

Original Research

Received 29 May 2026

Revised 28 July 2026

Accepted 06 August 2026

Natural Resources for Human Health 2026, Vol.6(14s):1073–1083

KEYWORDS:

digital divide, social capital, educational outcomes, digital inclusion, meaningful connectivity, educational technology, generative AI, educational equity.

Bridging the Digital Divide: Technology Access, Social Capital, and Educational Outcomes in 2026

Dr. Vimala Venugopal¹, Dr. Jeffrey A. Lucero², Dr. Oliver C. Requilman³, Dr. Arvy N. Osma⁴

¹Senior Lecturer, Post Graduate Department, Faculty of Business, Unitar International University, Malaysia

²Professor, Saint Paul University Quezon City, Philippines

³Associate Professor, Graduate Studies, College of Business and Accountancy National University – Philippines

⁴Mariners Polytechnic Colleges Foundation of Canaman Cam Sur Philippines, OP Jindal Global University, India

Email: vimala.venugopal@unitar.my

ABSTRACT: Roughly three-quarters of the world now uses the internet, yet the promise that connectivity would equalize learning has not been kept. This integrative review examines why, exploring how technology access, digital skills and social capital interact to shape educational outcomes in 2026. Drawing on peer-reviewed studies, meta-analyses, experimental and quasi-experimental evaluations, and large-scale survey data from the ITU, UNESCO, OECD and India's ASER survey, the evidence was synthesized thematically against a three-level model of digital inequality. Four main findings arise. Gaps in basic access are narrowing, but differences in the quality, cost and continuity of connectivity are widening. Distributing devices or broadband rarely improves achievement on its own, whereas programs that pair technology with structured pedagogy, adaptive content or human support produce substantial gains. Social capital, in the form of parental guidance, peer networks and institutional agents such as teachers, largely determines whether access is converted into learning. Generative artificial intelligence, meanwhile, is opening a new layer of inequality that rests less on hardware than on guidance, critical judgement and language. Building on these findings, the review proposes an integrated framework, grounded in the capability approach, that links resources, conversion factors and outcomes. It argues that digital inclusion should be measured as meaningful connectivity rather than simple access, and that investment in devices must be matched by investment in teachers, families and mentoring. The review is limited to English-language sources, and evidence on generative AI remains short-term, pointing to a need for longitudinal and multilingual research in low- and middle-income countries.

1. INTRODUCTION

For most of the past quarter-century, the digital divide was described as a simple line: people with computers and internet connections stood on one side, and those without stood on the other. Policy followed the metaphor. Governments bought laptops, wired classrooms and 1073 subsidized data plans, expecting that once the line was erased, learning gaps would narrow on their own. The record since then has been humbling. Connectivity has spread quickly, yet differences in what young people actually gain from it have proven stubborn, and in some places they have grown.

Recent figures show both sides of this. According to the International Telecommunication Union (ITU, 2025), about six billion people, close to three-quarters of the global population, were using the internet in 2025, while some 2.2 billion remained offline.

The global average hides wide differences. Usage reaches 94% in high-income countries but only 23% in low-income ones, and 85% of urban residents are online compared with 58% of rural residents. Schools mirror the same pattern. UNESCO's *Global Education Monitoring Report* estimated that only 40% of primary, 50% of lower secondary and 65% of upper secondary schools worldwide were connected to the internet, with government schools in countries such as India far less likely to be online than private ones (UNESCO, 2023).

India illustrates how quickly the terms of the debate can shift. The 2024 Annual Status of Education Report (ASER) found that roughly nine in ten rural adolescents aged 14 to 16 had a smartphone at home, and 82.2% said they could use one (Pratham, 2025). On paper, access is nearly universal. Ownership, however, is another matter: 36.2% of boys reported owning their own phone, against 26.9% of girls. A shared family device, used after a parent returns from work, is a very different learning resource from a personal one. Access alone no longer explains the gap.

Scholars anticipated this turn. Hargittai (2002) described a *second-level* divide rooted in skills, and van Dijk (2005, 2020) argued that inequality travels through a sequence of motivation, physical access, skills and usage. Later work added a *third level*, concerned with the unequal offline returns people draw from going online (van Deursen & Helsper, 2015; Ragnedda, 2017). Across these accounts, a recurring explanation is social: the people around a learner, and the resources embedded in those relationships, help decide whether a device becomes a tool for study or a source of distraction. This is the concern of social capital theory (Bourdieu, 1986; Coleman, 1988; Lin, 2001).

