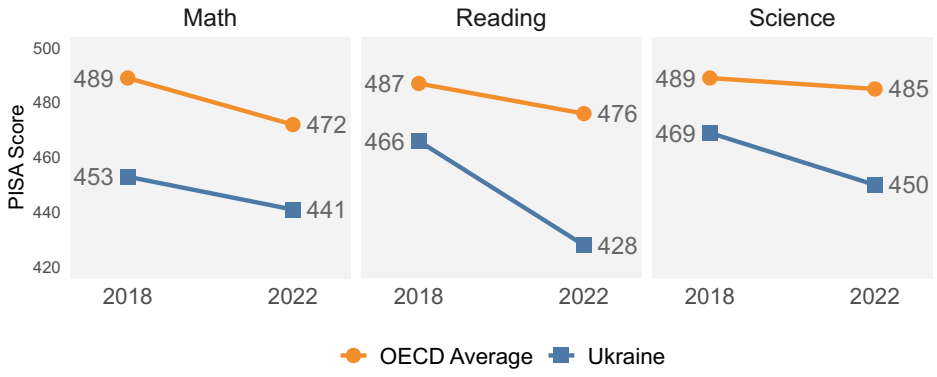


Figure 2. Trends in average performance in mathematics, reading, and science in Ukraine and OECD countries between the 2018 and 2022 PISA cycles

Source: Adapted from The Ukrainian Center for Educational Quality Assessment (UCEQA, 2023), author's own visualization

This leads to the following research question: what is the association between different types of ICT use at school and educational outcomes in Ukraine, and what role do mobile phone bans play in shaping these relationships among 15-year-olds? To answer this, the following hypotheses are tested:

- H1: The ban of mobile phones usage on school premises is positively associated with students' educational outcomes
- H2: Longer hours of ICT use at school for learning are negatively associated with learning outcomes

- H3: Longer hours of ICT use at school for leisure are negatively associated with learning outcomes

Numerous studies have examined ICT use across countries using PISA data, but there is no research utilizing PISA data on ICT use for Ukraine. The results of studies conducted in other countries cannot be directly applied to Ukraine as the literature shows that there are mixed results and they depend on the country (Odell et al. 2020). Similarly, research on the effectiveness of mobile phone bans shows mixed results (Campbell et al., 2024). However, there is no research conducted on the relationship between school phone ban for Ukraine where educational system and educational policies implementation differ. This study aims to address this gap by conducting an analysis based on Ukrainian data. The analysis focuses mainly on schools with in-person schooling[2] due to data availability constraints.

The research is done based on the results PISA 2022. In Ukraine, over 3,800 students from 164 schools participated in this survey in 2022. Using PISA microdata, the study estimates regression models examining the relationship between ICT use types at school and educational outcomes, as well as the relationship between school phone bans and educational outcomes in Ukraine.

The results suggest that the ICT use at school both for learning and leisure are associated with worse learning outcomes. The empirical estimates indicate no difference in educational outcomes between schools with mobile phone bans and without mobile phone bans. The exploratory analysis suggests that mobile phone bans are not enforced.

[2] PISA data collection in Ukraine took place only in schools with appropriate shelters (UCEQA, 2023), which were also more likely to operate in person.

The empirical models control for a wide range of independent variables. However, they are based on cross-sectional data. So, the findings should be interpreted as correlational rather than causal.

Policy implications include the need for a nationwide policy in Ukraine on digital device restrictions for in-person schooling, with particular attention to enforcement mechanisms and the security considerations under wartime circumstances.

The structure of the thesis is organized as follows: Chapter 2 presents a literature review of the existing research on the role of ICT use and mobile phone bans at school in shaping learning outcomes, Chapter 3 discusses the methodology and the model specifications applied in the thesis, Chapter 4 describes the data and key variables, Chapter 5 describes the estimation results. Finally, Chapter 6 presents a summary of the main findings and discusses their policy implications.

Chapter 2

LITERATURE REVIEW

A lot of research has been done on the impact of ICT use on educational outcomes over the last few decades. A portion of the literature consists of experimental studies on ICT use in education. The results of research depend significantly on experimental design, so they cannot be generalized to the broader population. Therefore, this review does not cover this part of the literature.

The last few decades were decades of high-speed technological changes and accessibility of ICT. According to the Lorenceau, Marec, and Mostafa (2019), among the 40 countries that participated in PISA 2003, the share of students with Internet access at home increased from 57% in 2003 to 92% in 2015. Today, this figure is close to 100% in many countries. It is worth noting the emergence and rapid adoption of cloud storage services, learning management systems, and online meeting platforms, which continue to reshape how ICT is used for educational purposes. So, when seeking policy advice on ICT use and mobile phone ban on school premises, it is sensible to focus on relatively recent research.

2.1 Empirical evidence on the role of ICT use at school in educational outcomes

In addition to changes in technology and accessibility, a lot of variations of the possible technology application might prevent the researchers from getting a definitive answer of ICT role in educational outcomes. Literature review done by Odell et al. (2020) summarizes examples of research showing examples of negative, positive and neutral relationships between performance scores in mathematics and science and the ICT use. In their systematic review of factors predicting

mathematics achievement in PISA, Wang et al. (2023) identified 16 studies that considered ICT as a factor. For most of these studies, mixed results were reported, with substantial cross-national variation.

The mixed results of the ICT role can also be explained by difficulty in capturing ICT use patterns. Following the structure of PISA questionnaires, prior literature generally focuses on three possible ways to use ICT: ICT use at school, at home for education and at home for leisure. For example, Skryabin et al. (2015) follows this structure for 15-year-olds. Some studies look at other aspects of ICT use, like students' ICT competence and ICT access at school and at home, for example Gubbels et al. (2020), in their study of Dutch 15-year-olds. It is rarer to include ICT autonomy and ICT inclusion in social interaction (Martínez-Abad, 2019). Some studies include country-level variables. Skryabin et al. (2015) includes overall country's level of ICT development. European Commission: Directorate-General for Education, Youth, Sport and Culture (2023) use the country's level of ICT use in education.

Further, the focus is on the results of the research addressing the most common angle of the reviewed literature: ICT use at school, at home for educational purposes, and at home for leisure. Results concerning ICT use at school are considered, as this is the focus of the present study. Two large-scale cross-country studies by Skryabin et al. (2015) and Petko et al. (2017) based on PISA 2012 shows negative influence on mathematics, science and reading of ICT use at school for 15-year-olds. Similar conclusions are shown on research by Saarinnen (2021) relying on PISA 2015 for Finnish students. The study by Yilmaz Koğar (2019), which utilizes data from PISA 2015, links the use of digital devices for educational purposes with better mathematics scores, but not for science performance. A positive relationship between subject-related ICT use at school and performance across all PISA domains (reading, mathematics, and science) is reported in the study by SANFO (2023) for Japanese students.

Some of the studies suggest that the effect can be non-linear and may differ by intensity of use: low, moderate, or high. The Reboot Foundation (2019) reported that users who use ICT moderately have better educational outcomes than low and high-intensity users in the PISA 2015 data. Biagi and Rodrigues (2017) suggest that only low-intensity ICT users improve their science scores from increasing hours of ICT use at school, but the optimal amount of usage corresponds to a relatively low level of intensity. According to Lorenceau, Marec, and Mostafa (2019), there is an inverted U-shaped relationship between ICT use at school and educational achievement based on research using data from PISA 2012 and 2015. The report suggests that moderate use of ICT at school is the most beneficial.

To conclude this part, the findings of the body of research examining ICT use at school are mixed. There is substantial heterogeneity across countries in the relationship between ICT use and educational outcomes (Petko et al. 2017, Biagi and Rodrigues 2017). Much depends on context: year, country, subject. An additional insight is that it is important to check for non-linear effects of ICT use intensity.

2.2 Empirical evidence on mobile phone bans in schools

In this literature review section, the focus is on the relationship between academic outcomes and school mobile phone bans. Other aspects like students' well-being, incidence of bullying fall outside the scope of the present study.

The scoping review done by Campbell et al. (2024) listed seven studies that examined the relationship between educational outcomes and mobile phone bans. The results are mixed: four shows the positive effect, and three reported no difference in educational outcomes regardless the mobile phones.

One of the most influential studies is Beland and Murphy (2016), that used longitudinal data from four cities in the UK, and reported scores increase for low-

achieving and low SES students as a result of the mobile phone ban. The authors estimate that the effect of a mobile phone ban is equivalent to approximately one additional hour of instruction per week. Guldvik and Kvinnsland (2018) examined the same question based on survey of 493 schools in Norway. They differentiated between strict and partial bans. The study reports no significant effect of strict mobile phone bans on the exam scores. The study done by Kessel et al. (2020) replicated the study Beland and Murphy (2016) on the national level using Swedish longitudinal data and no relation between students' academic outcomes and mobile phone bans. Beneito and Vicente-Chirivella (2022) examined the effect on mobile phone bans at the regional level in Spain using PISA achievement data. They have found positive effect on mathematics and science scores in one of the regions that provided ban that are equivalent more than half a year of learning. It is important to note that all mentioned studies except Beland and Murphy (2016) do not provide any information on the compliance rate of the bans that could explain the difference in the results.

In a recent cross-country study, Rau (2025) examines the relationship between school mobile phone bans and educational outcomes using PISA data. One of the main findings is that improvements in PISA scores are observed only when the bans are effectively enforced.

2.3 ICT use and mobile phone bans in Ukrainian schools

To the best of our knowledge, no studies have yet directly analyzed the relationship between ICT use and educational outcomes using PISA 2022 data. Since the PISA data were published in 2023–2024, it is likely that related research papers are still in progress. Nevertheless, as previous literature shows, the relationship between ICT use and educational outcomes is context-dependent, and research for Ukraine is currently lacking.

In Ukraine, mobile phone bans are permitted at the school level; however, research on the effectiveness of this policy at the school level is currently unavailable.

2.4 Methodological approaches applied in the existing literature

Different approaches were used for the PISA-based research on ICT use. In a scoping review done by Odell et al. (2020), there are three approaches that are used in at least several studies: multiple linear regression, multi-level modelling (MLM) and structural equation modelling (SEM).

Multilevel modelling is widely used in educational and healthcare research where data have a natural nesting structure: students are nested within schools, schools are nested within countries, patients are nested within hospitals. A multilevel model is also referred to as a hierarchical linear model (HLM) in some literature. MLM is commonly applied in research based on PISA data as it aligns with the PISA sampling process: at the first stage, schools are sampled, then students are sampled from the selected schools. Students are not truly independent in this kind of sampling process, because students in one school have some shared experiences. In this case, standard OLS that is used in multiple linear regression can provide biased standard errors that lead to incorrect statistical significance of the estimated coefficients (O'Dwyer and Parker 2014). Multilevel modelling is applied to account for the nested structure that includes both fixed effects (explanatory variables) and random effects (variables by which students are clustered) (Theobald 2018).

Structural Equation Modelling (SEM) is "a comprehensive and flexible statistical technique for analyzing the structural relationship between measured variables and latent constructs with multiple pathways" (Ogundari 2021). It is more complicated as it consists of two models: the measurement model and the structural

model. The structural model deals with relationships between latent constructs, the variables that are not directly observable. As an example, Joshi et al. (2025) have several latent variables, among them are the *use of digital resources at school* and *self-efficacy in digital competencies*. Each latent variable matches several observable variables in the data. Relationships between latent variables and observable variables are managed by the measurement model. In PISA-based research, SEM is sometimes used for group comparisons through multigroup SEM (MG-SEM). Another extension is multilevel SEM (ML-SEM), which accounts for the nested structure of the data (students within schools).

Multilevel SEM is an appropriate method for research based on PISA data, but it adds complexity and can make the interpretation of results more difficult. In this study, an MLM approach is used to estimate association between ICT use at school and educational outcomes.

Most of the studies on mobile phone bans mentioned above use longitudinal data and apply either a difference-in-differences (DiD) approach or, in the case of Beneito and Vicente-Chirivella (2022), the synthetic control method (SCM). A notable exception is Rau (2025), which is based on PISA data and employs cross-sectional OLS regression with country fixed effects.

As no longitudinal data are available for Ukraine and cross-sectional PISA data are used, DiD and SCM are not applicable and this study applies MLM approach. The choice of MLM for the current study is motivated by the cross-sectional nature of the PISA dataset. MLM is more appropriate than OLS due to the nested structure of the data, as discussed above. This choice is further supported by Wang et al. (2023), who report that MLM is the most used method among 156 PISA-based studies investigating factors predicting mathematics achievement, applied in 30% of the selected studies.

In summary, the literature provides mixed evidence of the relationship between ICT use and educational outcomes. The results are heterogeneous; they differ by year of the survey, country and subject. The literature reports mixed results on the relationship between mobile phone bans at school and educational outcomes (positive or no difference). Among the most common research methodologies based on PISA data is multilevel modelling (MLM). There is no research using the latest PISA results for Ukraine, so it remains unclear what the relationship between ICT use and educational outcomes is, as well as the relationship between school phone bans and educational outcomes is in Ukraine.

