<u>**Written Testimony**</u>

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To The Joint Standing Committee on Education and Cultural Affairs
Thursday, January 22, 2026, 10:00am

**Testimony in support of LD 2052**

*Resolve, to Study the Use of Technology in Classrooms and Study Safeguards Related to Its Use*

My name is Dr. Jared Cooney Horvath and I'm a former teacher turned cognitive neuroscientist who focuses on human learning. I do not receive funding, nor have I ever, from Big Tech.

I am writing in support of LD 2052 - *Resolve, to Study the Use of Technology in Classrooms and Study Safeguards Related to Its Use* and submit the following for your consideration of this important study. Thank you.

**Executive Summary**

Over the past two decades, the cognitive development of children across much of the developed world has stalled and, in many domains, reversed. Literacy, numeracy, attention, and higher order reasoning have declined despite increased school attendance and expanded public investment.

One major structural change distinguishes today's classrooms from those of prior generations: the rapid and largely unregulated expansion of educational technology (EdTech). Digital devices now occupy a significant share of instructional time, assessment, homework, and student attention.

The available evidence (from international assessments, largescale academic studies, and metaanalyses) shows that increased classroom screen exposure is generally associated with weaker learning outcomes, not stronger ones. In narrow circumstances (e.g., tightly constrained adaptive practice and remediation), digital tools can support surfacelevel skill acquisition, but in most core academic contexts screens slow learning, reduce depth of understanding, and weaken retention.

This is not primarily a question of teacher quality, student motivation, or access to devices. It reflects a structural mismatch between how human cognition develops and

how digital platforms are engineered to capture attention, fragment focus, and accelerate task switching.

If state policy continues to incentivize largescale digital adoption without demanding independent efficacy evidence, privacy protections, and developmental safeguards, it risks compounding longterm educational and workforce harm.

## 1. What Has Changed

For most of the twentieth century, cognitive performance steadily improved across generations, driven largely by expanding access to formal education and improved instructional quality[1]. Beginning in the mid-2000s, this trend plateaued then reversed in many Western nations. Multiple indicators now show stagnation or decline in literacy, numeracy, problem solving, creativity, and general cognitive performance among adolescents[2-6].

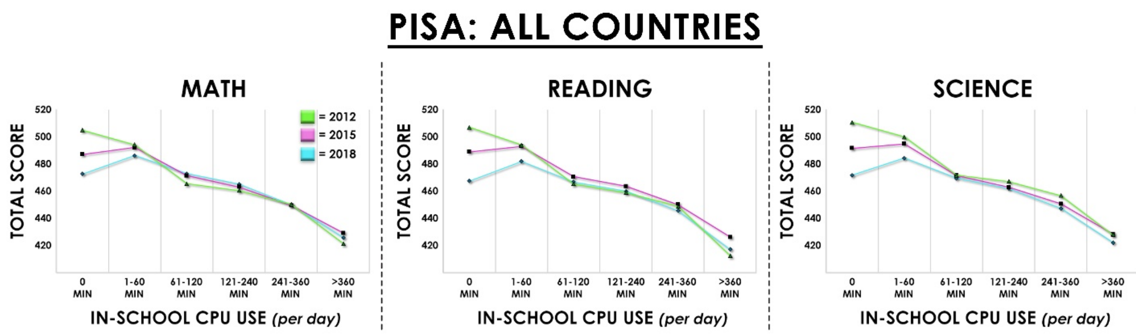
At the same time, classroom environments underwent a rapid digital transformation. Onetoone device programs, cloud platforms, online assessments, adaptive software, and constant connectivity became standard practice in many districts - often without independent longitudinal validation.

Over half of our children now use a computer at school for one to four hours each day, and a full quarter spend *more than* four hours on screens during a typical seven-hour school day[7]. Unfortunately, studies suggest that less than half of this time is spent actually learning, with students off-task for up to 38 minutes of every hour when on classroom devices[8].