The link between social capital and digital inequality is often acknowledged but rarely placed at the center of analysis. Reviews of the digital divide have tended to catalogue determinants of access and skill (Scheerder et al., 2017; Lythreath et al., 2022), while reviews of educational technology have focused on whether particular tools raise achievement (Escueta et al., 2020). Fewer studies bring the two conversations together, and fewer still consider how the arrival of generative artificial intelligence (AI) since late 2022 has altered the picture.

This paper addresses that gap. Drawing on research published up to 2026, it asks three questions:

1. **RQ1.** What is the current state of the digital divide in education across the levels of access, skills and outcomes?
2. **RQ2.** How does social capital shape the conversion of technology access into educational outcomes?
3. **RQ3.** Which interventions have narrowed digital and educational gaps, and under what conditions?

In answering these questions, the review makes three contributions. It updates the evidence on digital inequality in education to 2026, including early experimental work on generative AI. It places social capital at the center of the analysis rather than at its margins. And it proposes an integrated framework, grounded in the capability approach, that links resources, conversion factors and outcomes. The remainder of the paper describes the review method (Section 2), presents the synthesized evidence (Section 3), interprets it through the framework (Section 4) and closes with limitations and implications (Section 5).

2. METHODS

2.1 Review design

An integrative review design was chosen because the topic draws on evidence of very different kinds: experimental trials, longitudinal panels, cross-national surveys, qualitative fieldwork and theoretical essays. A conventional systematic review or meta-analysis would have excluded much of this material. The integrative approach, as set out by Whitemore and Knafl (2005) and refined by Torraco (2016), allows such diverse sources to be read together while keeping the process transparent. Reporting was guided by the relevant items of the PRISMA 2020 statement (Page et al., 2021).

2.2 Search strategy and sources

Searches were run in Scopus, Web of Science Core Collection, ERIC and Google Scholar, using combinations of terms for the three core constructs. Grey literature from intergovernmental bodies and national surveys was added because much of the most current data on connectivity is published there first. Reference lists of key papers were also checked by hand (backward snowballing), and recent citing articles were traced forward. Table 1 summarises the protocol.

Table 1. Search protocol and eligibility criteria

Element	Specification
Databases	Scopus; Web of Science Core Collection; ERIC; Google Scholar (first 200 results per string)
Grey literature	ITU <i>Facts and Figures</i> ; UNESCO <i>GEM Report</i> ; OECD PISA reports; UNICEF; ASER (India); World Bank
Search string (core)	("digital divide" OR "digital inequality*" OR "digital inclusion" OR "internet access" OR "meaningful connectivity") AND ("social capital" OR "social network*" OR "parent* mediation" OR "peer support") AND ("educational outcome*" OR "academic achievement" OR "learning" OR "attainment")
Supplementary string	("generative AI" OR "ChatGPT" OR "artificial intelligence") AND ("equity" OR "divide") AND ("education" OR "student*")
Time window	2000 to mid-2026, with earlier foundational theory retained
Language	English
Inclusion	Empirical or theoretical work addressing at least two of the three constructs; school-age or tertiary learners; any country
Exclusion	Opinion pieces without evidence; studies of workplace training only; technical papers on network engineering
Quality appraisal	Mixed Methods Appraisal Tool (MMAT) for empirical studies; authority, recency and transparency for grey literature

Note. MMAT = Mixed Methods Appraisal Tool; ERIC = Education Resources Information Center.

2.3 Selection and appraisal

Titles and abstracts were screened first, followed by full-text reading of potentially relevant items. Priority was given to studies with credible identification strategies, such as randomized controlled trials and natural experiments, and to large, representative surveys. Smaller qualitative studies were retained when they helped explain processes that quantitative work could not capture, particularly the everyday role of families, peers and teachers. Each empirical study was appraised with the Mixed Methods Appraisal Tool (Hong et al., 2018), and lower-quality studies were used to illustrate rather than to establish findings.

2.4 Analysis and synthesis

The material was coded thematically following Braun and Clarke (2006). An initial deductive frame, built on the three-level model of digital inequality, was gradually opened up to themes that emerged from the data, especially the role of institutional agents and the new questions raised by generative AI. Findings were then organized around the three research questions and integrated into a framework presented in the Discussion.

3. RESULTS

The evidence is organized around the three research questions. Section 3.1 maps the present shape of the divide; Section 3.2 turns to social capital; Section 3.3 reviews what interventions have achieved; and Section 3.4 considers generative AI as an emerging fault line.