Chapter 3

METHODOLOGY

To answer the research question, this study applies multilevel modeling, which is commonly used in the analysis of large-scale educational assessments such as PISA. Students within the same school share common experiences, such as the duration of school closures, potential teacher staff shortages, disciplinary practices, and the availability of material resources. As a result, observations at the student level are not independent.

The model comprises two levels: students at the first level and schools at the second level. Dependent variables are scores in mathematics, reading and science.

3.1 Null model

As an initial step in the preliminary analysis, the null model is estimated. This model, also referred to as the unconditional model, does not include any level-1 or level-2 predictors. The model is described by the following equations. The level-1 model:

$$Score_{ij} = \beta_{0j} + r_{ij} \quad (1)$$

where:

- $Score_{ij}$ is educational outcome for one of the PISA domains (mathematics, reading, science) for student *i* in school *j*
- r_{ij} is a person effect for student *i* in school *j*

The assumption is that level-1 effect, r_{ij}, is normally distributed with a mean of 0 and constant level-1 variance, σ^2:

$$r_{ij} \sim iidN(0, \sigma^2) \tag{2}$$

This model predicts the score for each student with only one level-2 parameter β_{0j}, that in this case is the mean score of the school *j*. The level-2 model is described by equation:

$$\beta_{0j} = \gamma_{00} + u_{oj} \tag{3}$$

where:

- γ_{00} is the grand-mean outcome in the population
- u_{oj} is the random effect associated with school *j (*a level-2 effect of school *j)*

The assumption is that level-2 effect, u_{oj}, has mean of 0 and variance τ_{00}:

-

$$u_{0j} \sim N(0, \tau) \tag{4}$$

The combined model equation is:

$$Score_{ij} = \gamma_{00} + u_{oj} + r_{ij} \tag{5}$$

Null model gives point estimate and confidence interval for the grand mean, γ_{00}. Also, the τ_{00} presents between-group variability (how much school differ from each other), σ^2 presents the variance within-group (how much students differ within school).

3.2 Intraclass correlation coefficient

The null model enables the calculation of intraclass correlation coefficients (ICC), which measure the proportion of variance at each level. It allows to decide whether the 2-level model is justified.

The between group variance τ_{00} and within-group variance σ^2 are used to calculate the intraclass correlation coefficient (ICC), which is given by the following equation:

$$\rho = \frac{\tau_{00}}{\tau_{00} + \sigma^2} \tag{6}$$

If ICC is low (<0.05) it signals that MLM approach may not be necessary (Theobald 2018).

3.3 Random intercept model with control variables

At the second stage, I estimate the model with control variables only. There are several control variables added to the model. In particular, gender and economic, social, and cultural status (ESCS) are well-known predictors of the educational outcomes.

The random intercept model with control variables is described by the following equation:

$$Score_{ij} = \gamma_{00} + \boldsymbol{X'_{ij}} * \boldsymbol{\gamma} + \boldsymbol{W'_j} * \boldsymbol{\delta} + u_{0j} + r_{ij} \quad (7)$$

where*:*

- $\boldsymbol{X}_{ij}$ is the vector of individual level control variables
- $\boldsymbol{W}_j$ is the vector of school-level control variables
- $\boldsymbol{\gamma}$ is the vector of fixed-effect coefficients for student-level control variables
- $\boldsymbol{\delta}$ is the vector of fixed-effect coefficients for school-level control variables

The details of all student-level and school-level variables are described in Table 1.

The multi-level models are very prone to numerical instability especially if quadratic terms are added. The common practice is centering all the student-level variables to mitigate this issue and make results interpretation more straightforward. The grand-mean centering is the standard way to center the variables in MLM (Raudenbush and Bryk 2002) and is applied to all student-level variables described above. School-level variables are not centered, as for group-level variables the centering does not impact interpretation and do not lead to numerical instability (Raudenbush and Bryk 2002).

Table 1. Control variables

Variable	Exp. Sign	Comments
Individual-Level Variables		
Gender (male)	+ (math)	Being male is associated with higher mathematics performance in the majority of studies analyzed by Wang et al. (2023). Though overall it depends on the country, UCEQA (2023) reports higher average mathematics outcomes for males in Ukraine based on PISA 2022
	- (reading)	In the cross-country research Skryabin et al. (2015) states that female have better reading performance, it also aligns with higher average reading outcome for females reported by UCEQA (2023) for Ukraine
	0 (science)	In the cross-country research Skryabin et al. (2015) report better female science performance but the gap is small based on PISA 2015. UCEQA (2023) reports no gender gap for Ukraine on average for science outcomes
ESCS, nationally adjusted	+	PISA index of economic, social, and cultural status (nationally adjusted) The review done by Wang et al. (2023) reports consistent positive association between the mathematics achievement and the socio-economic status, but it is also the result shown in a lot of studies for different PISA domains, for example Skryabin et al. (2015).

Table 1. Control variables - Continued

Variable	Exp. Sign	Comments
Institution-Grade (ref: School-Grade 10)		
Vocational/College (1-2 year)	-	UCEQA (2023) reports lower average educational outcomes for this type of institutions relative to School Grade 10.
School-Grade 9	-	A negative association is expected, as 9th graders have one less year of learning compared to 10th graders.
School-Grade 11	+	A positive association is expected, as 11th graders have one more year of learning compared to 10th graders.
School-Level Variables		
School in Urban Area	+	Binary variable, if school is located in urban or rural area. UCEQA (2023) reports significant inequality if the educational outcomes between students of urban and rural schools. Living in urban area is associated with higher achievement across all PISA domains.
School-Average ESCS	+	School-average ESCS (also sometimes referred to as school ESCS composition) is positively associated with educational outcomes in mathematics in the majority of studies analyzed by Wang et al. (2023).

3.4 Random intercept full model with mobile phone ban

To estimate the relationship between mobile phone ban at school and students' educational outcomes, I extend the model (7) by adding new school-level variable for mobile phone ban:

$$Score_{ij} = \gamma_{00} + \boldsymbol{X'_{ij}} * \boldsymbol{\gamma} + \boldsymbol{W'_j} * \delta + \beta * Ban_j + u_{0j} + r_{ij} \quad (8)$$

where:

- Ban_j is a school-level variable, it is binary and it is equal to 1 if school $\boldsymbol{j}$ has mobile phone ban policy on school premises and 0 otherwise.
- β is the fixed effect coefficient of the mobile phone ban variable

A positive relationship between mobile phone bans and educational outcomes is expected. ICT use variables in this model are not included in this model, as effective ban affects ICT use at school. If these variables are included in this model, it may block part of the effect of the mobile phone bans.

3.5 Random intercept full model with ICT variables

To estimate the relationship between ICT use at school and educational outcomes, I extend the model (7) by adding ICT use variables to equation:

$$Score_{ij} = \gamma_{00} + \boldsymbol{X'_{ij}} * \boldsymbol{\gamma} + \boldsymbol{W'_j} * \delta + \boldsymbol{ICT'_{ij}} * \boldsymbol{\beta} + u_{0j} + r_{ij} \quad (9)$$

where*:*

- $\boldsymbol{ICT_{ij}}$ is the vector that contains students' ICT use variables

- $\boldsymbol{\beta}$ is the vector of fixed-effect coefficients for ICT use variables
- There are several ICT variables: two variables of interest and two control variables.

Two variables of interest ICT use at school for learning and ICT use at school for leisure. They are measured in hours per day and grand-mean centered.

Additionally, there are two control variables: intensity of ICT use outside of school and ICT use type outside of school (learning vs leisure). It is also added quadratic term for intensity of ICT use outside of school to account for possible inverted U-shape relationship. ICT Control variables are constructed using Principal Component Analysis (PCA). They are grand-mean centered by design. There is more detail about variables construction in the Chapter 4. The detail of all ICT use variables is described in Table 2.

Table 2. ICT variables

ICT variable	**Exp. Sign**	**Comments**
At school for learning	-	There is a negative relationship between ICT use for learning at school students' learning outcomes.
At school for leisure	-	Longer hours of ICT use at school for leisure are negatively associated with learning outcomes.
Intensity of ICT use outside of school	+	There is an inverted U-shaped relationship between ICT use for learning outside of school both for weekend and weekend and students' learning outcomes.
Quadratic form	-	
Type of use outside of school	+	This variable reflects balance between learning and leisure. The hypothesis is that shift toward learning is associated with higher educational outcomes.

3.6 Model assumptions

Model misspecification can occur when an incorrect functional form is chosen, when relevant variables are omitted from the model, or when variables are measured with error. In MLM, "specification assumptions apply at each level. Moreover, misspecification at one level can affect results at other levels" (Raudenbush and Bryk 2002).

The model assumes that all relevant independent variables are included. Omitted variables correlated both with the educational outcome and independent variables could bias the estimated coefficients. In the dataset, there is only some data about teacher's staff at school level, but no data are available on the teachers of the individual students. So, the teacher's quality is omitted from the model. Additionally, as Wang et al. (2023) reports mixed results in the reviewed studies on the classroom characteristics like class size and disciplinary climate. Therefore, they are not included as the controls in the model specification.

The formal assumptions to check for our full model are following:

1. Conditional on the full set of student-level variables included in the model, the within-school errors are independent and normally distributed with mean zero in each school and with constant variance across schools (see Equation 2).
2. Any omitted student-level variables are assumed to be independent of the variables of interest. This assumption is assessed by examining whether the student-level residuals are independent of the variables of interest:

$$Cov(X_{qij}, r_{ij}) = 0 \tag{10}$$

3. The residual school effects u_{0j} are normally distributed with mean 0 and variance τ (see Equation 3).

4. The random intercepts (u_{0j}) should be independent of any omitted school-level predictors. Since the intercept is not the focus of this research and only the fixed-effect coefficients are of interest, this assumption can be skipped, as it does not affect the fixed-effect estimates at the student level.

5. The student-level residuals are independent of the residual school effects (u_{0j}):

$$Cov(r_{ij}, u_{0j}) = 0 \tag{11}$$

6. The predictors at each level are not correlated with the random effects at the other level:

$$Cov(X_{qij}, u_{0j}) = 0 \tag{12}$$

$$Cov(r_{ij}, is_urban_j) = 0$$

Turning to another potential source of model misspecification, measurement error may arise from several sources in the specified model.

The student's real ability is not directly observable. To account for it, PISA does not report students' educational outcome as single point estimate but set of plausible values. The explanation provided by Adams and Wu (2002):

"It is very important to recognise that plausible values are not test scores and should not be treated as such. They are random numbers drawn from the distribution of scores that could be reasonably assigned to each individual."

To deal with the measurement error for dependent variable, PISA provides plausible values to correct the uncertainty in the test score. Therefore, it is important to use the estimation approach that account for plausible values.

As for independent variables, the measurement error can play different role for the level-1 and level-2 predictors. A lot of level-1 variables are self-reported and may contain measurement error. Such error can reduce the reliability of these measures and lead to attenuation bias in the estimated coefficients, as well as potentially larger standard errors. As for level-2 variables, one of them is school location (urban or rural), as it is directly observed, it would not add substantial bias. The second variable school-average ESCS may introduce measurement error, and it depends heavily on the number of students sampled per school.

3.7 Estimation method

As mentioned previously, PISA has complex two-stage sampling design. The students and schools are not selected at random, so to present the population, the weights should be added for schools and students. Balanced repeated replication (BRR) approach was used to create replicate weights for PISA observations (OECD 2024).

As mentioned earlier, students' educational outcomes are reported as a set of plausible values. In PISA 2022, students have 10 plausible values for each domain. Technically, according to OECD (2024), it implies that any analysis should be run 10 times and the results should be aggerated properly with accounting for replicate weights.

The modelling is done using specialized package for large-scale educational assessments *EdSurvey*. The well-known packages like lme4 that exist in R for MLM cannot be used with PISA data due to weights design and plausible values. The *EdSurvey* package also applies the appropriate PISA method for adjusting unscaled weights before fitting the multilevel (MLM) model, as failing to do so may result in biased estimates (Nguyen and Kelley 2018).

The *EdSurvey* package uses the estimation technique adapted for large-assessment educational surveys. It applies maximum likelihood estimation using adaptive quadrature for estimation (Nguyen and Kelley 2018). The package also correctly aggerates the results of regression for each plausible value using Rubin's rule for multiple imputation with accounting for replicate weights (American Institutes for Research, n.d.). Moreover, the EdSurvey package uses WeMix package for multi-level modelling which reports robust standard errors by default (Huang, 2024).

Chapter 4

DATA DESCRIPTION

The research is based on the results of the Programme for International Student Assessment (PISA) 2022. The dataset contains responses to students', schools', parents' and teachers' questionnaires. The survey was administered to 15-year-old students. In Ukraine, the PISA 2022 dataset was collected in October 2022, covering only for 18 regions[3] due to wartime restrictions (see Figure 3).

