

Beyond limit versus no limit: parental screen-time rule type and assessed digital competence across 29 education systems in ICILS 2023

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Abstract

Background.

Parental screen-time rules are usually recorded as present or absent. ICILS 2023 separates limits that include time spent on schoolwork from limits that exempt it, but the international report analysed the item as a binary contrast between having a limit and having none. This study asks what that collapse conceals.

Methods.

We analysed public-use student files for 100,528 grade 8 students in 29 education systems. Models were estimated within each system using five plausible values, final student weights, and 75 jackknife replicate weights applied to every plausible value, adjusting for socioeconomic background, gender, test language spoken at home, and immigrant background. Estimates were synthesised by random-effects meta-analysis, with restricted maximum likelihood estimation, a Hartung-Knapp correction and prediction intervals as sensitivity analyses. The binary coding was fitted to the same sample, and the two learning-setting scales were compared through a difference-score model.

Results.

Students reporting schoolwork-inclusive limits scored 24.9 points lower in computer and information literacy than students reporting schoolwork-exempt limits (95% CI [-28.2, -21.6]). The contrast was negative and statistically significant in all 29 systems, and it replicated on computational thinking in the 19 systems administering that assessment (-32.9 points, 95% CI [-38.1, -27.7]). Fitted to the same sample, the binary coding gave - 8.6 points for any limit versus no limit (95% CI [-11.8, -5.5]), one third the size of the disaggregated contrast and with higher between-system heterogeneity. Students reporting no limit differed from those reporting schoolwork-exempt limits by -0.4 points (95% CI [-3.2, 2.3]), meeting the equivalence criterion at the pooled level, although system-specific differences varied substantially. The association was larger for learning reported outside school than at school (contrast - 0.53 points, 95% CI [-0.77, -0.29]).

Conclusions.

Distinguishing reported rule types revealed patterns obscured by binary coding of rule presence. The findings demonstrate the value of preserving substantively meaningful response categories in international assessment questionnaires. The estimates are associational: the data are cross-sectional and rule type is student-reported.

1. Introduction

Guidance to parents about adolescent screen time is framed largely in terms of quantity: how many hours, and whether a ceiling is imposed. Research has followed the same emphasis. Evidence relating total screen exposure to sleep, wellbeing and academic achievement yields small pooled associations that are sensitive to how exposure is measured (Adelantado-Renau et al., 2019; Marciano & Camerini, 2021), and survey instruments typically represent restriction through the presence, duration or strictness of a limit.

Restrictions also differ in what they cover. Two households may set an identical two-hour ceiling and still differ in whether homework falls inside it. Conceptually, the activities included in a rule can be distinguished from whether a rule exists and how strictly it is applied, and this coverage is seldom represented as a separate survey dimension. The distinction carries practical weight because adolescents now do much of their formal learning on screens: a rule that treats an hour of homework and an hour of video as interchangeable constrains the activity through which digital competence is most plausibly acquired.

ICILS 2023 allows the distinction to be examined directly. It pairs performance-based assessments of computer and information literacy and computational thinking with a questionnaire item that asks not only whether a screen-time limit exists but whether it counts time spent on schoolwork. The combination is unusual: reported rule type can be related to demonstrated competence rather than to self-reported skill, across a large number of education systems assessed on a common metric.

The international report analysed this item as a dichotomy. Significant differences in literacy between students with and without limits appeared in 16 systems, and in 14 of these students without limits scored higher. The report noted, without tabulating, that approximately half of students reporting a limit said it excluded schoolwork, and it called for further work on limit-setting and on parental expectations regarding children's work on computers (Rožman et al., 2025). Collapsing the item creates a measurement problem: if the two limit categories describe substantively different situations, a binary indicator averages them, and the resulting contrast between limit and no limit is difficult to interpret.

Four questions organise the analysis.

RQ1. How are the three reported rule types distributed within and across education systems?

RQ2. Do students reporting schoolwork-inclusive limits differ in computer and information literacy from students reporting schoolwork-exempt limits, and does any difference replicate on computational thinking?

RQ3. Does the apparent advantage of reporting no limit persist once the two limit types

are separated?

RQ4. Does the association differ between learning reported outside school and learning reported at school?

This study makes three contributions. First, it extends parental mediation research from rule presence to reported rule type, distinguishing limits by whether schoolwork is counted within them. Second, it evaluates that distinction against performance-based measures of computer and information literacy and computational thinking across 29 education systems. Third, it shows how collapsing substantively different questionnaire categories can alter the interpretation of an international assessment result. The contribution therefore concerns both parental digital mediation and the analytical treatment of questionnaire response categories.

2. Background

2.1 Restrictive and active parental mediation

Parental mediation of digital technology is conventionally described along two dimensions. Restrictive mediation constrains access, duration or content; active or instructive mediation involves conversation, co-use and guidance (Livingstone & Helsper, 2008). Vaala and Bleakley (2015) distinguish monitoring, mediating and modelling as separable dimensions of parental involvement in adolescent computer and internet use, and report that these operate through different pathways. Across this literature, restriction is treated as a quantity. Instruments ask whether rules exist, how strict they are, or how many hours are permitted.