3.1 The shape of the divide in the mid-2020s (RQ1)

The first finding is that the divide has not disappeared so much as changed shape. Basic mobile coverage is now close to universal, but gaps in income, geography, gender and age remain wide, and the gap between being *online* and being *meaningfully connected* is wider still. Table 2 gathers the most recent headline indicators.

Table 2. Selected indicators of digital inequality relevant to education

Indicator	Value	Year	Source
Global population using the internet	~6.0 billion (about 74%)	2025	ITU (2025)
People still offline	~2.2 billion	2025	ITU (2025)
Internet use, high- vs low-income countries	94% vs 23%	2025	ITU (2025)
Internet use, urban vs rural	85% vs 58%	2025	ITU (2025)
Internet use, ages 15–24 vs rest of population	82% vs 72%	2025	ITU (2025)
5G population coverage, high- vs low-income countries	84% vs 4%	2025	ITU (2025)
Schools connected to the internet (primary / lower secondary / upper secondary)	40% / 50% / 65%	2023	UNESCO (2023)
School-age children (3–17) without home internet	~1.3 billion (two-thirds)	2020	UNICEF & ITU (2020)
Rural Indian youth (14–16) with a smartphone at home	~90%	2024	Pratham (2025)
Rural Indian youth (14–16) owning a smartphone, boys vs girls	36.2% vs 26.9%	2024	Pratham (2025)

Note. Figures are rounded as reported by the original sources. ITU = International Telecommunication Union.

Three observations follow from these figures. The first concerns *quality*. Users in high-income countries consume far more mobile data than those in low-income countries, and the gulf in 5G coverage means that the same app, video lesson or AI tutor performs very differently depending on where a learner lives. Access measured as a yes-or-no question hides these differences. Researchers increasingly speak of *meaningful connectivity*, meaning regular use, an appropriate device, enough data and adequate speed, as a more honest benchmark.

The second concerns *continuity*. The pandemic school closures of 2020–2021 acted as a natural stress test. In the Netherlands, a country with excellent broadband and a short lockdown, students lost about three percentile points in national assessments, and losses were up to 60% larger among children from less-educated homes (Engzell et al., 2021). If inequality widened there, it is no surprise that losses were steeper where connectivity was patchy and home learning environments were crowded.

The third concerns *the move from access to use*. As devices spread, the divide reappears in what people do with them. Table 3 sets out the three-level model that frames much of the literature, along with how each level shows up in schooling.

Table 3. Levels of the digital divide and their educational expressions

Level	Core question	How it appears in education	Key sources
First level: access	Who has devices and a connection?	Home broadband, device ownership vs sharing, school connectivity, data costs	DiMaggio & Hargittai (2001); van Dijk (2005)
Second level: skills and use	Who can use technology well, and for what?	Information-seeking, evaluating sources, creating content, using digital tools for study rather than only entertainment	Hargittai (2002); van Deursen & van Dijk (2014)
Third level: outcomes	Who turns use into tangible benefit?	Grades, course completion, college applications, scholarships, networks that lead to opportunity	van Deursen & Helsper (2015); Ragnedda (2017)
Emerging: AI literacy	Who can use AI to learn rather than to bypass learning?	Prompting, verifying output, knowing when not to rely on AI, working in one's own language	Bastani et al. (2025); UNESCO (2023)

Source: Compiled by the authors from the cited literature.

Large-scale assessments confirm that more use is not the same as better use. In PISA 2022, students who spent up to an hour a day on digital devices for leisure at school outperformed those spending much longer, while moderate use of devices for learning was associated with higher scores (OECD, 2023). The relationship is curved rather than straight: some purposeful use helps, but heavy, unstructured use is associated with lower performance.

3.2 Social capital as a conversion factor (RQ2)

The second body of evidence shows that relationships shape what technology does for learners. Coleman (1988) argued that a family's resources benefit a child only when they are passed on through close, attentive relationships; Bourdieu (1986) emphasized that networks are unevenly distributed and convertible into other forms of advantage. Both insights apply directly to digital learning. A device in the home is a resource; whether it becomes an educational asset depends on who is around to help, guide and connect. Table 4 organizes the evidence by type of social capital.