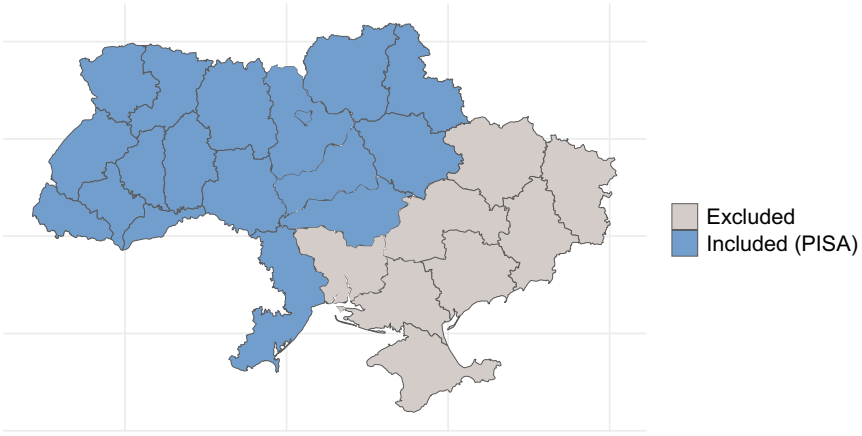


Figure 3. Ukrainian regions included in PISA 2022

Source: Author's own visualization based on PISA 2022 Database, Ukrainian Regions (OECD 2023a).

[3] The designation "Ukrainian regions (18 of 27)" refers to the 18 PISA-participating jurisdictions of Ukraine: Cherkasy Oblast, Kirovohrad Oblast, Poltava Oblast, Vinnytsia Oblast, Chernihiv Oblast, Kyiv Oblast, Sumy Oblast, the City of Kyiv, Zhytomyr Oblast, Odesa Oblast, Chernivtsi Oblast, Ivano-Frankivsk Oblast, Khmelnytskyi Oblast, Lviv Oblast, Rivne Oblast, Ternopil Oblast, Volyn Oblast and Zakarpattia Oblast (OECD 2023b)

Over 3,800 students from 164 schools participated in this survey in Ukraine. PISA 2022 took place in Ukraine only in educational institutions that had appropriate shelters or were located close to appropriate shelters (UCEQA 2023). Since the presence of a shelter was a prerequisite for in-person schooling, the sampled schools most likely operated in person.

Observations with missing values on the variables included in the model were excluded from the analysis. The educational outcomes that are presented as plausible values, contain no missing values. The number of missing values for independent variables are presented in the Table A1.

The majority of missing values are for the ICT use variables. After removing missing values, the sample for analysis contains 3196 observations.

4.1 Educational outcomes

For reporting student performance, PISA uses plausible values for scores for mathematics, reading, and science. The descriptive statistics shown in Table 3 are statistics for final estimates of scores that are calculated using plausible values.

Table 3. Descriptive statistics of mathematics, reading, science scores

Variable	Min.	Q1	Mean	Median	Q3	Max.	SD
Math	178.47	381.97	444.96	440.61	503.87	773.96	87.80
Reading	133.71	367.86	432.30	433.35	496.44	752.97	93.25
Science	153.04	392.08	455.95	453.70	519.57	754.74	89.99

4.2 Mobile phone ban

The binary variable indicating a mobile phone ban is constructed based on principals' responses to the school questionnaire. In the analytical sample, around 13.7% of students study at school with mobile phone bans (see Table 4).

Figure 4 show no statistically significant differences in average educational outcomes between schools with and without mobile phone bans.

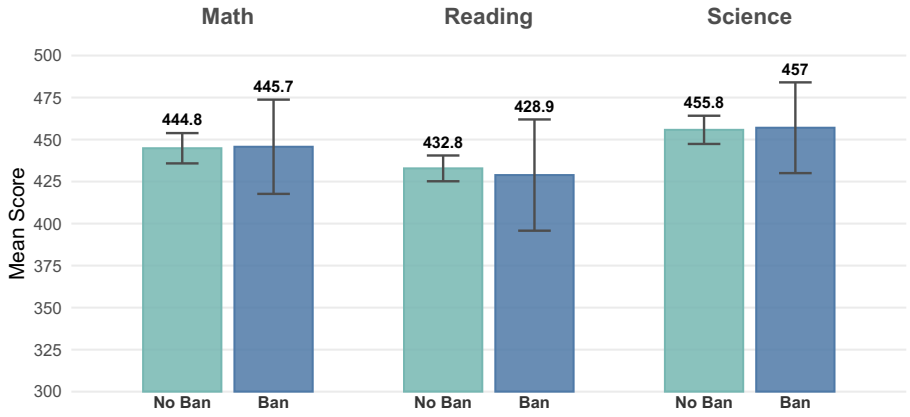


Figure 4. Weighted average scores in mathematics, reading, and science by mobile phone ban status

Source: Author's own visualization based on PISA 2022 Database, Ukrainian Regions (OECD 2023a).

Table 4. Descriptive statistics of mobile phone ban status

Mobile Phone Ban	**N**	**Weighted N**	**(%)**	**SE (%)**	**mean**	**SE (mean)**
0 (no ban)	472	18668.99	13.74	4.1	472	18667
1 (ban)	2724	117189.98	86.26	4.1	2724	117190

The sample consists of 160 schools, of which 26 report implementing a mobile phone ban. Since mobile phone bans are not randomly assigned across schools, it is useful to examine whether schools with and without bans differ in observable characteristics. Table 5 provides a descriptive comparison of school location and mobile phone ban status and Table 6 of school-average ESCS quartile and mobile phone ban status.

Table 5. Distribution of schools by mobile phone ban status and location

Mobile phone ban status	**School location**	**N**	**(%)**
1 (with ban)	rural	9	34.6%
	urban	17	65.4%
0 (without ban)	rural	51	38.1%
	urban	83	61.9%

Table 6. Distribution of schools by mobile phone ban status and school-average ESCS quartile

Mobile phone ban status	**ESCS quartile**	**N**	**(%)**
1 (with ban)	Q1	9	34.6%
	Q2	5	19.2%
	Q3	6	23.1%
	Q4	6	23.1%
0 (without ban)	Q1	38	28.4%
	Q2	41	30.6%
	Q3	24	17.9%
	Q4	31	23.1%

The distribution of mobile phone bans is relatively balanced across urban and rural schools (34.6% vs 38.1% rural share), suggesting limited systematic differences in school locations between schools with and without mobile phone ban.

The distribution of school socioeconomic status differs somewhat between schools with and without mobile phone bans. However, differences across quartiles are moderate, indicating that observable ESCS composition is broadly comparable between groups.

4.3 ICT use

Dataset contains students' responses about the following categories of ICT use:

1. At school for learning
2. At school for leisure
3. Outside of school for learning on weekday
4. Outside of school for learning on weekend
5. Outside of school for leisure on weekday
6. Outside of school for leisure on weekend

The item in questionnaire formulation is: This school year, about how many hours a day do you usually use <digital resources> in the following situations? The variable is measured in ordered categories from "None" to "More than 7 hours," with stepwise hourly intervals. The question contains also suggest thinking about different types of digital resources such as desktop computers, laptops and tablets as well as educational software and other digital learning tools.

In the model, the recoded variables are used, with response categories mapped into hours as follows: 'None' is coded as 0, 'Up to 1 hour' as 0.5, and subsequent categories are converted accordingly, up to 7.5.

These questionnaire items may have significant measurement errors. As students rarely monitor their digital activities precisely, it may be difficult for them to report the exact number of hours spent using ICT. As the number of hours increases, estimating usage with the same level of precision becomes more challenging, even though the response categories in the questionnaire increase in fixed one-hour intervals. The descriptive statistics is presented in the Table 7.

Table 7. Descriptive statistics of ICT use variables

ICT Use, hours	**Min.**	**Q1**	**Mean**	**Median**	**Q3**	**Max.**	**SD**
At School for Learning	0	0.5	3.0	2.5	5.5	7.5	2.4
At School for Leisure	0	0.5	1.6	1.5	2.5	7.5	1.7
Outside of School for Learning on Weekday	0	1.5	2.8	2.5	3.5	7.5	2.0
Outside of School for Learning on Weekend	0	0.5	2.4	2.5	3.5	7.5	2.1
Outside of School for Leisure on Weekday	0	0.5	2.8	2.5	4.5	7.5	2.2
Outside of School for Leisure on Weekend	0	1.5	3.8	3.5	6.5	7.5	2.6

The weighted percentage of students' responses is shown in Figure 5.

Hours if ICT use at school for learning has one peak at 0.5 and with minimum of students that specified 0 hours of usage at school (5.5%). The percentage of students that use ICT at school for learning from 3.5 to 7.5 hours are in range 6-10%. ICT use at school for leisure shows a single peak at 0.5 hours, with only a small proportion of students reporting more than five hours of use.

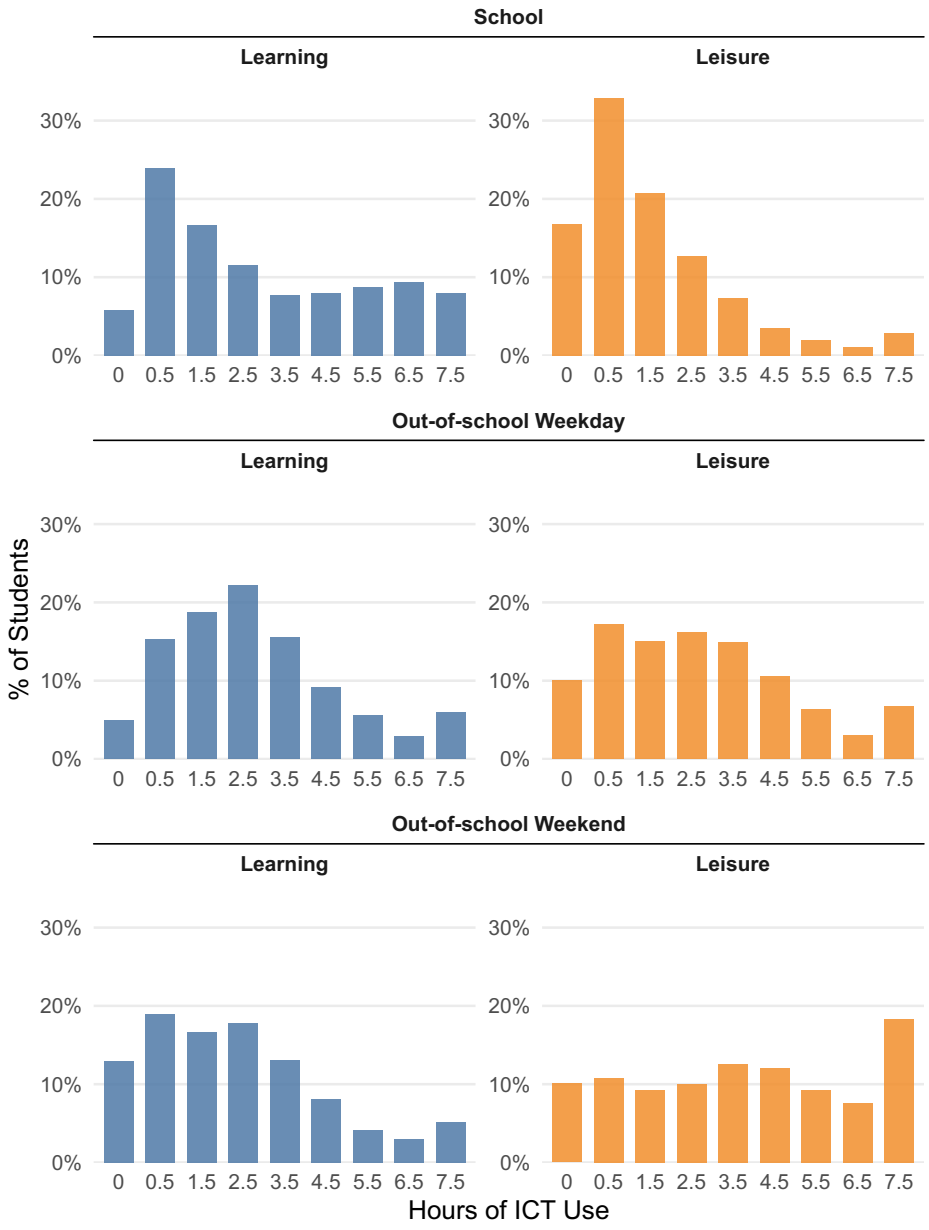


Figure 5. Distribution of students by ICT use type and intensity, weighted percentages

Source: Author's own visualization based on PISA 2022 Database (OECD 2023a)

The distribution of ICT use for learning on weekdays and weekends outside of school are similar with one big peak and smaller peak for 7.5 hours. The increase observed at 7.5 hours may be explained by the questionnaire item design, as the variable is right-censored at the upper category.

The students' percentage of ICT use for leisure outside of school both on weekend and weekdays are more evenly distributed with large peak on weekend at 7.5 hours. Overall, distributions of ICT use are not normal.

Variation in ICT use for learning within schools is substantial, which supports the assumption that schools predominantly rely on in-person teaching. Figure 6 shows that the majority of schools include both students who do not use or minimally use ICT at school for learning and students who are heavy ICT users.