## 2. Evidence from International Assessments

<u>PISA</u>

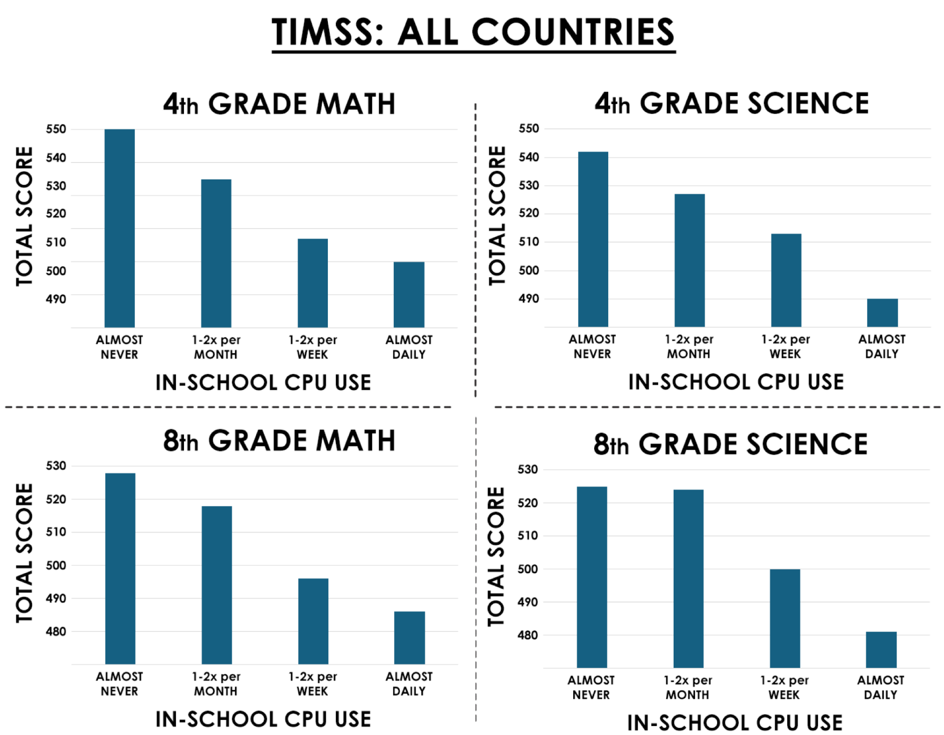
The Programme for International Student Assessment (PISA) tracks the academic performance of 15yearolds across dozens of countries. When students selfreport classroom computer use, higher daily screen exposure consistently corresponds to lower scores in reading, mathematics, and science. The relationship is monotonic: more screen time, lower performance.




Apparent small advantages sometimes reported for minimal computer exposure disappear once test mode effects are accounted for. When assessments shifted from paper to digital delivery, students with limited device familiarity experienced artificial score penalties, creating the illusion of benefit for moderate screen users rather than genuine learning gains[9].

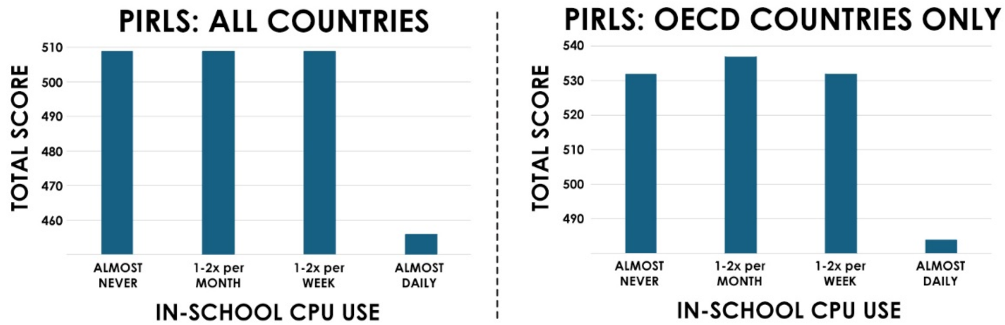
TIMSS

The Trends in International Mathematics and Science Study (TIMSS) shows a similar pattern among younger students. Frequent inclass computer use correlates with significantly lower math and science performance across both highincome and middleincome countries.



PIRLS

The Progress in International Reading Literacy Study (PIRLS) historically shows weaker reading performance among students with high classroom computer use. More recent U.S. data confirm that even modest daily digital exposure is associated with lower reading comprehension[10].




Collectively, these assessments involve millions of students over decades and converge on the same conclusion: heavy classroom screen exposure is not improving learning outcomes at scale.

## 3. Evidence from MetaAnalysis

Metaanalyses aggregate hundreds of individual studies to estimate overall impact. Most EdTech metaanalyses report small positive effect sizes. However, education research systematically inflates positive effects because comparison conditions vary widely and often lack rigorous baselines.

When educational interventions are benchmarked against established instructional methods, meaningful impact typically begins around moderate effect thresholds (approximately 0.40 – 0.50)[11]. Most digital interventions fall below this range, particularly in:

- Onetoone device programs
- Fully online instruction
- General classroom technology integration
- Programs targeting disadvantaged populations

Only narrowly constrained tools (such as adaptive drills for foundational skills and targeted remediation) consistently approach meaningful gains. These tools succeed because they automate repetition in welldefined domains, not because they enhance deep learning.