Table 4. Forms of social capital and their role in digital learning

Form	Typical actors	Mechanism	Illustrative evidence
Bonding (within family)	Parents, siblings, extended kin	Supervising use, modelling purposeful use, sharing know-how, setting routines	Coleman (1988); Livingstone & Helsper (2008); Lareau (2011)
Bonding (reversed)	Children as "media brokers" for parents	Children translate and navigate technology for families, building skills but also carrying burdens	Katz (2014); Katz & Gonzalez (2016)
Bridging (peers and communities)	Classmates, online communities, interest groups	Exchanging tips, learning together, exposure to new uses and aspirations	Ito et al. (2013); Ellison et al. (2007)
Linking (institutional agents)	Teachers, librarians, counsellors, mentors	Translating access into academic use, opening doors to opportunities and information	Stanton-Salazar (2011); Warschauer & Matuchniak (2010)
Digital-native networks	Online mentors, alumni groups, professional platforms	Access to information about scholarships, admissions and careers	Robinson et al. (2015); Dettling et al. (2018)

Source: Compiled by the authors, drawing on Bourdieu (1986), Coleman (1988) and Stanton-Salazar (2011).

Studies of parental mediation show that active, talk-based guidance is linked to broader online opportunities for children, while purely restrictive rules mainly reduce risk without raising benefit (Livingstone & Helsper, 2008). Better-educated parents are more likely to mediate actively, which means family background shapes not only whether children are online, but how (Lareau, 2011; Hargittai & Hinnant, 2008).

Lower-income households face a different set of conditions. In immigrant households in the United States, children often act as technology brokers, helping parents with forms, apps and school portals (Katz, 2014). This role can build confidence and skill, yet it also places adult responsibilities on young shoulders. Where homes rely on mobile-only or unreliable connections, families are what Rideout and Katz (2016) describe as under-connected: online, but in ways too fragile to support sustained study. Katz and Gonzalez (2016) argue that such cases call for a measure of meaningful connectivity rather than simple access.

Bridging networks matter too. The connected learning framework shows that young people learn most deeply when personal interests, peer culture and academic opportunity are linked (Ito et al., 2013). Privileged youth tend to have such links already; others depend on schools, libraries and community programs to create them. At this point, linking social capital carries the most weight. Teachers and other institutional agents can turn a phone or a laptop into a pathway to coursework, applications and mentoring (Stanton-Salazar, 2011). Warschauer and Matuchniak (2010) found that the same technology deployed in schools serving different communities was used in very different ways: for creative, analytical work in some, and for drill and remediation in others.

3.3 What interventions have achieved (RQ3)

The third finding is the most policy-relevant. Device and connectivity programs on their own seldom improve academic results. Interventions that pair technology with pedagogy, adaptive content or human contact do much better. Table 5 summarizes influential studies with strong research designs.

Table 5. Selected evaluations of technology-based educational interventions

Study	Setting	Intervention	Design	Main finding
Malamud & Pop-Eleches (2011)	Romania	Vouchers for home computers	Regression discontinuity	Higher computer skills, but lower school grades; effects shaped by parental rules
Fairlie & Robinson (2013)	California, USA	Free home computers for students	Randomized trial	Ownership rose sharply; no effect on grades, test scores or attendance
Vigdor, Ladd & Martinez (2014)	North Carolina, USA	Arrival of home broadband	Panel, natural experiment	Modest declines in maths and reading, larger for disadvantaged students
Cristia et al. (2017)	Peru	One Laptop per Child in schools	Randomized trial	No gains in math or language; small gains in some cognitive skills
Banerjee et al. (2007)	Vadodara, India	Computer-assisted math learning	Randomized trial	Substantial maths gains, especially for lower achievers; effects faded after programme ended
Dettling, Goodman & Smith (2018)	USA	Expansion of high-speed internet	Natural experiment	More students sat admissions tests and applied to a wider range of colleges
Muralidharan, Singh & Ganimian (2019)	Delhi, India	Mindspark adaptive software in after-school centres	Randomized trial	Large gains in maths and Hindi within 4.5 months, especially for weakest students
Angrist, Bergman & Matsheng (2022)	Botswana	SMS messages plus teacher phone calls during school closures	Randomized trial	Numeracy improved at low cost; the phone-call component drove most gains
Escueta et al. (2020)	Global	Review of experimental evidence	Systematic review	Access alone has little effect; computer-assisted learning and behavioural nudges are most promising

Note. Effect sizes are reported in the original studies; Escueta et al. (2020) provide a comparative summary.

