



Digital Preconditions for Equitable Human–AI Partnership in Secondary Education: Evidence from Slovak Students [†]

Andrej Kóna 

Institute of Political Sciences and Public Administration, Faculty of Social Sciences, University of Ss. Cyril and Methodius in Trnava, Bučianska 4/A, 917 01 Trnava, Slovakia; andrej.kona@ucm.sk

[†] Presented at The 1st International Online Conference on Urban Sciences (IOCUS 2026), 20–22 May 2026;

Available online: <https://sciforum.net/event/IOCUS2026>.

Abstract

Background: Equitable engagement with technology-mediated learning, including artificial intelligence (AI)-supported pedagogies envisioned in current education policy, depends on material preconditions—school and home connectivity, device access—that are unevenly distributed. Empirical baselines for these preconditions in Central European secondary education remain sparse. This study examines digital infrastructure conditions among Slovak secondary-school students and tests whether connectivity and device access predict curriculum exposure to the smart-city concept, used here as one observable indicator of access to technology-mediated curricular content rather than as a direct measure of AI literacy. **Methods:** A cross-sectional survey collected data from $N = 419$ Slovak secondary-school students recruited through the Ministry of Education of the Slovak Republic, regional school authorities, and cooperating secondary schools. Self-rated school internet quality, home internet quality, and total household connected devices were analysed individually and combined into a standardised composite digital readiness index. Curriculum exposure to the smart-city concept (binary: any exposure vs. none/unsure) served as the outcome. Logistic regression was applied in unadjusted and gender-adjusted models (valid $n = 383$); component-level models tested which infrastructure dimension carried the association. **Results:** School internet quality was rated low (1–2 on a five-point scale) by 47.6% of students (mean = 2.59), whereas home internet quality was rated high (4–5) by 69.3% (mean = 3.89), indicating a substantial school–home connectivity gap. Only 35.8% of students (148/413) reported any curriculum exposure to the smart-city concept. School internet quality was the principal predictor: each one-standard-deviation (SD) increase corresponded to an odds ratio of 1.564 (95% CI: 1.261–1.939, $p < 0.001$), and in component-level models, neither home internet (OR = 1.038, $p = 0.74$) nor household device count (OR = 0.977, $p = 0.83$) carried independent predictive value. The composite index (OR = 1.337, 95% CI: 1.081–1.654, $p = 0.0075$ unadjusted; OR = 1.328, $p = 0.0095$ gender-adjusted) was essentially a noisier reflection of the school-connectivity signal. Male students were significantly more likely to report exposure than female students (OR = 1.794, 95% CI: 1.166–2.762, $p = 0.0079$). A readiness $\times$ gender interaction approached significance (OR = 0.641, $p = 0.064$), tentatively suggesting a steeper connectivity gradient for female students—an exploratory finding warranting replication. Model discrimination was modest (area under the curve, AUC = 0.621); the association, not predictive performance, is the quantity of interest. **Conclusions:** School-level connectivity—not home infrastructure or device count—is the infrastructure dimension associated with curriculum exposure to technology-mediated content. These findings indicate that school connectivity should be treated as a precondition for equitable participation in technology-mediated and AI-supported learning, and that pedagogical designs should function under infrastructural constraints. Limitations include



Academic Editor: Teodoro Georgiadis

Published: 1 July 2026

Copyright: © 2026 by the author.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

reliance on self-rated measures, school-mediated convenience sampling, an observational cross-sectional design, and the indirect mapping between smart-city curriculum exposure and AI literacy proper.

Keywords: AI literacy; human–AI partnership; digital inequality; education; sustainable development; connectivity; household devices; socio-cultural AI

1. Introduction

The emergence of generative artificial intelligence and AI-assisted learning tools has catalysed renewed interest in what it means for students and educators to work alongside AI systems rather than merely consume their outputs. Scholars and practitioners increasingly frame this relationship as a human–AI partnership—a collaborative dynamic in which AI acts as a cognitive partner, extending human reasoning, supporting inquiry, and amplifying creative capacity [1]. In secondary education, this framing has significant implications for curriculum design, teacher professional development, and, critically, for the physical infrastructure that makes AI-supported learning possible at all.

The policy discourse around AI in education has moved swiftly. International frameworks, from UNESCO's Recommendation on the Ethics of AI to the OECD's AI Principles, emphasise the importance of AI literacy and equitable access as foundational conditions for beneficial AI adoption [2]. Yet the operational assumption embedded in many AI-in-education proposals is that students and schools already possess adequate connectivity and device infrastructure. This assumption is rarely interrogated empirically, and it risks reproducing or amplifying existing inequalities rather than dissolving them.

Slovakia offers an instructive case. As a Central European EU member state, it has invested in digital transformation at the policy level, yet rural–urban disparities in internet infrastructure and between-school variation in connectivity remain notable [3]. Slovak secondary students are at an age when AI literacy dispositions are forming—when exposure to AI-relevant curricula and hands-on digital problem-solving can either open or foreclose trajectories into technology-mediated futures. Understanding the material conditions they face is therefore a matter of both educational equity and sustainable development.

This study approaches the problem through the lens of smart city education. Smart city concepts, which encompass sensor networks, data-driven urban management, citizen engagement platforms, and AI-powered services, have been proposed as a rich context for AI-supported project-based learning at secondary level [4]. Exposure to smart city topics in the curriculum serves, in this paper, as a practical proxy for engagement with AI-relevant, technology-mediated educational content. This choice is explicitly acknowledged as imperfect and is discussed in Section 7; however, it provides a concrete and measurable outcome that links digital infrastructure questions to curriculum reality.