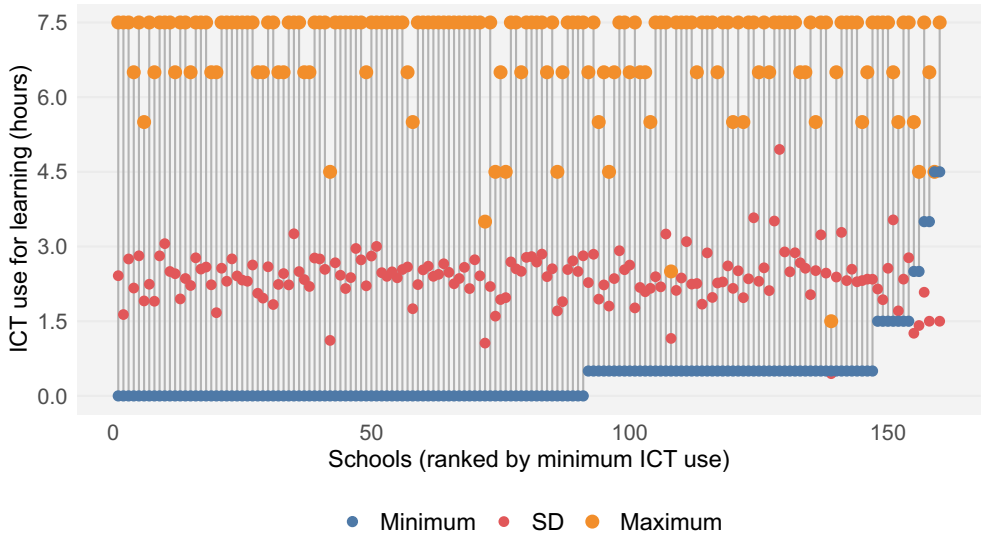


Figure 6. Variation in ICT use for learning across schools

Source: Author's own visualization based on PISA 2022 Database (OECD 2023a)

The weighted average scores by ICT use and subject are shown in Figure 7. The ICT use for different subjects have very similar behavior; it may indicate that effect of the ICT use is similar across the subjects.

The weighted average score peaks at 0.5 hours of ICT use for learning at school and then declines, reaching a minimum at 4.5 hours, and then shows signs of an increase, although the increase is relatively slow.

The distribution of the weighted average score by ICT use at school for leisure shows a sharp decrease starting from 0.5 hours, with a zigzag pattern at the end. These irregular fluctuations can be explained by a very small percentage of students reporting these higher numbers of hours.

For ICT use for learning outside of school, both on weekends and weekdays, the weighted average score exhibits an inverted U-shape pattern consistent with expectations. A similar pattern is observed for ICT use for leisure outside of school; however, the range associated with the highest scores is shifted to the right and displays a flatter ending on weekends, suggesting that higher-performing students engage in leisure ICT use more extensively, particularly on weekends.

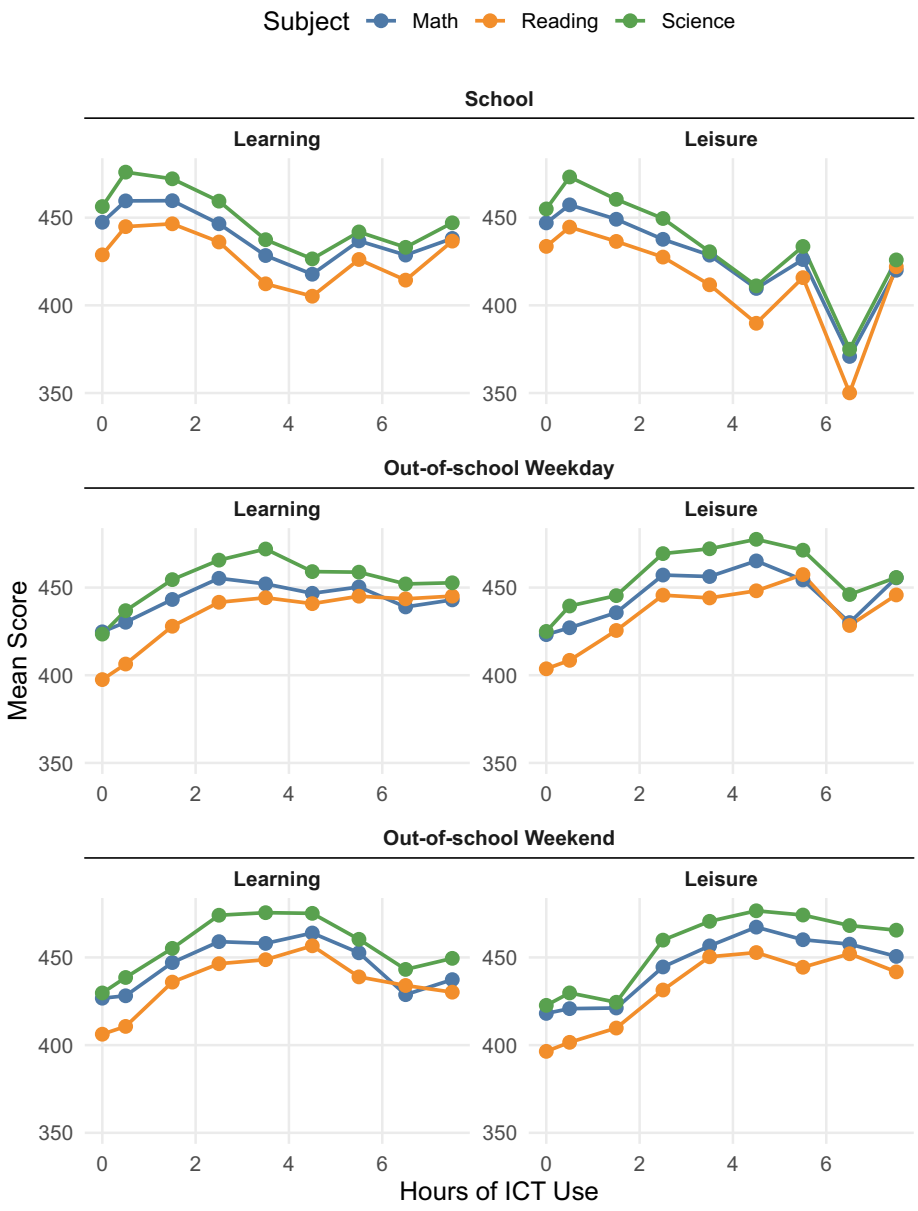


Figure 7. Weighted average score by ICT use intensity and subject

Source: Author's own visualization based on PISA 2022 Database (OECD 2023a)

4.4 PCA construction of ICT use outside of school

There are 4 variables for ICT use outside of school, they all have measurements errors. They are not variables of interest, and they are correlated. To reduce dimensionality, I apply Principal Component Analysis (PCA). The analysis starts from analyzing scatterplot matrix for the chosen variables. The correlation is highest between ICT use for leisure on weekend and weekday (0.65), following the pair of ICT variables for learning on weekend and weekday (0.52). All other pairs correlations are in range 0.26-0.3 (see Figure 8).

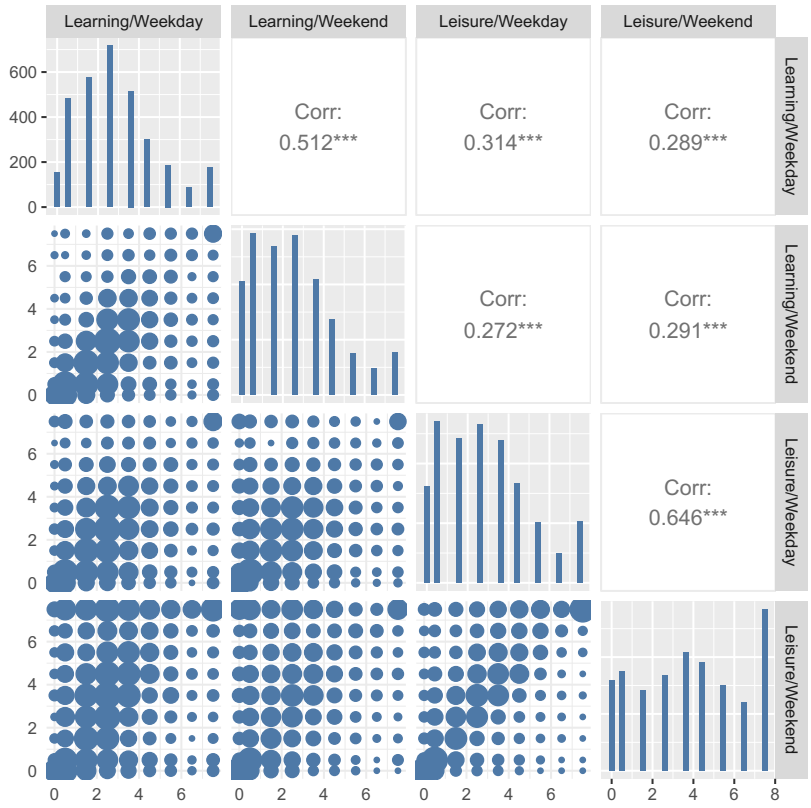


Figure 8. Scatterplot matrix of ICT Use for learning and leisure outside of school

Source: Author's own visualization based on PISA 2022 Database, Ukrainian Regions (OECD 2023a).

The next step is to check the appropriateness of the PCA by running Bartlett test and measure of sampling adequacy (MSA) (Hair et al. 2019). Bartlett's test of sphericity strongly rejects the null hypothesis of no correlation among variables ($\chi^2 = 3823.6$, $p < 0.001$), indicating that the data are suitable for principal component analysis. Kaiser-Meyer-Olkin factor adequacy estimates overall MSA as 0.63 that is categorized as mediocre but acceptable (Hair et al. 2019). Individual variables have MSA higher than 0.6.

The next step is deriving the principal components and deciding how many to use. Latent root tests suggest extracting two factors. The cumulative variance explained for two factors is ~79% that is acceptable for study in social sciences (Hair et al. 2019).

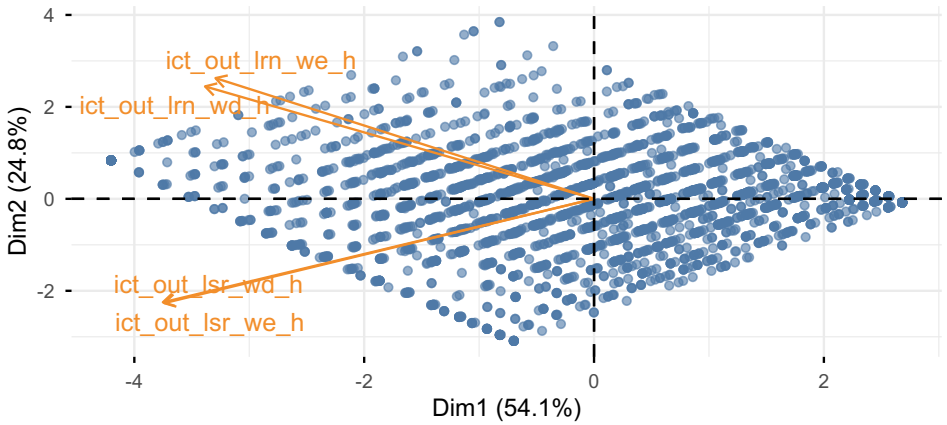


Figure 9. PCA biplot of ICT use outside of school

Source: Author's own visualization based on PISA 2022 Database, Ukrainian Regions (OECD 2023a).

The PCA biplot suggests that the first principal component reflects overall ICT use intensity outside of school, as all variables load in a similar direction. To

facilitate interpretation, the first principal component was standardized and its sign was reversed, so that higher values indicate greater ICT use intensity.

The second principal component appears to capture the balance between learning and leisure use, where negative values correspond to leisure-oriented use and positive values correspond to learning-oriented use. Descriptive statistics for the final variables are presented in Table 8.

Table 8. Descriptive statistics of PCA-constructed ICT use variables

Variable	Min.	Q1	Mean	Median	Q3	Max.	SD
ICT use intensity outside of school	-1.82	-0.73	0.00	-0.05	0.64	2.86	1.01
ICT use purpose outside of school	-3.09	-0.56	-0.01	0.05	0.57	3.85	1.00

Both ICT variables are standardized by construction. ICT use purpose outside of school demonstrates slightly greater variability than ICT use intensity outside of school, reflected in its wider minimum–maximum range. Median values close to zero suggest that both distributions are approximately centered around the average level.

4.5 Other control variables

Economic, social, and cultural status (ESCS) is a composite score derived from three indicators that reflect on parents' occupation, parents' education and household material possessions. According to OECD (2023c), "the final ESCS variable is standardised, so that 0 is the score of an average OECD student and

1 is the standard deviation across approximately equally weighted OECD countries."

ESCS should be used with caution for the Ukrainian sample, as it is derived from students' responses to questions about family material possessions, which could have changed recently due to internal displacement.

To focus on within-country socioeconomic differences, the ESCS index was standardized within the national sample to have a mean of zero and a standard deviation of one, using student sampling weights. Descriptive statistics are shown in Table 9.

School-average ESCS is included in the model as control variable to capture school socio-economic composition and peer effect. It is used as a control variable and is calculated as the average of all students within each school on full dataset and then standardized. The resulting school-level measure is then merged back to the student-level dataset. Descriptive statistics is shown in Table 9.