2.2 Rule presence, rule strictness and activity coverage

A restriction also has a scope: the set of activities counted against it. Two households may impose an identical two-hour ceiling and yet differ in whether homework is inside or outside that ceiling. Conceptually, the activities counted against a limit can be distinguished from whether a limit exists and how strictly it is applied, and this coverage has rarely been operationalised as a separate dimension in survey research on parental mediation. The ICILS 2023 item is unusual in encoding it, and the international analysis of that item collapsed the distinction (Rožman et al., 2025).

2.3 Educational and recreational screen use

Where studies separate purposes of use, associations with academic outcomes diverge by purpose rather than accumulating with total exposure. The meta-analysis by Adelantado-Renau et al. (2019) found no association between overall screen media time and academic performance, with associations emerging only for specific activities. Marciano and Camerini (2021) found that adherence to an overall screen-time recommendation and engagement in media multitasking were separately associated with academic achievement, and in opposite directions, which illustrates that a single aggregate exposure

measure combines behaviours that behave differently. Person-centred work points the same way: Tan et al. (2026) identify distinct profiles of information and communication technology use among adolescents that relate differently to academic and social-emotional outcomes, with intensity alone a poor guide to outcome. A rule indifferent to purpose therefore cuts across a distinction the evidence treats as consequential.

2.4 Displacement and opportunity

Two mechanisms are usually invoked to explain why quantity of use is a weak predictor. Displacement accounts hold that recreational use crowds out study and sleep (Lissak, 2018), and academic-media multitasking has been linked longitudinally to lower achievement (van der Schuur et al., 2020). Opportunity accounts hold that competence develops through sustained, purposeful engagement, so that restricting purposeful use removes the occasions on which skill is built. The two accounts make different predictions about a rule that counts schoolwork: displacement logic implies such a rule should be neutral or beneficial, opportunity logic implies a cost. These perspectives provide competing explanations for why reported rule types may be associated with digital competence and motivate the empirical comparison.

2.5 Assessed competence and self-reported skill

Self-reported digital skill is a poor substitute for assessed competence. Palczyńska and Rynko (2021) show that respondents systematically overstate information and communication technology skills they cannot demonstrate on matched objective tasks, and that the propensity to overstate varies by education and gender. Within ICILS, self-efficacy is positively but moderately related to assessed literacy (Rohatgi et al., 2016; Hatlevik et al., 2018), and confidence in evaluating online information greatly exceeds measured performance on tasks requiring it (Fraillon, 2026). Performance-based instruments such as those used by ICILS and by Aesaert and van Braak (2015) are therefore necessary for questions of this kind.

2.6 Variation across education systems

Digital competence and its correlates vary substantially across education systems. Siddiq and Scherer (2019) document heterogeneous gender differences in students' literacy across studies; Gnamb (2021) traces divergence over middle adolescence; Campos and Scherer (2024) show that gaps in knowledge, attitudes and skills are interrelated and vary with national context. Because school digitalisation differs across systems, the practical meaning of a rule that counts schoolwork may also differ, which makes cross-system consistency an informative property rather than an assumption.

2.7 The present study

The ICILS 2023 item separates limits that include schoolwork from limits that exclude it, but the reported analysis pooled them. We examine whether that pooling accounts for the reported pattern, whether the disaggregated contrast is consistent across systems and outcomes, and whether the association differs between learning reported outside school and learning reported at school.

3. Methods

3.1 Data and analytic sample

We analysed the student files of the ICILS 2023 international database (International Association for the Evaluation of Educational Achievement [IEA], 2025; https://doi.org/10.58150/ICILS_2023_data_2). ICILS 2023 assessed students in their eighth year of schooling in 35 education systems using a two-stage stratified cluster design in which schools were sampled with probability proportional to size and intact classes were sampled within schools.

The screen-time item is an international option. Inspection of the public-use files established that it was administered in 32 of the 35 systems; it was not administered in Belgium (Flemish), Germany, or North Rhine-Westphalia (Germany). Following ICILS reporting conventions we excluded the United States and the Netherlands, both of which carry the annotation "did not meet guideline for sampling participation rate" in the ICILS 2023 CIL and CT item almanacs, and Romania, which is excluded from the ICILS 2023 international average. Cases missing the exposure or any covariate were excluded. The analytic sample comprised 100,528 students in 29 education systems; 19 of these systems, comprising 62,514 students, also administered the computational thinking assessment. Systems carrying other sampling annotations in the international report are retained and identified in Additional file 1 and in Figs. 1 and 2, and are removed in a sensitivity analysis: three met participation guidelines only after replacement schools were included, thirteen have a national defined population covering 90% to 95% of the national target population, and one has coverage of 61%.

3.2 Measures

Students reported whether their parents or guardians place a limit on screen time on school days, selecting one of three options: a limit that includes time spent on schoolwork; a limit that excludes time spent on schoolwork; or no limit. The schoolwork-exempt limit is the reference category throughout. A parallel item referring to non-school days supports an internal replication. It was answered by 100,149 students in these systems, of whom 95,865 had complete data for the corresponding adjusted model.

Computer and information literacy and computational thinking were measured by the ICILS performance assessments and reported as five plausible values each, on scales with an international mean of 500 and standard deviation of 100.

Two IEA-derived scales record the extent to which students report having learned six internet-related tasks at school and outside school: finding information, refining searches, evaluating the reliability of information, referencing internet sources, judging whether a message is a scam, and managing privacy settings. Both are weighted likelihood estimates scaled to a mean of 50 and standard deviation of 10. Because the two scales comprise identical items, response options and metrics, differences between them are not attributable to item content or response format.