To assess practical significance, effect sizes must be interpreted relative to a meaningful benchmark rather than an arbitrary zero. Large-scale syntheses of education research indicate that the average impact of ordinary classroom instruction is approximately +0.42[11]. An intervention that falls below this threshold does not meaningfully outperform standard practice, even if its effect size is technically positive. In practical terms, schools should not invest in tools that perform worse than the average classroom already does without them.

For clarity, the table below presents effect sizes re-centered against this instructional benchmark to show whether each category of educational technology exceeds or underperforms typical instructional impact[11, 12].

| | *# Of Meta-Analyses* | *# of Research Studies* | *Effect Size (Cohen's D)* |
|---|---|---|---|
| *General Learning* | 398 | 21,155 | -0.13 *(SE=0.09)* |
| SPECIFIC MODERATORS | | | |
| *Online/Distance Learning* | 42 | 1,767 | -0.22 *(SE=0.06)* |
| *Primary Years* | 27 | 781 | *-0.03 (SE=0.04)* |
| *Secondary Years* | 10 | 745 | -0.11 *(SE=0.05)* |
| *Intelligent Tutoring Systems* | 5 | 283 | +0.10 *(SE=0.03)* |
| *1-to-1 Laptops* | 3 | 162 | *-0.30 (SE=0.07)* |
| *Disadvantaged Students* | 4 | 195 | -0.26 *(SE=0.02)* |
| *Literacy* | 31 | 1,109 | -0.09 *(SE=0.15)* |
| *Mathematics* | 41 | 3,479 | -0.09 *(SE=0.13)* |
| *Science* | 10 | 547 | -0.18 *(SE=0.19)* |
| *Learning Disorders* | 9 | 245 | +0.05 *(SE=0.08)* |

| |
|---|
| *NOTE: Reported effect sizes from published meta-analyses have been re-centered relative to the estimated average impact of typical classroom instruction (+0.42). Values shown represent the difference between each intervention's effect and this instructional benchmark (Adjusted Effect = Reported d – 0.42). This does not alter the underlying study results; it clarifies whether an intervention meaningfully exceeds, matches, or underperforms ordinary instructional impact.* |

Interpreted this way, most general-use educational technologies perform below the effectiveness of ordinary classroom instruction, while only narrowly constrained adaptive tools modestly exceed baseline impact.

**4. Mode Effects: Reading and Writing**

Independent research consistently shows that reading comprehension and retention are stronger on paper than on screens, particularly for complex or extended texts. Spatial stability, reduced scrolling, and embodied interaction support memory formation and comprehension[12].

| | *# Of Meta-Analyses* | *# of Research Studies* | *Effect Size (Cohen's D)* |
|---|---|---|---|
| *Reading Comprehension* | 10 | 377 | -0.16 *(SE=0.05)* |
| SPECIFIC MODERATORS | | | |
| *Adult Supports* | 1 | 7 | -0.22 *(SE=0.22)* |
| *Adult vs Digital Supports* | 1 | 10 | -0.22 *(SE=0.07)* |
| *NOTE: All studies compare screens to hard-copy texts, meaning the baseline of 'reading from paper' is 0.00.* | | | |

Similarly, handwritten notetaking reliably outperforms laptop notetaking for longterm learning. Typing encourages verbatim transcription and shallow processing; handwriting forces summarization, organization, and conceptual encoding[12].

| | *# Of Meta-Analyses* | *# of Research Studies* | *Effect Size (Cohen's D)* |
|---|---|---|---|
| *General Learning* | 4 | 238 | -0.21 *(SE=0.04)* |
| SPECIFIC MODERATORS | | | |

| | | | |
|---|---|---|---|
| *Allowed to Review Notes* | 1 | 9 | -0.42 *(SE=0.07)* |
| *Class Length: >30min* | 1 | 5 | -0.58 *(SE=0.01)* |
| *NOTE: All studies compare typing to handwriting, meaning the baseline of 'handwritten notes" is 0.00.* | | | |

These effects are not marginal curiosities. They directly affect how students process information across subjects and grade levels.

## 5. Why Screens Undermine Learning: A Core Mechanism

Human attention systems evolved to sustain focus on a single task at a time. The prefrontal control system cannot reliably manage competing goal states without significant performance costs[13]. When attention is repeatedly interrupted, three predictable costs emerge:

1. Time loss from task switching overhead[14].
2. Higher error rates from cognitive interference[15].
3. Weaker memory formation as learning shifts from deep encoding toward habitbased processing[16].