Two lessons follow. First, access without guidance can do harm. In Romania and North Carolina, new technology at home displaced homework and reading time, and the damage was smallest where parents set rules (Malamud & Pop-Eleches, 2011; Vigdor et al., 2014). Second, the most successful programmes carry a human or pedagogical element. Mindspark adapted to each child's level and was used in supervised centres. The Botswana intervention worked largely because teachers called families. In both cases, technology extended social capital rather than replacing it.

The evidence on the third-level divide is encouraging in a different way. Dettling et al. (2018) showed that faster internet broadened students' college search, likely because it opened access to information that well-networked families already possessed. Here, connectivity served as a partial substitute for missing bridging capital.

3.4 Generative AI and a new form of inequality

Since the public release of ChatGPT in November 2022, generative AI has become part of everyday study for many students. In the United States, the share of teenagers using ChatGPT for schoolwork doubled from 13% in 2023 to 26% in 2024 (Pew

Research Center, 2025). Early experimental work suggests that design and guidance matter a great deal. Table 6 summarises key studies.

Table 6. Early experimental evidence on generative AI and learning

Study	Setting	Condition	Main finding
Bastani et al. (2025)	High schools, Turkey	Open GPT-4 vs a tutor version with guardrails	Open access raised practice scores but lowered later exam performance; the guided tutor avoided this harm
Kestin et al. (2025)	University physics, USA	AI tutor built on pedagogical principles vs in-class active learning	Learning gains with the AI tutor were substantially larger, in less time
De Simone et al. (2025)	Secondary schools, Nigeria	Teacher-supported after-school sessions with GPT-4	Meaningful gains in English after six weeks, at low cost per student

Note. All three studies report short-term outcomes; durability of effects has not yet been established.

The pattern is a familiar one. AI tools help most when they are structured as tutors and embedded within teacher guidance; left open, they can let students outsource thinking. Students whose families and schools can teach them to use AI critically are likely to benefit, while others may become dependent on tools they do not fully understand. Language adds a further layer, since most large models perform best in English and other high-resource languages (UNESCO, 2023; Kasneci et al., 2023).

4. DISCUSSION

This review set out to explain why the spread of connectivity has not delivered the educational equality once expected. The answer holds across settings and methods: technology is a resource, but learning depends on the human and institutional relationships that turn that resource into practice. Where those relationships are thin, access can be neutral or even harmful; where they are strong, modest technology can produce large gains.

4.1 An integrated framework

To draw the findings together, we propose a framework that borrows its logic from Sen's capability approach (Sen, 1999; Robeyns, 2005). In that approach, resources matter only insofar as people can convert them into valued outcomes, and conversion depends on personal, social and environmental factors. Applied here, devices and connectivity are the resources; social capital and pedagogy are the principal conversion factors; and educational outcomes are the result. Table 7 lays out the framework.

Table 7. An integrated framework linking access, social capital and educational outcomes

Component	Elements	What can go wrong	What helps
Resources	Devices, connectivity, data, electricity, digital content in local languages	Shared or mobile-only access; unaffordable data; weak signal; content in an unfamiliar language	Universal school connectivity; affordable data; device lending; multilingual content
Personal conversion factors	Motivation, digital and AI literacy, prior learning, time	Low confidence; distraction; using AI to bypass thinking	Explicit skill-building; guided practice; age-appropriate AI tutors
Social conversion factors	Bonding, bridging and linking social capital	Parents unable to guide use; isolated learners; few mentors	Parent engagement; peer learning; teachers and librarians as institutional agents

Component	Elements	What can go wrong	What helps
Institutional conversion factors	School leadership, curriculum, teacher capacity, policy	Technology added without pedagogy; teachers untrained	Teacher professional development; structured, adaptive programmes
Outcomes	Achievement, completion, transitions, wellbeing, civic participation	Gains concentrated among already advantaged	Targeting support toward students with least social capital

Source: Authors' synthesis, adapted from the capability approach (Sen, 1999; Robeyns, 2005).

The framework makes one point clear: interventions acting on resources alone address only the first row. The randomized evidence in Table 5 shows that this is rarely enough. Successful programmes work on two or more rows at once, combining a device or connection with adaptive content, teacher contact or family engagement.

4.2 Theoretical implications

The review contributes to theory in three ways. First, it supports the move from a binary to a graduated understanding of digital inequality (Livingstone & Helsper, 2007; van Dijk, 2020), while showing that the levels are tied together by social relationships rather than by individual skill alone. Second, it suggests that social capital is not merely a parallel influence on learning but a *mediator* and *moderator* of technology's effects. The contrasting findings from Romania, where parental rules softened the harm of home computers, and from Botswana, where teacher calls produced most of the benefit, illustrate both roles. Third, generative AI appears to shift the divide once more. When a capable AI tutor costs little or nothing, the scarce resource is no longer information but judgement: knowing what to ask, when to doubt, and how to learn rather than simply obtain an answer. That kind of judgement is learned socially.