Models adjust for the international index of socioeconomic background, gender, whether the language of the test is spoken at home, and immigrant background. Computer experience and home internet access may lie between rule design and competence and are therefore reported in a supplementary specification rather than the primary model.

3.3 Estimation

Models were estimated separately within each education system and the resulting estimates synthesised; students were not pooled across systems. For each system we fitted

$$Y = b_0 + b_1(\text{Inclusive}) + b_2(\text{NoLimit}) + g'X + e$$

where Inclusive and NoLimit are indicators contrasted against the schoolwork-exempt category. To represent the coding used in the international report, the same model was also fitted with a single indicator for reporting any limit, whether schoolwork-inclusive or schoolwork-exempt, contrasted against reporting no limit. To compare the two learning settings directly, the model was fitted to the difference between the outside-school and at-school learning scales, which share items, response options and metric; the coefficient on Inclusive in that model is the between-setting contrast.

Each model was fitted separately for each of the five plausible values using final student weights. For every plausible value, sampling variance was estimated by jackknife repeated replication across the 75 replicate weights supplied with the database. The five plausible-value-specific sampling variances were averaged and the average was combined with the between-plausible-value imputation variance, following Eq. 3.3 of the ICILS 2023 user guide (Meyer et al., 2025). The reported coefficient is the mean of the five plausible-value-specific estimates, and its standard error incorporates both sampling and imputation variance. Across systems, imputation variance accounted for a median of 14.6% of the total variance of the primary estimate. For the two learning scales, which are single measured variables rather than plausible values, imputation variance is zero by construction and the standard error reflects sampling variance alone.

System-specific estimates were combined by random-effects meta-analysis. The primary synthesis used the DerSimonian and Laird (1986) estimator of between-system variance, and we report the pooled estimate, its 95% confidence interval, tau-squared and I-squared. Sensitivity analyses used restricted maximum likelihood estimation of the between-system variance and a Hartung-Knapp correction to the interval of the primary random-effects model. These are separate procedures: the first is an alternative variance estimator, the second an alternative interval for the same pooled estimate. We also report a 95% prediction interval for the difference in a further education system (Table 2). Equivalence was evaluated through confidence-interval containment within specified margins (Lakens, 2017). We applied a conservative criterion requiring the 95% confidence interval, rather than the conventional 90% interval corresponding to two one-sided tests at $\alpha = .05$, to fall entirely within the equivalence margin. The principal margin for the achievement scales was 10 scale points, which corresponds to 0.10 international standard deviations and approximately 12% of the width of an 85-point ICILS proficiency

band. The principal margin for the learning scales was 0.30 points, or 0.03 standard deviations of those scales, for which no external benchmark is available. Both margins are judgements rather than established conventions, so each equivalence result is reported across three margins: 5, 10 and 15 points for the achievement scales and 0.20, 0.30 and 0.50 points for the learning scales.

Table 2
Principal results under alternative synthesis methods, with prediction intervals

Analysis	k	DerSimonian-Laird	REML	Hartung-Knapp	tau2 (DL)	tau2 (REML)	95% prediction interval
Schoolwork-inclusive versus schoolwork-exempt limit (CIL)	29	-24.90 [-28.18, -21.63]	-24.95 [-28.28, -21.62]	-24.90 [-28.39, -21.42]	50.13	52.77	[-39.83, -9.98]
Schoolwork-inclusive versus schoolwork-exempt limit (CT)	19	-32.91 [-38.09, -27.72]	-32.99 [-38.26, -27.71]	-32.91 [-38.53, -27.28]	71.83	76.33	[-51.64, -14.17]
Any limit versus no limit, binary coding (CIL)	29	-8.63 [-11.81, -5.45]	-8.64 [-11.90, -5.38]	-8.63 [-12.00, -5.26]	62.74	66.63	[-25.22, 7.96]
No limit versus schoolwork-exempt limit (CIL)	29	-0.45 [-3.17, 2.27]	-0.44 [-3.22, 2.34]	-0.45 [-3.31, 2.42]	40.05	42.48	[-13.74, 12.85]
Learning internet-related tasks outside school	29	-0.73 [-0.93, -0.52]	-0.73 [-0.93, -0.52]	-0.73 [-0.91, -0.54]	0.00	0.00	[-0.94, -0.51]
Learning internet-related tasks at school	29	-0.09 [-0.40, 0.22]	-0.09 [-0.40, 0.22]	-0.09 [-0.40, 0.22]	0.35	0.35	[-1.34, 1.16]
Learning outside school minus learning at school	29	-0.53 [-0.77, -0.29]	-0.53 [-0.77, -0.29]	-0.53 [-0.76, -0.31]	0.00	0.00	[-0.78, -0.28]

Note. Each row reports the same system-specific estimates synthesised three ways: random-effects meta-analysis with the DerSimonian and Laird (1986) estimator of between-system variance, the same model with restricted maximum likelihood estimation of that variance, and the DerSimonian and Laird estimate with a Hartung-Knapp correction, whose interval uses the t distribution on $k - 1$ degrees of freedom. The point estimate is identical for the first and third methods, which differ only in the interval. The 95% prediction interval describes the range in which the difference in a further education system would be expected to fall and uses the t distribution on $k - 2$ degrees of freedom. Estimates for the achievement scales are in scale points and estimates for the learning scales are in learning-scale points. Reference categories are as in Table 1. k = number of education systems. All models adjust for the international index of socioeconomic background, gender, whether the language of the test is spoken at home, and immigrant background. CIL = computer and information literacy; CT = computational thinking.