Digital platforms are optimized for rapid switching, novelty, and continuous engagement capture. Even when used for academic tasks, they cue the same behavioral patterns students practice during recreational screen use: frequent checking, rapid scrolling, and multitasking.

As a result, screens structurally train attentional habits that conflict with sustained learning. This is not a matter of discipline or willpower; it is a function of repeated conditioning.

## 6. State Implications

Sustained declines in cognitive skill development have downstream consequences for:

- Workforce adaptability and productivity
- Scientific and technological innovation
- Civic reasoning and institutional trust

- Economic competitiveness[17]
- Public health and wellbeing[18]

Education policy shapes longterm human capital. Decisions made today will influence national capacity for decades.

## Conclusion

This is not a debate about rejecting technology. It is a question of aligning educational tools with how human learning actually works. Evidence indicates that indiscriminate digital expansion has weakened learning environments rather than strengthened them[12].

State policy can restore balance by demanding evidence, protecting children's developmental needs, and ensuring that innovation serves learning rather than attention capture.

Our responsibility is not to maximize screen exposure, but to maximize the cognitive capacity and long-term flourishing of the next generation.

## REFERENCES

1 - Trahan, L. H., Stuebing, K. K., Fletcher, J. M., & Hiscock, M. (2014). The Flynn effect: a meta analysis. *Psychological bulletin*, *140*(5), 1332.

2 - Mullis, I. V. S., von Davier, M., Foy, P., Fishbein, B., Reynolds, K. A., & Wry, E. (2023). *PIRLS 2021 International Results in Reading*. Boston College, TIMSS & PIRLS International Study Center. https://doi.org/10.6017/lse.tpisc.tr2103.kb5342

3 - OECD (2023), *PISA 2022 Results (Volume I): The State of Learning and Equity in Education*, PISA, OECD Publishing, Paris, https://doi.org/10.1787/53f23881-en.

4 - Andrzejewski, D., Zeilinger, E. L., & Pietschnig, J. (2024). Is there a Flynn effect for attention? Cross-temporal meta analytical evidence for better test performance (1990–2021). *Personality and Individual Differences*, *216*, 112417.

5 - Kim, K. H. (2021). Creativity crisis update: America follows Asia in pursuing high test scores over learning. Roeper Review, 43(1), 21-41.

6 - Dutton, E., van der Linden, D., & Lynn, R. (2016). The negative Flynn Effect: A systematic literature review. *Intelligence*, *59*, 163-169.

7 - Fittes, E.K. (2022). How much time are students spending using EdTech? Education Week, March 1 2022. https://marketbrief.edweek.org/meeting-district-needs/how-much-time-are-students-spending-using-ed-tech/2022/03

8 - Ragan, E. D., Jennings, S. R., Massey, J. D., & Doolittle, P. E. (2014). Unregulated use of laptops over time in large lecture classes. *Computers & Education*, *78*, 78-86.

9 - OECD (2016), *PISA 2015 Results (Volume I): Excellence and Equity in Education*, PISA, OECD Publishing, Paris, https://doi.org/10.1787/9789264266490-en.

10 - Salmerón, L., Vargas, C., Delgado, P., & Baron, N. (2023). Relation between digital tool practices in the language arts classroom and reading comprehension scores. *Reading and Writing*, *36*(1), 175-194.

11 - Hattie, J. (2023). Visible learning: The sequel. *New York*.

12 – Horvath, J. C. (2026). The Digital Delusion. LME Global Press, Arizona.

13 - Kirschner, P. A., & De Bruyckere, P. (2017). The myths of the digital native and the multitasker. *Teaching and Teacher education*, *67*, 135-142.

14 - Jolicoeur, P., Dell'Acqua, R., & Crebolder, J. (2000). Multitasking performance deficits: forging links between the attentional blink and the psychological refractory period. *Control of cognitive processes: attention and performance MIT, Cambridge*, 309-330.

15 – Wu, C., & Liu, Y. (2008). Queuing network modeling of the psychological refractory period (PRP). *Psychological review*, *115*(4), 913.

16 - Foerde, K., Knowlton, B. J., & Poldrack, R. A. (2006). Modulation of competing memory systems by distraction. *proceedings of the National Academy of Sciences*, *103*(31), 11778-11783.

17 - Bergman, L. R., Corovic, J., Ferrer-Wreder, L., & Modig, K. (2014). High IQ in early adolescence and career success in adulthood: Findings from a Swedish longitudinal study. *Research in Human Development*, *11*(3), 165-185.

18 - Wraw, C., Deary, I. J., Gale, C. R., & Der, G. (2015). Intelligence in youth and health at age 50. *Intelligence*, *53*, 23 32.