4.3 Implications for policy and practice

Policies that focus on headline access numbers risk declaring victory too early. India's near-universal smartphone access among rural adolescents, set against lower ownership among girls and modest educational use, is a reminder that equal presence does not mean equal opportunity. Table 8 translates the findings into actions for different stakeholders.

Table 8. Policy and practice recommendations

Stakeholder	Recommended action	Rationale from the evidence
National governments	Measure meaningful connectivity (speed, device, data, regularity), not just access	Binary access figures conceal quality and continuity gaps
National governments	Prioritise connecting public and rural schools	School connectivity lags most where home access is weakest
Education ministries	Pair device programmes with teacher training and structured, adaptive content	Device-only programmes show little effect on learning
Schools	Train teachers as institutional agents who guide digital and AI use	Linking social capital converts access into academic use
Schools and communities	Run parent workshops on active mediation and AI awareness	Active mediation widens opportunities; restriction alone does not
Libraries and NGOs	Offer supervised learning spaces with connectivity and mentoring	Supervised settings explain much of the success of programmes like Mindspark
EdTech developers	Design AI tools as tutors with guardrails and support local languages	Open AI access can undermine learning; language bias excludes many learners

Stakeholder	Recommended action	Rationale from the evidence
Researchers	Track gender gaps in device ownership and use, not just household access	Shared devices disadvantage girls in particular

Source: Authors' synthesis of the evidence reviewed in Section 3.

4.4 Directions for future research

Several gaps deserve attention. Longitudinal studies are needed to follow how students' social networks and digital practices co-evolve, particularly in low- and middle-income countries where most of the evidence is cross-sectional. Experimental research on AI in education is promising but still concentrated in a few countries and short time frames; replication in multilingual, low-resource contexts is urgent. Measures of social capital in digital settings remain uneven, and validated instruments that capture online bridging and linking ties would strengthen future work. Finally, more attention should go to learners at the intersections of disadvantage, such as rural girls, students with disabilities and children in displaced communities, whose experiences are often lost in national averages.

5. CONCLUSION

The digital divide of 2026 is less a wall than a slope. Most young people can now get online in some fashion, but the distance between a shared, unreliable phone and a well-supported, purposeful digital life remains vast, and it maps closely onto existing inequalities of income, place and gender. This review finds that what most helps learners cross that distance is social: families who can guide, peers who can share, and teachers who can connect learners to opportunity.

The practical message is straightforward. Hardware and bandwidth are necessary but not sufficient. Investment pays off when it comes with people: trained teachers, engaged parents, mentors and well-designed tutoring, whether human or AI-assisted. As generative AI makes information abundant, the ability to use it wisely will become the new marker of advantage. Closing the divide in the years ahead will therefore depend as much on building social capital as on extending networks.

Limitations

This review has limits that readers should keep in mind. As an integrative rather than a statistical synthesis, it does not produce pooled effect sizes, and the selection of studies, though guided by explicit criteria, involves judgement. Only English-language sources were included, which may under-represent research from Latin America, francophone Africa and parts of Asia. Much of the experimental evidence comes from a handful of countries, and findings on generative AI rest on a small number of recent studies whose long-term effects are not yet known. Finally, social capital is measured in many different ways across the literature, which complicates direct comparison.

DECLARATIONS

Funding: This research received no specific grant from any funding agency in the public, commercial or not-for-profit sectors.

Conflict of interest: The author(s) declare no conflict of interest.

Data availability: No new data were generated. All sources analysed are publicly available and listed in the references.

Ethics statement: Not applicable, as the study is a review of published literature.

Use of AI tools: [Authors to complete according to the target journal's policy on AI-assisted writing.]

Author contributions (CRediT): [Author 1]: Conceptualisation, Methodology, Formal analysis, Writing – original draft. [Author 2]: Validation, Writing – review and editing, Supervision. All authors have read and approved the final manuscript.

Acknowledgements: [Optional. Thank colleagues, reviewers or institutions who supported the work.]