Item non-response was addressed by inverse-probability weighting. Response propensity was modelled within each system by logistic regression of an indicator of item response on assessed achievement, summarised as the mean of the five computer and information literacy plausible values, together with socioeconomic background, gender, test language spoken at home, immigrant background, computer experience and home internet access. Achievement is observed for respondents and non-respondents alike and differs markedly between them, so it is the most consequential predictor available. Predictors with missing values entered mean-imputed alongside a missing indicator so that every student received a fitted propensity. Final weights were multiplied by the inverse of the predicted propensity and rescaled to preserve the weighted sample size; the same adjustment was applied to each replicate weight, with the response model treated as fixed rather than re-estimated within replicates. We report the resulting propensity range, the distribution of the rescaled weights, covariate balance before and after weighting, and a specification in which weights are trimmed at the 99th percentile. Within-school estimates were obtained by subtracting school means from the outcome and all predictors, so that comparisons are made among students attending the same school.

Analyses were conducted in R 4.3.3 using base functions. The coefficients are student-level associations estimated separately within each education system and subsequently synthesised across systems.

3.4 Use of generative AI

The author used OpenAI ChatGPT for English-language editing and to assist with revising and debugging R 4.3.3 scripts. The author reviewed and verified all code, analytical outputs, and manuscript text and takes full responsibility for the final work.

4. Results

4.1 Distribution of rule types

Across the 29 systems a median of 57.0% of students reported no screen-time limit on school days (range 22.4 to 74.9), 28.2% reported a limit excluding schoolwork (18.2 to 39.5), and 14.8% reported a limit including schoolwork (4.2 to 41.8). The schoolwork-inclusive group is therefore a substantial minority in most systems and a near-plurality in some. System-specific shares appear in Additional file 1.

4.2 Rule design and computer and information literacy

Students reporting a schoolwork-inclusive limit scored lower in computer and information literacy than students reporting a schoolwork-exempt limit. The pooled adjusted difference was – 24.9 scale points (95% CI [-28.2, -21.6]; tau-squared = 50.1; I-squared = 66.4%), approximately a quarter of an international standard deviation and about 29% of the width of an ICILS proficiency level. The difference was negative and statistically significant in all 29 systems, ranging from – 9.1 to -48.1 points (Fig. 1). The unadjusted difference was – 30.1 points (95% CI [-34.5, -25.8]).

Alternative synthesis methods produced similar estimates. Restricted maximum likelihood estimation gave – 24.9 points (95% CI [-28.3, -21.6]) and the Hartung-Knapp corrected interval was [-28.4, -21.4]. The 95% prediction interval, which describes where the difference in a further education system would be expected to fall, was [-39.8, -10.0] and lies entirely below zero (Table 1).

Table 1
Pooled differences by specification and coding

Analysis	k	n	Estimate	SE	95% CI	tau2	I2 (%)	p
Any limit versus no limit, binary coding (adjusted)	29	100528	-8.63	1.62	[-11.81, -5.45]	62.7	85.6	< .001
Computer and information literacy, unadjusted	29	100528	-30.12	2.22	[-34.48, -25.76]	105.9	78.0	< .001
Computer and information literacy, adjusted (primary specification)	29	100528	-24.90	1.67	[-28.18, -21.63]	50.1	66.4	< .001
Adjusted, adding computer experience and home internet access	29	100528	-22.76	1.56	[-25.82, -19.70]	41.0	62.5	< .001
Adjusted, within-school (school-demeaned)	29	100528	-20.63	1.67	[-23.91, -17.35]	53.5	70.6	< .001
Adjusted, inverse-probability weighted for item non-response	29	100528	-26.10	1.71	[-29.45, -22.74]	50.2	63.5	< .001
Adjusted, national index of socioeconomic background	29	100528	-24.90	1.67	[-28.18, -21.63]	50.1	66.4	< .001
Adjusted, non-school-day rule item	29	95865	-24.58	1.92	[-28.33, -20.82]	50.8	51.6	< .001
Computational thinking, adjusted	19	62514	-32.91	2.64	[-38.09, -27.72]	71.8	58.4	< .001
No limit versus schoolwork-exempt limit (adjusted)	29	100528	-0.45	1.39	[-3.17, 2.27]	40.1	75.5	0.746
Learning internet-related tasks outside school (adjusted)	29	100528	-0.73	0.11	[-0.93, -0.52]	0.0	0.0	< .001
Learning internet-related tasks at school (adjusted)	29	100528	-0.09	0.16	[-0.40, 0.22]	0.3	51.9	0.568
Learning outside school minus	29	100528	-0.53	0.12	[-0.77, -0.29]	0.0	0.0	< .001

Analysis	k	n	Estimate	SE	95% CI	tau2	I ² (%)	p
learning at school (adjusted)								
Adjusted, inverse-probability weighted, weights trimmed at the 99th percentile	29	100528	-25.73	1.72	[-29.10, -22.36]	52.8	66.0	< .001
Adjusted, systems carrying no sampling annotation	13	43113	-23.20	2.62	[-28.34, -18.06]	61.7	71.8	< .001