Table 9. Descriptive statistics of ESCS related variables

Variable	**Min.**	**Q1**	**Mean**	**Median**	**Q3**	**Max.**	**SD**
ESCS, nationally adjusted	-3.79	-0.70	0.04	0.08	0.82	4.78	0.99
School-average ESCS	-3.30	-0.99	-0.11	0.07	0.64	2.71	1.02

Gender. Descriptive statistics for gender show thar sample is roughly balanced by gender (see Table 10).

Table 10. Descriptive statistics of student gender

Gender	N	Weighted N	pct	SE (pct)	mean	SE (mean)
Female	1647	68720.56	50.58	1.63	438.66	4.10
Male	1549	67138.41	49.42	1.63	451.40	5.67

Institution-Grade Group. 15-year-old students study at different grades and different type of institutions. In this study, the institutions are divided into two big categories: schools and vocational schools/colleges. There are 3 possible grades for schoolers: Grade 9, Grade 10, Grade 11. Students in vocational schools/colleges (first and second year of study) are grouped together in PISA data as they are not mapped to international classification (*Ungraded*).

Majority of students are enrolled in schools, and among them most attend Grade 10 (see Table 11).

Table 11. Descriptive statistics of Institution-Grade pairs

Institution-Grade	N	Weighted N	pct	SE (pct)	mean	SE (mean)
School-Grade 9	94	3950.4	2.9	0.6	439.3	10.0
School-Grade 10	1866	77426.4	57.0	3.9	454.7	3.3
School-Grade 11	670	27460.8	20.2	1.7	458.3	4.3
Vocational schools/colleges (1-2 year)	566	27021.3	19.9	5.5	404.3	11.0

School Location. The rural–urban indicator was constructed from the stratum variable by collapsing its categories into urban and rural groups. In the analytic sample, around three quarters of students study at urban schools (see Table 12).

Table 12. Descriptive statistics of school location

School location	N	Weighted N	pct	SE (pct)	mean	SE (mean)
Rural	802	36708.15	27.02	2.16	408.93	5.94
Urban	2394	99150.82	72.98	2.16	458.29	5.38

Dataset contains also additional variables like subject motivation and perceived ease of subject that are used in robustness check models (see Table A2).

To summarize, the analytical sample contains 3196 observations. The includes a substantial share of students attending schools with mobile phone bans and exhibits variation in ICT use at school for both learning and leisure purposes.

Chapter 5

ESTIMATION RESULTS

This chapter consists of several parts following the model description in methodology section. Results of robustness checks are included in this chapter. It also has additional exploratory estimation results following the main findings.

5.1 Null models

The results of the null models are shown in Table 13. ICC is 32.9%, 32.3% and 29.9% for mathematics, reading and science score correspondingly. So, the between-school variation is about 30%, that means that around 30% of differences in educational outcomes can be attributed to schools and around 70% to individual students.

Table 13. Estimation results from null models for student outcomes

Statistic	**Math**	**Reading**	**Science**
Intercept	446.5 (4.7) ***	434.1 (5) ***	457.2 (4.8) ***
Between-School Variance	2533.8	2817.6	2443.1
Within-School Variance	5169.7	5904.2	5715.2
ICC	32.9%	32.3%	29.9%
Sample N (Schools)	160	160	160
Sample N (Students)	3196	3196	3196
Weighted N (Schools)	3808	3808	3808
Weighted N (Students)	135859	135859	135859

Note: Standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

High ICC justifies use of multi-level modelling.

5.2 Random intercept model with control variables

The models with control variables were estimated for all PISA domains. The estimation results serve as a baseline benchmark for comparison with models that include the variables of interest.

The outcome variables are measured in points. To better understand the magnitude of the association, we can consider the reference used by OECD (2023b): near 20 points gain over 1 year of schooling for students around age 15. This is an average pace that can differ considerably depending on country and domain.

The full estimation results are presented in Table 14 (Models 1, 3, and 5).

Adding control variables to the model substantially reduced between-school variance (around 70%) comparing to the null models, indicating important role of school composition in educational outcomes. Reduction in within-school variance is modest in comparison (3.8%-5.6%). This may be related to the fact that a lot of individual differences are not observed.

5.3 Random intercept model with mobile phone ban

The full estimation results are presented in Table 14 (Models 2, 4, and 6). The coefficients of control variables are in line with expectations and do not change significantly after adding mobile phone ban variable compared to models with control variables only (Models 1, 3, and 5).

Table 14. Estimation results from models with controls and mobile phone ban

	(1)	(2)	(3)	(4)	(5)	(6)
Statistic	**Math**		**Reading**		**Science**	
Fixed Effects						
Intercept	443.1 (11.5) ***	443.2 (11.6) ***	410.5 (12.7) ***	410.5 (12.7) ***	447.8 (12.3) ***	447.8 (12.3) ***
Mobile Phone Ban		1.3 (6.2)		-1.1 (6.3)		2.9 (6.6)
ESCS, Nationally Adjusted	13.7 (2.3) ***	13.7 (2.3) ***	14.9 (2.3) ***	14.9 (2.3) ***	14.4 (2.3) ***	14.4 (2.3) ***
Gender	20.8 (3.2) ***	20.8 (3.2) ***	-13.4 (3.7) ***	-13.4 (3.7) ***	9.8 (3.7) **	9.8 (3.7) **
School-Average ESCS	31.3 (3.8) ***	31.3 (3.8) ***	28.3 (3.8) ***	28.2 (3.9) ***	29.2 (3.8) ***	29.3 (3.8) ***
Urban school	3.6 (6.4)	3.5 (6.6)	14.8 (7.1) *	15 (7.3) *	6.6 (6.9)	6.3 (7)
Institution-Grade (ref: School-Grade 10)						
Vocational or college (Year 1–2)	-26.1 (7.7) ***	-25.9 (7.7) ***	-24 (8.4) **	-24.2 (8.4) **	-20.1 (7.8) **	-19.7 (7.7) *
School-Grade 9	-30.3 (10.5) **	-30.3 (10.5) **	-23.9 (11.5) *	-23.9 (11.5) *	-29.9 (10.5) **	-29.9 (10.5) **
School-Grade 11	11.7 (4.3) **	11.7 (4.3) **	10.1 (4.7) *	10.1 (4.7) *	9.5 (4.5) *	9.5 (4.5) *

Table 14. Estimation results from models with controls and mobile phone ban — Continued

	(1)	(2)	(3)	(4)	(5)	(6)
Statistic	**Math**		**Reading**		**Science**	
Random Effects						
Between-School Variance	693	692.2	852.8	852.7	762.1	760
Within-School Variance	4881	4881	5663.1	5663	5495.6	5495.7
Proportion Reduction in Between-School Variance	72.65%	72.68%	69.73%	69.74%	68.81%	68.89%
Proportion Reduction in Within-School Variance	5.59%	5.58%	4.08%	4.09%	3.84%	3.84%
ICC	12.4%	12.4%	13.1%	13.1%	12.2%	12.1%
Sample Size						
Sample N (Schools)	160	160	160	160	160	160
Sample N (Students)	3196	3196	3196	3196	3196	3196
Weighted N (Schools)	3808	3808	3808	3808	3808	3808
Weighted N (Students)	135859	135859	135859	135859	135859	135859

Note: Standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The coefficient for mobile phone ban policy is not statistically significant. Estimates are imprecise to draw conclusions (see Figure 10). The results provide no evidence that banning mobile phone use on school premises improves students' educational outcomes.

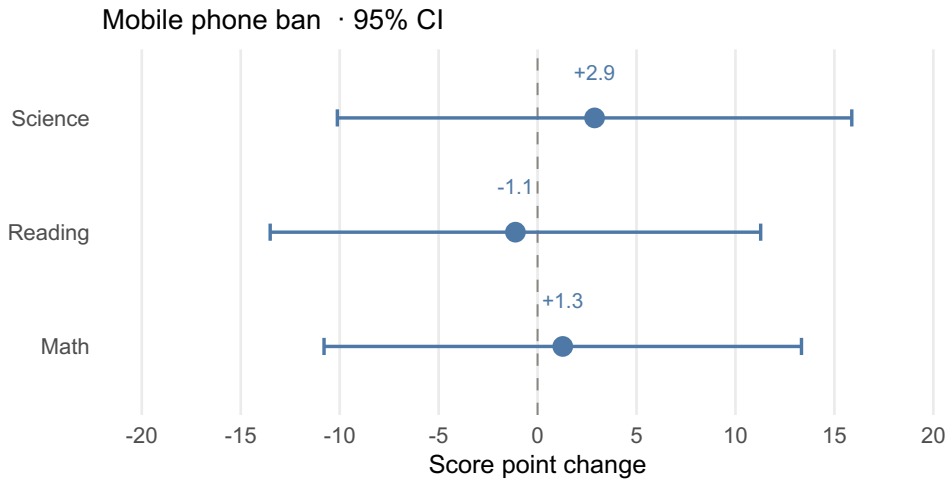


Figure 10. Estimated effect of mobile phone ban on PISA scores

Note: whiskers show 95% confidence intervals (±1.96 SE)

Source: Author's own visualization based on PISA 2022 Database, Ukrainian Regions (OECD 2023a).

5.4 Random intercept model with ICT variables

The estimation results of the model with ICT variables are presented in Table 15 (Models 2, 4, and 6). The sign and magnitude of the control variable coefficients remain largely the same as in the model with control variables only (Models 1, 3, and 5).

Hypotheses regarding the association between the ICT use at school for leisure and educational outcomes is supported by the data analysis (see Figure 11). Each additional hour of leisure at school is associated with a decrease around 7.2-9.4

points in educational outcomes across PISA domains. The coefficient is also practically meaningful, considering that the median ICT use for leisure at school is 1.5 hours. For a student with median ICT leisure use, this corresponds to an estimated decrease of approximately 10–14 points in educational achievement across subjects.

Similarly, hypotheses regarding the association between the ICT use at school for learning and educational outcomes is supported by the data analysis: each additional hour of learning using ICT at school is associated with an approximately 3.1-4.6 points decrease in scores across PISA domains. The coefficients are statistically significant. The coefficients are also practically meaningful, considering that the median ICT use for learning is 2.5 hours. For a student with median ICT use for learning, this corresponds to an estimated decrease of approximately 7.5-11.5 points in educational achievement across subjects.

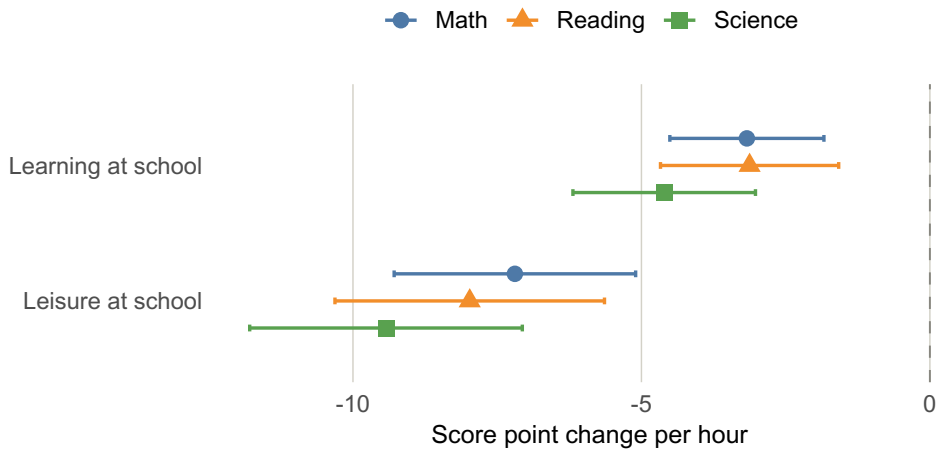


Figure 11. Estimated effect of ICT use at school on PISA scores

Note: whiskers show 95% confidence intervals (±1.96 SE)

Source: Author's own visualization based on PISA 2022 Database, Ukrainian Regions (OECD 2023a).