REFERENCES

- [1] Angrist, N., Bergman, P., & Matsheng, M. (2022). Experimental evidence on learning using low-tech when school is out. *Nature Human Behaviour*, 6(7), 941–950.
- [2] Banerjee, A. V., Cole, S., Duflo, E., & Linden, L. (2007). Remedying education: Evidence from two randomized experiments in India. *The Quarterly Journal of Economics*, 122(3), 1235–1264.
- [3] Bastani, H., Bastani, O., Sungu, A., Ge, H., Kabakcı, Ö., & Mariman, R. (2025). Generative AI without guardrails can harm learning: Evidence from high school mathematics. *Proceedings of the National Academy of Sciences*, 122(26), e2422633122.
- [4] Bourdieu, P. (1986). The forms of capital. In J. G. Richardson (Ed.), *Handbook of theory and research for the sociology of education* (pp. 241–258). Greenwood.
- [5] Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77–101.
- [6] Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology*, 94, S95–S120.
- [7] Cristia, J., Ibarrarán, P., Cueto, S., Santiago, A., & Severín, E. (2017). Technology and child development: Evidence from the One Laptop per Child program. *American Economic Journal: Applied Economics*, 9(3), 295–320.
- [8] De Simone, M. E., Tiberti, F. H., Barron Rodriguez, M. R., Manolio, F. A., Mosuro, W., & Dikoru, E. J. (2025). *From chalkboards to chatbots: Evaluating the impact of generative AI on learning outcomes in Nigeria* (Policy Research Working Paper No. 11125). World Bank.
- [9] Dettling, L. J., Goodman, S., & Smith, J. (2018). Every little bit counts: The impact of high-speed internet on the transition to college. *Review of Economics and Statistics*, 100(2), 260–273.
- [10] DiMaggio, P., & Hargittai, E. (2001). *From the "digital divide" to "digital inequality": Studying Internet use as penetration increases* (Working Paper No. 15). Center for Arts and Cultural Policy Studies, Princeton University.
- [11] Ellison, N. B., Steinfield, C., & Lampe, C. (2007). The benefits of Facebook "friends": Social capital and college students' use of online social network sites. *Journal of Computer-Mediated Communication*, 12(4), 1143–1168.
- [12] Engzell, P., Frey, A., & Verhagen, M. D. (2021). Learning loss due to school closures during the COVID-19 pandemic. *Proceedings of the National Academy of Sciences*, 118(17), e2022376118.
- [13] Escueta, M., Nickow, A. J., Oreopoulos, P., & Quan, V. (2020). Upgrading education with technology: Insights from experimental research. *Journal of Economic Literature*, 58(4), 897–996.
- [14] Fairlie, R. W., & Robinson, J. (2013). Experimental evidence on the effects of home computers on academic achievement among schoolchildren. *American Economic Journal: Applied Economics*, 5(3), 211–240.
- [15] Hargittai, E. (2002). Second-level digital divide: Differences in people's online skills. *First Monday*, 7(4).
- [16] Hargittai, E., & Hinnant, A. (2008). Digital inequality: Differences in young adults' use of the Internet. *Communication Research*, 35(5), 602–621.
- [17] Hong, Q. N., Fàbregues, S., Bartlett, G., Boardman, F., Cargo, M., Dagenais, P., Gagnon, M.-P., Griffiths, F., Nicolau, B., O'Cathain, A., Rousseau, M.-C., Vedel, I., & Pluye, P. (2018). The Mixed Methods Appraisal Tool (MMAT) version 2018 for information professionals and researchers. *Education for Information*, 34(4), 285–291.
- [18] International Telecommunication Union. (2025). *Measuring digital development: Facts and figures 2025*. ITU. <https://www.itu.int/itu-d/reports/statistics/facts-figures-2025/>
- [19] Ito, M., Gutiérrez, K., Livingstone, S., Penuel, B., Rhodes, J., Salen, K., Schor, J., Sefton-Green, J., & Watkins, S. C. (2013). *Connected learning: An agenda for research and design*. Digital Media and Learning Research Hub.
- [20] Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., ... Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103, 102274.
- [21] Katz, V. S. (2014). *Kids in the middle: How children of immigrants negotiate community interactions for their families*. Rutgers University Press.
- [22] Katz, V. S., & Gonzalez, C. (2016). Toward meaningful connectivity: Using multilevel communication research to reframe digital inequality. *Journal of Communication*, 66(2), 236–249.
- [23] Kestin, G., Miller, K., Klales, A., Milbourne, T., & Ponti, G. (2025). AI tutoring outperforms in-class active learning: An RCT introducing a novel research-based design in an authentic educational setting. *Scientific Reports*, 15, 17458.
- [24] Lareau, A. (2011). *Unequal childhoods: Class, race, and family life* (2nd ed.). University of California Press.
- [25] Lin, N. (2001). *Social capital: A theory of social structure and action*. Cambridge University Press.