Note. Each row is a separate random-effects meta-analysis of system-specific estimates using the DerSimonian and Laird (1986) estimator of between-system variance. *k* is the number of education systems, *n* the number of students, tau-squared the estimated between-system variance, and *I*² the percentage of total variability attributable to it. *p* values are two-sided. The reference category is a limit that excludes time spent on schoolwork, except in the binary row, where it is reporting no limit. Unless stated otherwise, models adjust for the international index of socioeconomic background, gender, whether the language of the test is spoken at home, and immigrant background. Rows differ as follows: the unadjusted row omits all covariates; one row adds computer experience and home internet access; the within-school row subtracts school means from the outcome and all predictors; two rows reweight for item non-response, untrimmed and trimmed at the 99th percentile; one row substitutes the nationally standardised socioeconomic index; one row substitutes the parallel rule item for non-school days; the outside-minus-at-school row is fitted to the difference between the two learning scales and gives the direct between-setting contrast; the final row restricts the sample to systems carrying no sampling annotation in the international report. Achievement scales have an international mean of 500 and standard deviation of 100. The learning scales are weighted likelihood estimates with a mean of 50 and standard deviation of 10, so estimates on those scales are not comparable in magnitude to the achievement estimates. Superscripts in Figs. 1 and 2 and in Additional file 1 reproduce sampling annotations from the ICILS 2023 international report: a, the system met the guidelines for sampling participation rates only after replacement schools were included; b, the national defined population covers 90% to 95% of the national target population; c, coverage is 61%.

4.3 Binary coding of the same item

Estimating the coding used in the international report on the same sample gave a pooled difference of -8.6 scale points between students reporting any limit and students reporting no limit (95% CI [-11.8, -5.5], *p* < .001; tau-squared = 62.7; *I*-squared = 85.6%), with no limit as the reference category. The binary contrast was negative in 25 of the 29 systems and statistically significant in 19, all of them negative; no system showed a significant positive coefficient. Its magnitude is about one third of the schoolwork-inclusive versus schoolwork-exempt contrast, its between-system heterogeneity is higher (*I*-squared 85.6% against 66.4%), and its 95% prediction interval, [-25.2, 8.0], includes zero, whereas the prediction interval for the disaggregated contrast does not.

The three codings therefore describe the item differently. Under binary coding, reporting any limit is associated with - 8.6 points. Separating the limit categories attributes - 24.9 points to schoolwork-inclusive limits relative to schoolwork-exempt limits, and - 0.4 points to reporting no limit relative to the same category. The binary coefficient combines two limit types whose adjusted relationships with

literacy differ by about a quarter of an international standard deviation, and the mixture of those types varies across systems.

4.4 Students reporting no limit

The pooled difference between students reporting no limit and students reporting a schoolwork-exempt limit was -0.4 points (95% CI $[-3.2, 2.3]$, $p = .75$), which falls within the 10-point equivalence margin. The estimate was insensitive to the synthesis method (restricted maximum likelihood -0.4 points; Hartung-Knapp interval $[-3.3, 2.4]$, $p = .75$) and to the removal of any single system, with leave-one-out pooled estimates ranging from -1.5 to -0.1 and remaining within the margin in every case.

The equivalence conclusion held across margins. The 95% confidence interval fell inside margins of 5, 10 and 15 points, so the pooled result does not depend on the choice among them.

Between-system heterogeneity in this contrast was nevertheless substantial ($\tau^2 = 40.1$; $I^2 = 75.5\%$), and the 95% prediction interval, $[-13.7, 12.8]$, extends beyond the equivalence margin at both ends. Seven of the 29 systems showed a statistically significant difference, ranging from -11.2 points in Oman to $+26.2$ points in Kazakhstan (Fig. 2). The equivalence result therefore applies to the pooled average and should not be read as equivalence within every education system.

The apparent advantage of reporting no limit that appears under dichotomous coding therefore arises from combining two categories whose members differ from one another, on average, by about a quarter of a standard deviation.

4.5 Replication on computational thinking

In the 19 systems administering the computational thinking assessment, the same contrast yielded a pooled difference of -32.9 points (95% CI $[-38.1, -27.7]$; $\tau^2 = 71.8$; $I^2 = 58.4\%$). The difference was negative and significant in all 19 systems, and the 95% prediction interval, $[-51.6, -14.2]$, lies entirely below zero.

4.6 Learning reported outside and at school

Schoolwork-inclusive limits were associated with lower reported learning of internet-related tasks outside school (-0.73 points, 95% CI $[-0.93, -0.52]$), with no detectable between-system heterogeneity ($\tau^2 = 0.00$; $I^2 = 0.0\%$). The corresponding association with learning the same six tasks at school was smaller and not statistically significant (-0.09 points, 95% CI $[-0.40, 0.22]$, $p = .57$).

Because the two scales share items, response options and metric, their difference is itself a measured variable, and the same model was fitted to it. A direct difference-score model yielded a between-setting contrast of -0.53 points (95% CI $[-0.77, -0.29]$, $p < .001$; $\tau^2 = 0.00$; $I^2 = 0.0\%$), indicating that the association was larger for learning reported outside school than for learning reported at school. The at-school estimate is smaller and less precise. Equivalence to zero is not established for it at

margins of 0.20 or 0.30 points; at the 0.50-point margin its confidence interval falls inside the margin, so the equivalence verdict for learning at school depends on the margin chosen.