Table 15. Estimation results from models with controls and ICT use variables

	(1)	(2)	(3)	(4)	(5)	(6)
Statistic	**Math**		**Reading**		**Science**	
Fixed Effects						
Intercept	443.1 (11.5) ***	445.8 (11.1) ***	410.5 (12.7) ***	413.8 (12) ***	447.8 (12.3) ***	451.8 (11.6) ***
ICT Use						
For leisure at school, hours		-7.2 (1.1) ***		-8 (1.2) ***		-9.4 (1.2) ***
For learning at school, hours		-3.2 (0.7) ***		-3.1 (0.8) ***		-4.6 (0.8) ***
Intensity outside of school		13.7 (2) ***		18.9 (2.2) ***		19.1 (2.2) ***
Intensity outside of school, squared		-3.1 (1.2) *		-2.7 (1.3) *		-4.5 (1.2) ***
Purpose outside of school		-4.6 (1.8) *		-2.7 (1.9)		-3.3 (1.8)
ESCS, Nationally Adjusted	13.7 (2.3) ***	12.2 (2.2) ***	14.9 (2.3) ***	12.9 (2.2) ***	14.4 (2.3) ***	12.2 (2.2) ***
Gender	20.8 (3.2) ***	20 (3.1) ***	-13.4 (3.7) ***	-13 (3.5) ***	9.8 (3.7) **	9.4 (3.6) **
School-Average ESCS	31.3 (3.8) ***	28.6 (3.7) ***	28.3 (3.8) ***	25.1 (3.7) ***	29.2 (3.8) ***	25.4 (3.6) ***
Urban school	3.6 (6.4)	3.9 (6.2)	14.8 (7.1) *	14.6 (6.8) *	6.6 (6.9)	6.9 (6.6)

Table 15. Estimation results from models with controls and ICT use variables — Continued

	(1)	(2)	(3)	(4)	(5)	(6)
Statistic	**Math**		**Reading**		**Science**	
Fixed Effects						
Institution-Grade (ref: School-Grade 10)						
Vocational or college (Year 1–2)	-26.1 (7.7) ***	-25.4 (7.2) ***	-24 (8.4) **	-23.8 (7.8) **	-20.1 (7.8) **	-19.5 (7.2) **
School-Grade 9	-30.3 (10.5) **	-25.6 (10.2) *	-23.9 (11.5) *	-17.8 (10.8)	-29.9 (10.5) **	-23.7 (10.4) *
School-Grade 11	11.7 (4.3) **	11.1 (4.2) **	10.1 (4.7) *	9 (4.5) *	9.5 (4.5) *	8.5 (4.3) *
Random Effects						
Between-School Variance	693	652.9	852.8	764.1	762.1	678.1
Within-School Variance	4881	4602.1	5663.1	5322.5	5495.6	5004.5
Proportion Reduction in Between-School Variance	72.65%	74.23%	69.73%	72.88%	68.81%	72.24%
Proportion Reduction in Within-School Variance	5.59%	10.98%	4.08%	9.85%	3.84%	12.43%
ICC	12.4%	12.4%	13.1%	12.6%	12.2%	11.9%
Sample Size						
Sample N (Schools)	160	160	160	160	160	160
Sample N (Students)	3196	3196	3196	3196	3196	3196
Weighted N (Schools)	3808	3808	3808	3808	3808	3808
Weighted N (Students)	135859	135859	135859	135859	135859	135859

Note: Standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The predicted achievement difference between students reporting no ICT use and those reporting the heaviest use amounts to approximately 22.5-34.5 points, which corresponds to more than one year of learning according to OECD (2023b) benchmark.

ICT use intensity outside of school is positively associated with educational outcomes. 1 SD increase is associated with 13-20 increase in educational outcomes across domains. It is statistically and practically significant.

The negative squared term indicates that the relationship changes direction only at very high levels of ICT use intensity, suggesting that the inverted U-shape peaks beyond the range typical for most students. In contrast to ICT use at school, ICT use outside of school is positively associated with student learning outcomes.

The ICT use purpose is not significant or marginally significant in case of mathematics. There is no evidence that shift of ICT use outside of school toward learning is associated with better learning outcomes.

The proportion of reduction in within-school variances is increased notably, and the proportion of reduction in between-school variance is relatively small, indicating that ICT use variables capture mostly variation at the individual level, not school differences.

5.5 Robustness and sensitivity analyses.

To test our main models for robustness, I conduct similar model estimations while changing specification, and changing dataset excluding implausible data.

5.5.1 Random intercept model with mobile phone ban

To assess the robustness of the random intercept model estimates with mobile phone ban, the following checks were performed:

Check 1 (checking for heterogeneity). Drawing on evidence that mobile phone ban policies disproportionately benefit socioeconomically disadvantaged students (Beland and Murphy, 2016), the interaction term between mobile phone ban and ESCS quartile is introduced to examine whether the effect of ban policies on educational performance varies across the socioeconomic distribution. To avoid multicollinearity, the continuous ESCS measure included in the main model is replaced by ESCS quartiles.

Check 2 (adding control variables). To verify the robustness of the coefficients, the subject motivation and the perceived ease of subject are added in the model 2. They are well-known predictors of students' performance. They were not included in the main model because of additional substantial sample reduction due to missing values for these variables (from 3196 to around 2800, or nearly 12.5%).

The estimation results are presented in Table B1. The coefficient for mobile phone ban policy is not statistically significant across any models and PISA domains (see Figure 12). The robustness check confirms this result is stable, with no change in statistical significance. Furthermore, the interaction term between mobile phone ban and ESCS quartile are not statistically significant, there is no evidence the mobile phone ban on school premises benefits socioeconomically

disadvantaged students (Models 1, 3, and 5). Adding control variables do not provide new evidence of an effect of mobile phone bans (Model 2, 4, 6).

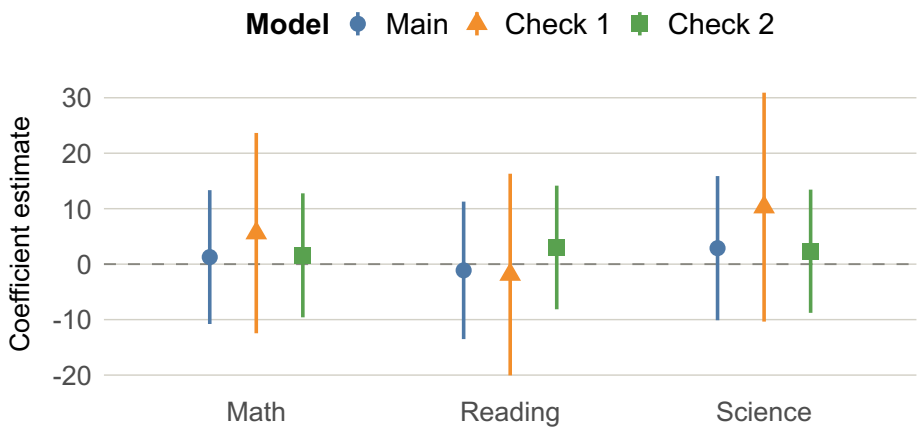


Figure 12. Robustness check: effect of mobile phone ban

Note: whiskers show ±1.96 SE. Estimates are horizontally dodged for clarity

Source: Author's own visualization based on PISA 2022 Database, Ukrainian Regions (OECD 2023a).

5.5.2 Random intercept model with ICT variables

To assess the robustness of the random intercept model estimates with ICT variables, the following checks were performed:

Check 1 (functional form). Based on the literature, the inverted U-shape relationship between educational outcomes and ICT use variables are probable. Therefore, the model 1 has functional form with added squared terms for ICT use at school for learning and for leisure.

Check 2 (PCA construction). As a robustness check, the main specification is estimated replacing the principal component measure of ICT use with the

disaggregated original ICT variables. This tests whether the results are sensitive to the construction approach.

Check 3 (outlier robustness check). Some students choose implausible values for ICT use categories when combined there are more than 12 hours of use at school, or more than 12 hours of use outside of school on weekdays. These observations from the analytical sample and check the robustness of coefficients.

Check 4 (adding control variables). To verify the robustness of the coefficients, the subject motivation and the perceived ease of subject are added in the model 4. They are well-known predictors of students' performance. They were not included in the main model because of additional substantial sample reduction due to missing values for these variables (from 3196 to around 2800, or nearly 12.5% reduction).

The estimation results are presented in Table B2, Table B3, and Table B4 for mathematics, reading and science, respectively. The results for robustness check 1 shows that the quadratic term for ICT use for learning at school is statistically significant for mathematics (at the 10% level), reading (at the 5% level), and science (at the 5% level). However, contrary to the hypothesized inverted U-shaped relationship, the results reveal a U-shaped relationship between ICT use for learning at school and student performance. The turning point is approximately at 4.1 hours[4] for mathematics, slightly less than 5.2 hours for reading, and 5.9 hours for science. The low-usage users have the highest achievement, the lowest predicted achievement are for the users at the turning point, the achievement partially

[4] The turning point was calculated using the centered variable and converted to the original scale by adding the grand mean (mean is approximately 3 hours).

recovered for the heavy users (higher than turning point). The predicted test score by ICT use for learning at school is presented in Figure 13.

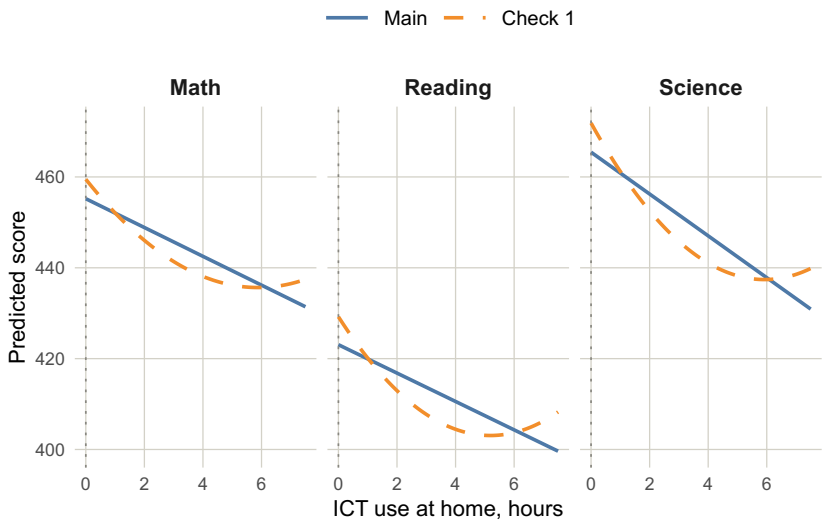


Figure 13. Predicted test score by ICT use for learning at school, robustness check for functional form

Source: Author's own visualization based on PISA 2022 Database, Ukrainian Regions (OECD 2023a).

The sign, magnitude and statistical significance of ICT use for learning at school did not change comparing to the main model for robustness checks 2-4 (see Table B2, Table B3, and Table B4). The coefficients for ICT use for learning at school with the confidence intervals for robustness checks 2-4 are presented in Figure 14.

The estimated coefficient for ICT use for leisure at school for checks 1-4 with the confidence intervals are presented in Figure 15.

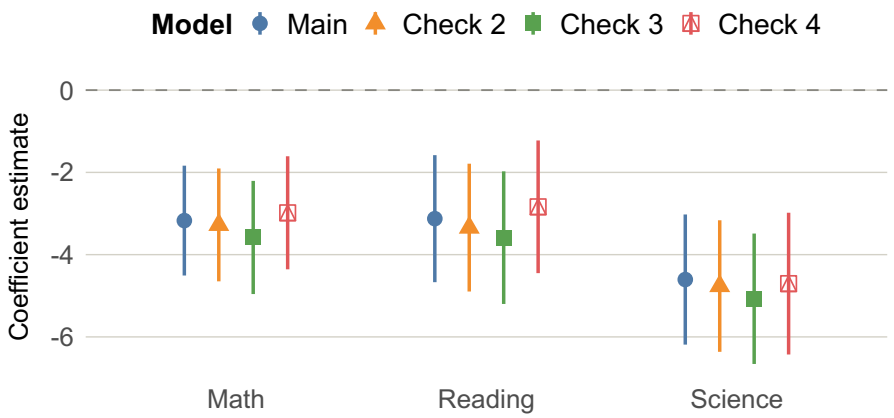


Figure 14. Robustness check: coefficient for ICT use for learning at school

Note: whiskers show ±1.96 SE. Estimates are horizontally dodged for clarity

Source: Author's own visualization based on PISA 2022 Database, Ukrainian Regions (OECD 2023a).

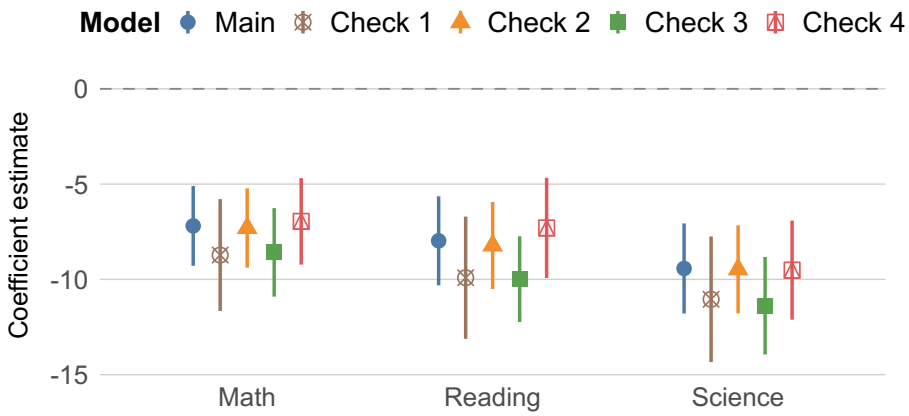


Figure 15. Robustness check: coefficient for ICT use for leisure at school

Note: whiskers show ±1.96 SE. Estimates are horizontally dodged for clarity

Source: Author's own visualization based on PISA 2022 Database, Ukrainian Regions (OECD 2023a).

The estimated results for robustness check 1 show that the quadratic term for ICT use for leisure at school is not statistically significant.

It is worth noting that removing implausible values (Check 3) makes the estimate even larger in magnitude across subjects and types of ICT use at school.