- [26] Livingstone, S., & Helsper, E. (2007). Gradations in digital inclusion: Children, young people and the digital divide. *New Media & Society*, 9(4), 671–696.
- [27] Livingstone, S., & Helsper, E. J. (2008). Parental mediation of children's internet use. *Journal of Broadcasting & Electronic Media*, 52(4), 581–599.
- [28] Lythreath, S., Singh, S. K., & El-Kassar, A.-N. (2022). The digital divide: A review and future research agenda. *Technological Forecasting and Social Change*, 175, 121359.
- [29] Malamud, O., & Pop-Eleches, C. (2011). Home computer use and the development of human capital. *The Quarterly Journal of Economics*, 126(2), 987–1027.
- [30] Muralidharan, K., Singh, A., & Ganimian, A. J. (2019). Disrupting education? Experimental evidence on technology-aided instruction in India. *American Economic Review*, 109(4), 1426–1460.
- [31] OECD. (2023). *PISA 2022 results (Volume II): Learning during – and from – disruption*. OECD Publishing.
- [32] Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, 372, n71.
- [33] Pew Research Center. (2025). *About a quarter of U.S. teens have used ChatGPT for schoolwork – double the share in 2023*. Pew Research Center.
- [34] Pratham. (2025). *Annual Status of Education Report (Rural) 2024*. ASER Centre.
- [35] Ragnedda, M. (2017). *The third digital divide: A Weberian approach to digital inequalities*. Routledge.
- [36] Rideout, V., & Katz, V. S. (2016). *Opportunity for all? Technology and learning in lower-income families*. Joan Ganz Cooney Center at Sesame Workshop.
- [37] Robeyns, I. (2005). The capability approach: A theoretical survey. *Journal of Human Development*, 6(1), 93–117.
- [38] Robinson, L., Cotten, S. R., Ono, H., Quan-Haase, A., Mesch, G., Chen, W., Schulz, J., Hale, T. M., & Stern, M. J. (2015). Digital inequalities and why they matter. *Information, Communication & Society*, 18(5), 569–582.
- [39] Scheerder, A., van Deursen, A., & van Dijk, J. (2017). Determinants of Internet skills, uses and outcomes: A systematic review of the second- and third-level digital divide. *Telematics and Informatics*, 34(8), 1607–1624.
- [40] Sen, A. (1999). *Development as freedom*. Oxford University Press.
- [41] Stanton-Salazar, R. D. (2011). A social capital framework for the study of institutional agents and their role in the empowerment of low-status students and youth. *Youth & Society*, 43(3), 1066–1109.
- [42] Torraco, R. J. (2016). Writing integrative literature reviews: Using the past and present to explore the future. *Human Resource Development Review*, 15(4), 404–428.
- [43] UNESCO. (2023). *Global education monitoring report 2023: Technology in education – A tool on whose terms?* UNESCO.
- [44] UNICEF & International Telecommunication Union. (2020). *How many children and young people have internet access at home? Estimating digital connectivity during the COVID-19 pandemic*. UNICEF.
- [45] van Deursen, A. J. A. M., & Helsper, E. J. (2015). The third-level digital divide: Who benefits most from being online? In L. Robinson et al. (Eds.), *Communication and information technologies annual* (Studies in Media and Communications, Vol. 10, pp. 29–52). Emerald.
- [46] van Deursen, A. J. A. M., & van Dijk, J. A. G. M. (2014). The digital divide shifts to differences in usage. *New Media & Society*, 16(3), 507–526.
- [47] van Dijk, J. A. G. M. (2005). *The deepening divide: Inequality in the information society*. Sage.
- [48] van Dijk, J. (2020). *The digital divide*. Polity Press.
- [49] Vigdor, J. L., Ladd, H. F., & Martinez, E. (2014). Scaling the digital divide: Home computer technology and student achievement. *Economic Inquiry*, 52(3), 1103–1119.
- [50] Warschauer, M., & Matuchniak, T. (2010). New technology and digital worlds: Analyzing evidence of equity in access, use, and outcomes. *Review of Research in Education*, 34(1), 179–225.
- [51] Whitemore, R., & Knafl, K. (2005). The integrative review: Updated methodology. *Journal of Advanced Nursing*, 52(5), 546–553.