4.7 Robustness

Pooled estimates for computer and information literacy were stable across specifications (Table 1). Substituting the national for the international socioeconomic index gave – 24.9 points and the non-school-day item gave – 24.6 points. Adding computer experience and home internet access attenuated the estimate to -22.8 points. Within-school estimation, which compares students attending the same school, gave – 20.6 points (95% CI [-23.9, -17.4]). Restricting the sample to the 13 systems that carry no sampling annotation in the international report gave – 23.2 points (95% CI [-28.3, -18.1]).

Covariate adjustment attenuated the pooled estimate by 17.3% of the unadjusted difference, from – 30.1 to -24.9 points, while the median within-system R-squared rose from 0.017 to 0.133.

Item response to the optional question was high but selective. Within-system response rates ranged from 77.7% to 95.1% (median 90.3%), and respondents scored substantially higher in literacy than non-respondents (weighted medians 502 and 419). Under the response-propensity model described in Methods, fitted propensities ranged from 0.105 to 1.000 and the rescaled weights were concentrated near one, with a median 95th percentile of 1.12 and a maximum of 8.74. Weighting reduced the largest standardised difference between the analytic sample and the full student sample from a median of 0.121 to 0.064. The untrimmed and trimmed inverse-probability-weighted estimates were similar to or more negative than the primary estimate: -26.1 points (95% CI [-29.5, -22.7]) untrimmed and – 25.7 points with weights trimmed at the 99th percentile.

5. Discussion

The principal contribution concerns category construction in international assessment questionnaires. Binary coding combines two reported parental rule types that show markedly different relationships with assessed digital competence. Retaining the original response categories reveals a consistent schoolwork-inclusive versus schoolwork-exempt contrast across 29 education systems and a parallel result for computational thinking.

Estimating both codings on the same sample shows what the collapse costs. The binary contrast between any limit and no limit is negative and statistically significant, at -8.6 points, and points in the direction reported internationally. Separating the categories locates that difference: it is -24.9 points for schoolwork-inclusive limits relative to schoolwork-exempt limits and – 0.4 points for reporting no limit relative to the same category. The binary coefficient therefore represents a composite contrast that combines a substantial difference with a negligible one, and because the mixture of limit types varies across systems, the binary coding also carries higher between-system heterogeneity, with I-squared of 85.6% against 66.4%. Its prediction interval includes zero, while the prediction interval for the

disaggregated contrast does not. Attributing the binary difference to having a limit describes a composite that no single reported rule type matches.

The disaggregated contrast shows substantial cross-system consistency. It is negative and statistically significant in all 29 systems and ranges from -9.1 to -48.1 points. Restricted maximum likelihood estimation and a Hartung-Knapp correction lead to the same substantive conclusion, and the 95% prediction interval, $[-39.8, -10.0]$, lies entirely below zero, so a negative difference would be expected in a further education system drawn from the same distribution. The computational thinking replication behaves the same way, with a prediction interval of $[-51.6, -14.2]$. The systems examined differ considerably in school digitalisation, curriculum and household technology access, which makes consistency of this degree an informative property of the pattern rather than a feature of any single national setting.

The outcomes are assessed rather than self-reported, which matters for a question of this kind. Self-reported digital skill diverges systematically from demonstrated skill (Palczyńska & Rynko, 2021), and within ICILS self-efficacy is only moderately related to measured literacy (Rohatgi et al., 2016; Hatlevik et al., 2018). Relating reported rule type to performance on two independently administered assessments places the pattern on demonstrated competence, and the replication on computational thinking shows that it is not specific to one assessed construct.

The two learning settings were compared directly. The direct difference-score model confirmed that the outside-school association was larger by 0.53 points (95% CI $[-0.77, -0.29]$). The at-school estimate is smaller and less precise, so the comparison establishes a difference in degree between settings and not the absence of an association at school.

One interpretation is that reported rules including schoolwork reduce opportunities for purposeful digital engagement. Another is that reported rule type reflects student or family circumstances that preceded the rule. Longitudinal evidence is needed to distinguish these possibilities.

The immediate implication concerns questionnaire and category design. International assessments often collapse response options for reporting convenience, but categories that appear to represent degrees of one construct may identify substantively different situations. Preserving the distinction between schoolwork-inclusive and schoolwork-exempt limits produces a more informative account of the ICILS pattern, and reporting the disaggregated categories alongside any binary indicator would let readers see where a pooled difference is located. The same question applies to other questionnaire scales in international assessments whose response options are combined before analysis.

6. Limitations

The study uses cross-sectional data and a single student-reported measure of parental rule type. Temporal ordering therefore remains uncertain, and reported rules may reflect both household practices and pre-existing student characteristics. The item distinguishes whether schoolwork is included in a limit

but does not separately measure duration, enforcement, device coverage or overall strictness, so reported rule type should not be read as activity coverage isolated from other dimensions of restriction. Some student and family characteristics relevant to both rule type and competence, among them prior achievement, self-regulation and parental digital competence, are unavailable in ICILS. Item response was selective, although untrimmed and trimmed inverse-probability-weighted estimates remained close to the primary result. The meaning of the same rule category may also vary across education systems with different levels of school digitalisation. Future longitudinal studies combining student and parent reports with measures of rule duration and actual digital activity would extend the present findings.