Overall, the estimation results show that coefficients for ICT use at school are stable across robustness checks: negative with similar magnitudes. This stability across specifications increases confidence that the negative association between ICT use at school and test scores reflects a systematic pattern rather than a modelling artefact.

5.6 Exploratory analysis

The study analysis show that using ICT for learning or leisure is negatively associated with educational outcomes, but mobile phone ban on school premises is not associated with any differences in educational outcomes. However, if the ban was enforced, we would expect the reduced time spent on ICT leisure at school. To be precise, the PISA questionnaire asks about leisure time in schools with digital devices. That means that leisure at school could be possibly spent using other devices. However, it is not typical for Ukrainian schools to have 1 device per student permanently, or all classrooms equipped with digital devices for each student. Therefore, mobile phones seem like the most obvious option for ICT leisure at school.

In the exploratory analysis, the first step is to examine what proportion of the variance in ICT use for leisure at school is explained by between-school differences and what proportion is explained by within-school differences. The results of null model shows that ICC is 4.6% (see Table 16).

Table 16. Estimation results from models for ICT use for leisure at school

	Null Model	**Model 1**	**Model 2**
Statistic	**ICT use for leisure at school**		
Fixed Effects			
Intercept	1.6 (0.04) ***	1.43 (0.19) ***	0.96 (0.19) ***
Mobile Phone Ban		-0.01 (0.1)	
ICT use for learning at school, hours			0.18 (0.02) ***
ESCS, Nationally Adjusted		0.02 (0.04)	0.02 (0.04)
Gender		-0.05 (0.09)	0.03 (0.08)
School-Average ESCS		-0.15 (0.06) **	-0.12 (0.05) *
Urban school		0.08 (0.12)	0.04 (0.11)
Institution-Grade (ref: School-Grade 10)			
Vocational or college (Year 1–2)		0.08 (0.15)	0.06 (0.13)
School-Grade 9		0.07 (0.22)	0.07 (0.21)
School-Grade 11		0.03 (0.09)	0.02 (0.09)
Random Effects			
Between-School Variance	0.14	0.12	0.1
Within-School Variance	2.9	2.9	2.71
ICC	4.6%	4.1%	3.6%
Sample Size			
Sample N (Schools)	160	160	160
Sample N (Students)	3196	3196	3196
Weighted N (Schools)	3808	3808	3808
Weighted N (Students)	135858.97	135858.97	135858.97

Note: Standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

It is borderline for the application of MLM. That means that between-school differences explain less than 5% in variance of ICT use for leisure at school.

Model 1 checks the relationship between mobile phone ban and ICT use for leisure at school. The coefficient for mobile phone ban policy is not practically or statistically significant (see Table 16). It indicates that mobile phone bans are either not enforced or students substituted the mobile phones with other personal devices like tablets or laptops. It might be partially explained by survey timing, as it was October 2022, 7 months into full-scale Russian invasion and school priorities might be shifted. However, it might suggest the absence of additional legal regulation that could help constrain mobile phone use in schools.

Model 2 shows the positive association between ICT use for learning and ICT use for leisure at school. Each additional hour spent on learning with ICT at school is associated with additional 10 minutes of ICT leisure. This may suggest that students find it difficult to avoid switching to ICT leisure activities when ICT is used for learning.

Chapter 6

CONCLUSIONS AND POLICY IMPLICATIONS

6.1 Conclusions

This study examines the association between different types of ICT use at school and educational outcomes in Ukraine, as well as the role of mobile phone bans in shaping these relationships among 15-year-olds. The research is based on data collected by PISA in 2022 and applies multi-level modelling.

The results show that ICT use at school for learning are associated with worse learning outcomes in the Ukrainian context, with effect sizes suggesting practical significance. Specifically, the predicted achievement difference between students reporting no ICT use and those reporting the heaviest use amounts for learning is equivalent to more than one full year of learning as defined by PISA benchmarks OECD (2023b). This finding remains robust across alternative model specifications.

The analysis demonstrates that ICT use at school for leisure has a negative relationship with educational outcomes in Ukraine. The estimated association across PISA domains is equivalent to approximately half a year of learning for a student with median ICT use at school for leisure. The results are stable across different model specifications.

The analysis does not provide statistical evidence of an association between mobile phone bans on school premises and students' educational outcomes. Robustness checks produced substantively similar results. Exploratory analysis does not provide evidence of an association between mobile phone bans and reduced ICT use for leisure at school. Possible interpretations are that bans may not be fully

enforced in practice, or that students may substitute mobile phone use with other digital devices during school hours.

The main limitation of the study is that it is based on cross-sectional data. So, the findings should be interpreted as correlational rather than causal.

6.2 Policy implications

Now, there is no nationwide policy on restricting use of digital devices on school premises in Ukraine. In comparison, UNESCO Global Education Monitoring Report team (2026) reports that "14 education systems now have a national ban on mobile phones in schools, representing 58% of countries worldwide", as of March 2026. Among the main reasons for introducing restrictions are not only concern about educational outcomes but also mental health and well-being of students, particularly decrease in cyberbullying behavior.

In Ukraine, decisions regarding mobile phone restrictions might be currently made at the school level, without supporting national legislation or ministerial guidance from the Ministry of Education (Mezha.net 2026).

As the current study indicates that the estimated negative association between ICT use and achievement is substantial in magnitude in Ukraine, and given that mobile phone bans are either not consistently enforced or may be substituted by the use of other digital devices, it is recommended to develop a nationwide policy on restricting digital device use on school premises in Ukraine. The following considerations must be taken into account:

1. For policy success, it is important to make the process iterative and involve school communities, parents, students into decision making and discussion of proposed solutions. European Commission: Directorate-General for Education, Youth, Sport and Culture (2026) recommends the consultative approach applied

in France and Sweden that used pilot projects, iterative stakeholder feedback and iterative refinement to develop and implement the policy.

2. For Ukrainian national policy on digital devices restrictions on school premises is mandatory to account for physical safety during wartime. Rather than allowing security concerns to delay policy development, authorities should conduct a systematic assessment of storage solutions, such as classroom storage versus personal bags, and provide clear safety guidelines to schools.

3. The introduction of mobile phone restrictions in Ukrainian schools requires a supporting legal framework, a concern explicitly raised by the representatives of school principals and teaching staff (Educational Ombudsman Service of Ukraine 2023). Case studies from Sweden and France show that legislative changes were implemented to strengthen schools' authority to enforce mobile phone bans, including clarifications regarding whether teachers have the right to confiscate mobile phones and legal restrictions on phone use on school premises (European Commission: Directorate-General for Education, Youth, Sport and Culture 2026).

4. The policy should include restrictions not only for personal smartphones but also other digital devices to avoid substitution effect: European Commission: Directorate-General for Education, Youth, Sport and Culture (2026) finds that when policies cover only one type of digital devices students might use other digital devices at school for leisure like tablets or laptops.

5. One of the additional policy measures is to prioritize solving the issue with delays and shortages of printed textbooks that are reported during recent years in Ukraine. Using PDFs and online textbooks leads to forced ICT use at school.

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APPENDIX A. ADDITIONAL DESCRIPTIVE STATISTICS

Table A1. Missing values for independent variables

Variable	**Missing Count**
Mobile Phone Ban on School Premises	0
ICT Use at School for Learning (hours)	437
ICT Use at School for Leisure (hours)	551
ICT Use Outside of School for Learning on Weekday (hours)	501
ICT Use Outside of School for Learning on Weekend (hours)	516
ICT Use Outside of School for Leisure on Weekday (hours)	550
ICT Use Outside of School for Leisure on Weekend (hours)	541
Gender	0
Grade	1
ESCS (Socioeconomic Status) Nationally Adjusted	201
School-Average ESCS	12
School in Urban Area	0

Note. Missing values include both unassigned entries and responses marked as *No Response*.

The following table presents descriptive statistics for variables used in robustness checks, including measures of student motivation and perceived ease of subjects. These variables are not included in the baseline specification.

Table A2. Descriptive statistics of perceived ease and subject motivation

Variable	**re-sponse**	**N**	**Wtd_N**	**(%)**	**SE(%)**	**mean**	**SE (mean)**
Mathematics is easy	SD	555	23495.9	21.3	1.2	424.9	4.7
	D	1144	48765.2	44.1	1.3	441.6	4.0
	A	698	30032.0	27.2	1.3	474.5	6.1
	SA	199	8212.3	7.4	0.5	503.1	10.8
Motivated in mathematics	SD	257	11301.8	10.2	0.9	422.5	6.5
	D	550	23720.8	21.5	1.2	430.3	5.3
	A	1272	53789.7	48.7	1.1	453.7	4.2
	SA	517	21693.2	19.6	1.0	484.5	7.0
Reading is easy	SD	185	8362.3	7.6	0.5	433.0	8.1
	D	609	25728.8	23.3	0.9	451.4	5.6
	A	1482	63174.2	57.2	1.1	451.8	4.7
	SA	320	13240.3	12.0	0.7	462.2	6.7
Motivated in reading	SD	162	7457.1	6.7	0.7	420.8	8.3
	D	431	18468.7	16.7	1.1	443.5	7.2
	A	1431	61269.5	55.4	1.1	452.4	4.1
	SA	572	23310.2	21.1	1.1	465.5	5.8
Science is easy	SD	301	12539.2	11.3	0.9	436.3	6.7
	D	1065	44085.6	39.9	1.3	449.5	4.6
	A	1007	44175.2	40.0	1.2	454.8	5.3
	SA	223	9705.5	8.8	0.7	465.5	9.6
Motivated in science	SD	229	9910.8	9.0	0.7	430.9	7.0
	D	552	23247.7	21.0	1.0	444.7	5.7
	A	1327	56802.7	51.4	0.9	450.4	4.3
	SA	488	20544.3	18.6	0.9	472.3	6.9

Note: SD = Strongly disagree; D = Disagree; A = Agree; SA = Strongly agree.

APPENDIX B. ROBUSTNESS CHECKS

Table B1. Robustness check: estimation results from models with mobile phone bans

	(1)	(2)	(3)	(4)	(5)	(6)
Statistic	**Mathematics**		**Reading**		**Science**	
Fixed Effects						
Intercept	429 (11.9) ***	412.2 (12.3) ***	395.1 (12.9) ***	416.4 (13.8) ***	433.3 (12.7) ***	426.4 (12.4) ***
Mobile Phone Ban	5.6 (9.2)	1.6 (5.7)	-1.9 (9.3)	3 (5.7)	10.3 (10.5)	2.3 (5.7)
ESCS Quartile (ref: Q1 - Lowest SES)						
Q2	7.5 (5.3)		7.9 (6.2)		9.4 (5.8)	
Q3	21 (5.3) ***		25.2 (6) ***		22.8 (5.9) ***	
Q4	32.7 (6) ***		33 (6.9) ***		32.9 (6.6) ***	
Mobile Phone Ban × SES Quartile Interactions (ref: No Ban, Q1 - Lowest SES)						
Ban*Q2	-10.7 (9.1)		-1.5 (12.2)		-16.7 (11.1)	
Ban*Q3	-15.1 (10.4)		-10.3 (12)		-17.4 (13.2)	
Ban*Q4	7.4 (11.1)		13.8 (13.3)		3.8 (12.5)	
ESCS, Nationally Adjusted	11.7 (6)	11.1 (2.3) ***	14.9 (5.9) *	13 (2.3) ***	16.4 (6.1) **	11.1 (2.3) ***
Gender	20.9 (3.2) ***	21.7 (3.5) ***	-13.3 (3.7) ***	25.4 (3.7) ***	10 (3.7) **	23.6 (3.6) ***

Table B1. Robustness check: estimation results from models with mobile phone bans - Continued

	(1)	(2)	(3)	(4)	(5)	(6)
Statistic	**Mathematics**		**Reading**		**Science**	
School-Average ESCS	32.2 (3.8) ***	29.2 (3.5) ***	29.2 (3.9) ***	30.5 (3.8) ***	30.6 (3.8) ***	30.9 (3.6) ***
Urban school	3.6 (6.8)	7.1 (6.5)	15.1 (7.5) *	3.5 (6.6)	6.1 (7.2)	3.4 (6.4)
ESCS, Nationally Adjusted		11.1 (2.3) ***		13 (2.3) ***		13 (2.3) ***
Perceived ease of subject (ref: SD) *						
D		12.1 (4.3) **		18.3 (7.6) *		12.4 (5.3) *
A		32.4 (5.7) ***		16.2 (7.8) *		14.4 (5.9) *
SA		40.3 (8.7) ***		16.2 (9.1)		11.3 (8.4)
Subject Motivation (ref: SD) *						
D		1.1 (6.8)		8 (9.8)		3.1 (6.5)
A		10.9 (6.4)		14.1 (8.7)		7.6 (7)
SA		23.8 (7.2) **		19.6 (9.2) *		16.7 (8.2) *
Institution-Grade (ref: School-Grade 10)						
Vocational or college (Year 1–2)	-25.9 (7.8) ***	-24.4 (7.6) **	-24.2 (8.4) **	-24.4 (7.6) **	-19.5 (7.7) *	-25.1 (7.5) ***
School-Grade 9	-31.8 (10.5) **	-29.7 (11.8) *	-25.4 (11.6) *	-29.7 (11.7) *	-31.4 (10.6) **	-29.5 (11.7) *
School-Grade 11	11.7 (4.3) **	14.3 (4.5) **	10.2 (4.7) *	12.7 (4.7) **	9.5 (4.5) *	13 (4.7) **