7. Conclusion

Binary coding of parental screen-time limits obscures a distinction among reported rule types in ICILS 2023. Across 29 education systems, students reporting limits that included schoolwork scored lower in computer and information literacy than students reporting limits that exempted schoolwork, and the contrast was negative and statistically significant in every system. The result replicated on computational thinking in all 19 systems administering that assessment. Fitted to the same sample, the binary any-limit contrast was about one third the size of the disaggregated contrast and carried higher between-system heterogeneity, which shows what the collapse conceals. At the pooled level, students reporting no limit and students reporting schoolwork-exempt limits met the specified equivalence criterion, although system-specific differences varied. Questionnaire categories that distinguish substantively different situations therefore merit preservation in analysis and reporting, and the disaggregated categories provide a more informative basis for research on parental digital mediation and digital competence. Longitudinal research can establish how these reported rule types develop and relate to later competence.

Abbreviations

CI: confidence interval; CIL: computer and information literacy; CT: computational thinking; DL: DerSimonian-Laird; ICILS: International Computer and Information Literacy Study; IEA: International Association for the Evaluation of Educational Achievement; IPW: inverse-probability weighting; PI: prediction interval; REML: restricted maximum likelihood; SD: standard deviation; SE: standard error.

Declarations

Author Contribution

J.A.M. designed the study, prepared and analysed the data, and wrote the manuscript.

Data Availability

This study analysed the public-use IEA International Computer and Information Literacy Study (ICILS) 2023 international database, available at https://doi.org/10.58150/ICILS_2023_data_2. Access requires acceptance of the IEA data licence on the repository page. No new data were generated. The system-level estimates underlying the analysis are provided in Additional file 1.CSV.

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Figures

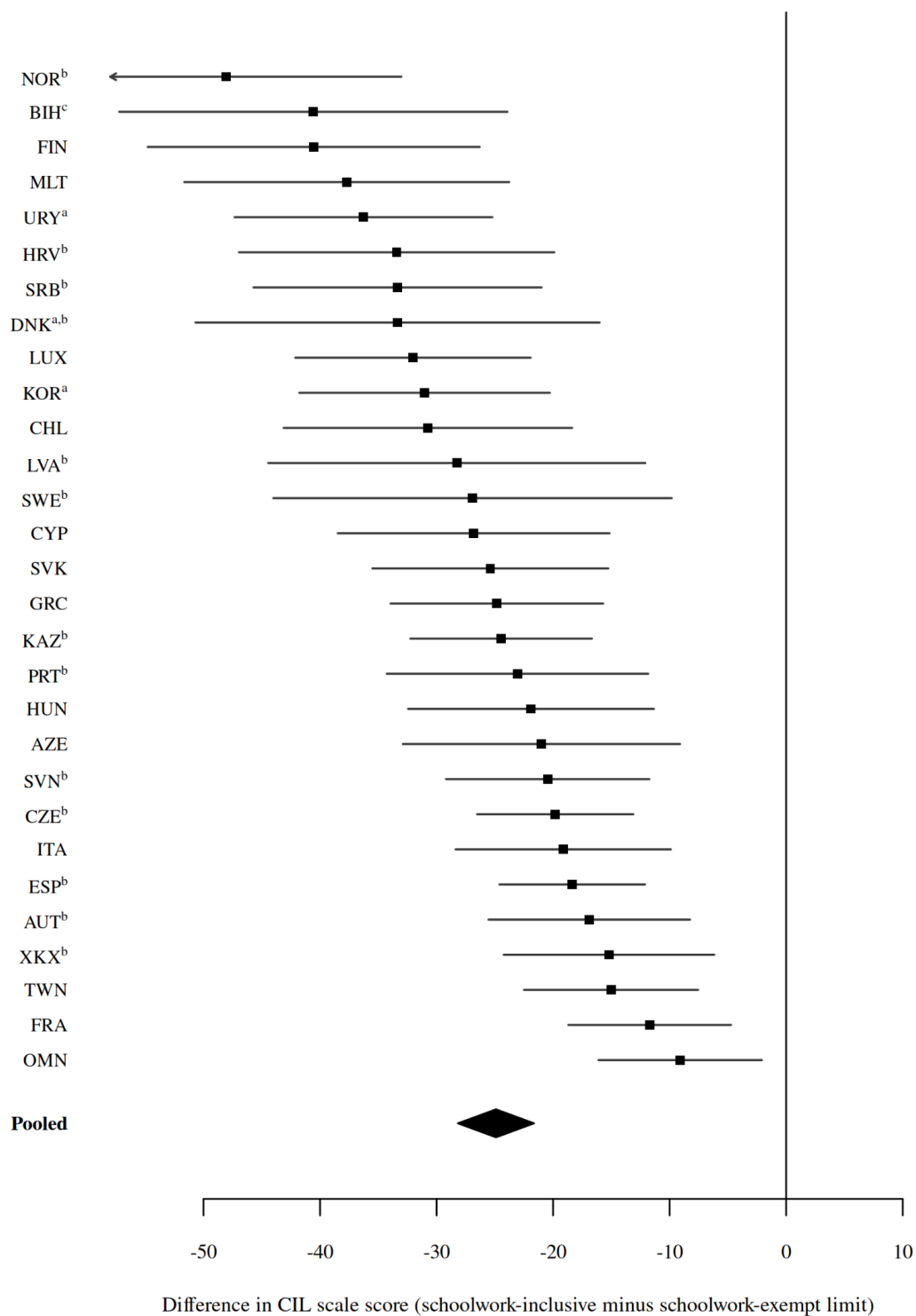


Figure 1

Adjusted computer and information literacy difference, schoolwork-inclusive versus schoolwork-exempt limit, by education system

Note. Squares are system-specific adjusted differences in scale points and horizontal lines their 95% confidence intervals, with a limit that excludes schoolwork as the reference category. The diamond is the

random-effects pooled estimate across the 29 systems (-24.90, 95% CI [-28.18, -21.63]). The arrowhead marks an interval extending beyond the plotted range. Covariates, scale metric and the superscripts are defined in the note to Table 1.

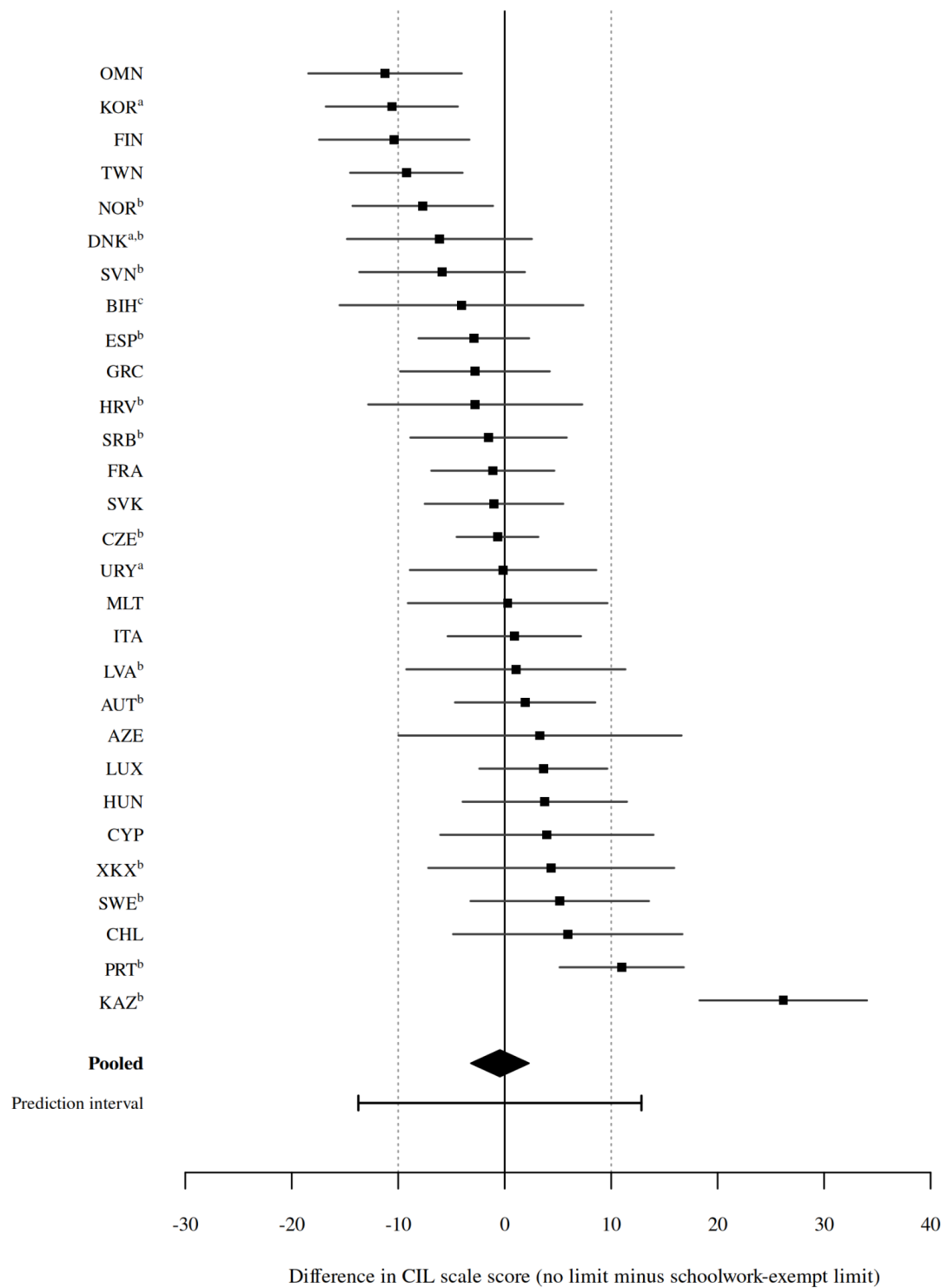


Figure 2

Adjusted computer and information literacy difference, no limit versus schoolwork-exempt limit, by education system

Note. Squares, lines, diamond and reference category are as in Figure 1; the pooled estimate is -0.45 (95% CI $[-3.17, 2.27]$). The capped bar is the 95% prediction interval, $[-13.74, 12.85]$. Dotted lines mark the 10-point equivalence margin. The pooled estimate falls within the margin while the prediction interval does not, and seven systems differ significantly, so the pooled result does not imply equivalence within every system.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [Additionalfile1.csv](#)