Table B1. Robustness check: estimation results from models with mobile phone bans - Continued

	(1)	(2)	(3)	(4)	(5)	(6)
Statistic	**Mathematics**		**Reading**		**Science**	
Random Effects						
Between-School Variance	682.9	596.8	854.1	641.1	749.6	628.6
Within-School Variance	4879.1	4701.1	5669.1	4893.2	5508.1	4897.9
ICC	12.3%	11.3%	13.1%	11.6%	12.0%	11.4%
Sample Size						
Sample N (Schools)	160	159	160	159	160	159
Sample N (Students)	3196	2784	3196	2813	3196	2818
Weighted N (Schools)	3808	3795	3808	3795	3808	3795
Weighted N (Students)	135859	118521.3	135859	119950.7	135859	120038.6

Note: Standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

* SD = Strongly disagree; D = Disagree; A = Agree; SA = Strongly agree

Table B2. Robustness check: estimation results from models for ICT use variables (mathematics)

Statistic	Baseline	Check 1	Check 2	Check 3	Check 4
	Mathematics				
Fixed Effects					
Intercept	445.8 (11.1) ***	441.5 (11.1) ***	442.7 (11.2) ***	448 (11.2) ***	438 (12.4) ***
ICT Use					
For leisure at school, hours	-7.2 (1.1) ***	-8.7 (1.5) ***	-7.3 (1.1) ***	-8.6 (1.2) ***	-7 (1.2) ***
For leisure at school, squared (hours^2)		0.6 (0.4)			
For learning at school, hours	-3.2 (0.7) ***	-4 (0.8) ***	-3.3 (0.7) ***	-3.6 (0.7) ***	-3 (0.7) ***
For learning at school, squared(hours^2)		0.7 (0.3) *			
Intensity outside of school	13.7 (2) ***	14.2 (2) ***		14.7 (2.1) ***	13.5 (1.9) ***
Intensity outside of school, squared	-3.1 (1.2) *	-4.1 (1.3) **		-5 (1.6) **	-3.5 (1.3) **
Purpose outside of school	-4.6 (1.8) *	-4.4 (1.8) *		-4.6 (1.9) *	-4.8 (1.8) **
For learning on weekend out-side of school, hours			0.4 (0.9)		
For learning on weekdays out-side of school, hours			0.8 (0.9)		
For leisure on weekend out-side of school, hours			3.4 (0.8) ***		
For leisure on weekdays out-side of school, hours			2.4 (1) *		

Table B2. Robustness check: estimation results from models for ICT use variables (mathematics) - Continued

Statistic	Baseline	Check 1	Check 2	Check 3	Check 4
	Mathematics				
ESCS, Nationally Adjusted	12.2 (2.2) ***	12.2 (2.2) ***	12.6 (2.2) ***	12.5 (2.2) ***	9.6 (2.2) ***
Gender	20 (3.1) ***	19.9 (3.1) ***	19.5 (3.1) ***	20.1 (3.3) ***	20.4 (3.4) ***
School-Average ESCS	28.6 (3.7) ***	28.6 (3.7) ***	28.7 (3.7) ***	28.7 (3.8) ***	26.8 (3.4) ***
Urban school	3.9 (6.2)	3.4 (6.3)	3.9 (6.3)	3.5 (6.3)	7.5 (6.2)
Perceived ease of subject(ref: SD) *					
D					11.5 (4) **
A					32.6 (5.5) ***
SA					39.8 (8.3) ***
Subject Motivation (ref: SD) *					
D					0.3 (7)
A					8 (6.3)
SA					19.1 (7.3) **
Institution-Grade (ref: School-Grade 10)					
Vocational or college (Year 1–2)	-25.4 (7.2) ***	-24.7 (7.2) ***	-25.5 (7.3) ***	-24.6 (7.5) **	-23.8 (7.1) ***
School-Grade 9	-25.6 (10.2) *	-25.6 (10.2) *	-25.9 (10.2) *	-25.5 (10.4) *	-25.1 (11.2) *
School-Grade 11	11.1 (4.2) **	11.3 (4.2) **	11.2 (4.2) **	11.5 (4.2) **	13.6 (4.5) **

Table B2. Robustness check: estimation results from models for ICT use variables (mathematics) - Continued

Statistic	Baseline Model	Check 1	Check 2	Check 3	Check 4
	Mathematics				
Random Effects					
Between-School Variance	652.9	645.3	657.4	660.7	561.4
Within-School Variance	4602.1	4585.5	4614.6	4590.7	4432.1
Proportion Reduction in Between-School Variance	74.23%	74.53%	74.06%	73.92%	77.84%
Proportion Reduction in Within-School Variance	10.98%	11.30%	10.74%	11.20%	14.27%
ICC	12.4%	12.3%	12.5%	12.6%	11.2%
Sample Size					
Sample N (Schools)	160	160	160	160	159
Sample N (Students)	3196	3196	3196	3037	2784
Weighted N (Schools)	3808	3808	3808	3808	3795
Weighted N (Students)	135859	135859	135859	128364.9	118521.3

Note: Standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

* SD = Strongly disagree; D = Disagree; A = Agree; SA = Strongly agree

Table B3. Robustness check: estimation results from models for ICT use variables (reading)

Statistic	Baseline	Check 1	Check 2	Check 3	Check 4
	Reading				
Fixed Effects					
Intercept	413.8 (12) ***	407.9 (12) ***	411.3 (12) ***	418.9 (11.5) ***	394.5 (15.1) ***
ICT Variables					
For leisure at school, hours	-8 (1.2) ***	-9.9 (1.6) ***	-8.2 (1.2) ***	-10 (1.1) ***	-7.3 (1.3) ***
For leisure at school, squared (hours^2)		0.7 (0.6)			
For learning at school, hours	-3.1 (0.8) ***	-4.3 (0.9) ***	-3.3 (0.8) ***	-3.6 (0.8) ***	-2.8 (0.8) ***
For learning at school, squared(hours^2)		1 (0.4) **			
Intensity outside of school	18.9 (2.2) ***	19.5 (2.2) ***		20.1 (2.4) ***	17.3 (2.4) ***
Intensity outside of school, squared	-2.7 (1.3) *	-4.1 (1.4) **		-5.5 (2) **	-2.3 (1.4)
Purpose outside of school	-2.7 (1.9)	-2.5 (1.9)		-2.9 (1.9)	-3 (1.9)
For learning on weekend out-side of school, hours			0.6 (0.9)		
For learning on weekdays out-side of school, hours			3.5 (1.1) **		
For leisure on weekend out-side of school, hours			3.3 (0.9) ***		
For leisure on weekdays out-side of school, hours			3.4 (1.1) **		

Table B3. Robustness check: estimation results from models for ICT use variables (reading) - Continued

Statistic	Baseline	Check 1	Check 2	Check 3	Check 4
	Reading				
ESCS, Nationally Adjusted	12.9 (2.2) ***	12.9 (2.2) ***	13.3 (2.2) ***	12.9 (2.3) ***	11.2 (2.4) ***
Gender	-13 (3.5) ***	-13.2 (3.5) ***	-13.5 (3.5) ***	-11.9 (3.5) ***	-7.2 (3.6) *
School-Average ESCS	25.1 (3.7) ***	25.1 (3.6) ***	25.2 (3.7) ***	25.6 (3.8) ***	24 (3.8) ***
Urban school	14.6 (6.8) *	14 (6.9) *	14.4 (6.8) *	12.7 (6.6)	15.1 (6.6) *
Perceived ease of subject (ref: SD) *					
D					18.3 (8.8) *
A					24.6 (8.3) **
SA					28.8 (8.9) **
Subject Motivation (ref: SD) *					
D					9.6 (10.8)
A					21.8 (9) *
SA					30.3 (10.6) **
Institution-Grade (ref: School-Grade 10)					
Vocational or college (Year 1–2)	-23.8 (7.8) **	-22.7 (7.8) **	-23.8 (8) **	-22.5 (7.6) **	-23.9 (7.7) **
School-Grade 9	-17.8 (10.8)	-17.6 (10.8)	-17.8 (10.7)	-14.9 (10.9)	-15.9 (12.1)
School-Grade 11	9 (4.5) *	9.3 (4.5) *	9.2 (4.5) *	9.7 (4.6) *	8.4 (4.7)

Table B3. Robustness check: estimation results from models for ICT use variables (reading) - Continued

Statistic	Baseline	Check 1	Check 2	Check 3	Check 4
	Reading				
Random Effects					
Between-School Variance	764.1	753.4	763.8	736.7	744.1
Within-School Variance	5322.5	5291.1	5327.4	5264.9	5266
ICC	12.6%	12.5%	12.5%	12.3%	12.4%
Sample Size					
Sample N (Schools)	160	160	160	160	159
Sample N (Students)	3196	3196	3196	3037	2813
Weighted N (Schools)	3808	3808	3808	3808	3795
Weighted N (Students)	135859	135859	135859	128364.9	119950.7

Note: Standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

* SD = Strongly disagree; D = Disagree; A = Agree; SA = Strongly agree

Table B4. Robustness check: estimation results from models for ICT use variables (science)

Statistic	Baseline	Check 1	Check 2	Check 3	Check 4
	Science				
Fixed Effects					
Intercept	451.8 (11.6) ***	446 (11.6) ***	447.1 (11.7) ***	453 (11.8) ***	459.2 (12.6) ***
ICT Variables					
For leisure at school, hours	-9.4 (1.2) ***	-11 (1.7) ***	-9.5 (1.2) ***	-11.4 (1.3) ***	-9.5 (1.3) ***
For leisure at school, squared (hours^2)		0.6 (0.4)			
For learning at school, hours	-4.6 (0.8) ***	-5.8 (0.9) ***	-4.8 (0.8) ***	-5.1 (0.8) ***	-4.7 (0.9) ***
For learning at school, squared(hours^2)		1 (0.3) **			
Intensity outside of school	19.1 (2.2) ***	19.7 (2.2) ***		20.5 (2.3) ***	19.1 (2.2) ***
Intensity outside of school, squared	-4.5 (1.2) ***	-5.7 (1.3) ***		-6.8 (1.6) ***	-4.7 (1.4) ***
Purpose outside of school	-3.3 (1.8)	-3.1 (1.9)		-3.4 (1.9)	-3.2 (1.9)
For learning on weekend outside of school, hours			1.5 (1.1)		
For learning on weekdays outside of school, hours			1.9 (1)		
For leisure on weekend outside of school, hours			4.5 (0.9) ***		
For leisure on weekdays outside of school, hours			2.2 (1.1) *		

Table B4. Robustness check: estimation results from models for ICT use variables (science) - Continued

Statistic	Baseline	Check 1	Check 2	Check 3	Check 4
	Science				
Perceived ease of subject (ref: SD) *					
D					12.3 (5.7) *
A					22.1 (6.1) ***
SA					8.4 (8.2)
Subject Motivation (ref: SD) *					
D					1.4 (5.7)
A					7.9 (6.1)
SA					17.2 (7.4) *
ESCS, Nationally Adjusted	12.2 (2.2) ***	12.2 (2.2) ***	12.8 (2.2) ***	12.8 (2.3) ***	11.1 (2.3) ***
Gender	9.4 (3.6) **	9.2 (3.6) **	8.8 (3.6) *	9.7 (3.8) *	11.6 (3.8) **
School-Average ESCS	25.4 (3.6) ***	25.5 (3.6) ***	25.6 (3.6) ***	25.2 (3.7) ***	24.8 (3.5) ***
Urban school	6.9 (6.6)	6.3 (6.6)	7 (6.6)	7.2 (6.7)	8.5 (6.3)
Institution-Grade (ref: School-Grade 10)					
Vocational or college (Year 1–2)	-19.5 (7.2) **	-18.4 (7.2) *	-19.5 (7.3) **	-19 (7.5) *	-18.8 (6.9) **
School-Grade 9	-23.7 (10.4) *	-23.5 (10.3) *	-24.1 (10.4) *	-23.2 (10) *	-24.9 (11) *
School-Grade 11	8.5 (4.3) *	8.8 (4.3) *	8.7 (4.3) *	9.3 (4.3) *	10 (4.6) *

Table B4. Robustness check: estimation results from models for ICT use variables (science) - Continued

Statistic	Baseline	Check 1	Check 2	Check 3	Check 4
	Science				
Random Effects					
Between-School Variance	678.1	667.2	681.2	685.4	600.5
Within-School Variance	5004.5	4976.3	5029	4986.7	4965.7
ICC	11.9%	11.8%	11.9%	12.1%	10.8%
Sample Size					
Sample N (Schools)	160	160	160	160	159
Sample N (Students)	3196	3196	3196	3037	2818
Weighted N (Schools)	3808	3808	3808	3808	3795
Weighted N (Students)	135859	135859	135859	128364.9	120038.6

Note: * SD = Strongly disagree; D = Disagree; A = Agree; SA = Strongly agree