The present study addresses three research questions. First (RQ1): What are the digital infrastructure conditions, in terms of internet quality and household device ecosystems, among Slovak secondary-school students? Second (RQ2): Is digital readiness, operationalised as a composite index of connectivity and device capacity, associated with curriculum exposure to smart city education? Third (RQ3): Do gender and school-level internet quality independently contribute to this association?

Addressing these questions contributes to a growing but still thin body of empirical work on the material preconditions of AI literacy in European secondary education. The findings have direct relevance to Sustainable Development Goal 4 (inclusive and equitable quality education), SDG 10 (reduced inequalities), and SDG 11 (sustainable cities and

communities), and they point toward concrete policy levers (school connectivity investment, compensatory pedagogies, and equity monitoring mechanisms) that can make human–AI partnership a genuinely shared opportunity rather than a privilege of the well-connected.

2. Theoretical Framework and Literature Review

2.1. Human–AI Partnership and the Socio-Cultural Turn

The concept of human–AI partnership in education draws implicitly on socio-cultural theories of learning, and particularly on Vygotsky’s notion of the zone of proximal development (ZPD): the space of cognitive tasks a learner can accomplish with support but not yet independently. Within this framing, AI systems function as technologically mediated cognitive partners—scaffolding reasoning, providing adaptive feedback, and dynamically adjusting the level of challenge [5]. The extension of an originally human–human framework to human–AI interaction is not unproblematic and is treated here as a heuristic motivation rather than an established theoretical equivalence; Vygotsky’s account was developed within a culturally situated activity system, and recent scholarship has rightly questioned the limits of mapping it directly onto AI tools [5]. The framing nevertheless remains useful for identifying the specific interactional features through which AI is hypothesised to support learning: dialogic feedback loops, dynamic adjustment of task difficulty, and just-in-time guidance during problem solving.

It is at this interactional level that infrastructure becomes constitutive rather than merely supportive. The scaffolding interactions implied by the ZPD framing are time-sensitive and bandwidth-sensitive: synchronous dialogue with AI tutors, real-time generation of multimodal feedback, and the streaming of adaptive content all require classroom connectivity adequate to sustain low-latency, sustained sessions. Where school connectivity is unreliable or low-bandwidth, these interaction types collapse to text-only, asynchronous, or one-shot exchanges that approximate look-up rather than scaffolding. Empirical work on AI tutoring systems and large-language-model interactions documents task completion and conceptual gains consistent with scaffolding dynamics under adequate infrastructural conditions [6,7]; the present study takes seriously the converse claim that infrastructural shortfalls foreclose particular categories of AI-supported interaction at the classroom level. The socio-cultural framing therefore foregrounds context, since the conditions under which a partnership can form are technical, institutional, cultural, and material at once.

A complementary strand of scholarship emphasises AI as a social artefact whose meaning and utility are constituted through social practice [5]. From this perspective, AI literacy operates as a socially situated practice shaped by the learner’s access to tools, the norms of their educational institution, and the broader sociotechnical imaginaries of their community, rather than as a context-free technical competency. Empirical work on the second-level digital divide further suggests that infrastructural access alone does not eliminate inequality: differences in how digital tools are used continue to stratify learners and citizens [8], making context-specific empirical work, including studies in under-researched national settings such as Slovakia, particularly valuable.

2.2. AI Literacy: Frameworks and Competency Dimensions

AI literacy has been conceptualised along several dimensions. The influential four-dimensional framework of Long and Magerko [9], introduced above, spans awareness of AI, understanding of AI capabilities and limitations, critical evaluation of AI outputs, and creative use or creation of AI applications, and has shaped subsequent curriculum design and assessment tool development. Overlapping frameworks from the European context, including the DigComp and DigCompEdu frameworks [10,11], emphasise that digital competence at the levels required for meaningful AI engagement presupposes a baseline of

reliable connectivity and access to contemporary devices. Crucially, these frameworks treat infrastructure as a given rather than as a variable to be studied, an assumption the present paper interrogates.

The progression from passive AI consumption to active AI partnership corresponds roughly to higher-order competency levels in these frameworks. Students must be able to run AI-assisted tools reliably (requiring connectivity), to experiment with outputs (requiring sufficient device processing capacity), and to critically compare results (requiring access and accumulated experience). A student whose school internet is persistently rated as poor is structurally disadvantaged at every step of this progression.

2.3. Digital Inequality: Three Levels

The digital inequality literature has evolved from a binary access/no-access framing to a multi-level model distinguishing first-level divides (physical access to devices and connectivity), second-level divides (skills and productive use), and third-level divides (outcomes and benefits derived from digital engagement) [12]. The present study is primarily concerned with first-level inequalities (school internet quality, home internet quality, and household device counts), but its conceptual logic connects these to second-level outcomes: curriculum exposure to AI-relevant content and, by extension, to the accumulation of AI literacy competencies.

First-level infrastructure matters in schools in ways that differ from household contexts. At home, students may compensate for low device counts with mobile phones or shared devices; institutional learning activities, however, often require simultaneous connectivity for an entire class, sustained throughput for data-heavy tasks, and reliable uptime that household mobile broadband may not guarantee. The school–home connectivity gap documented in this study therefore operates as a structural constraint on the kinds of pedagogical activities that can be designed and delivered, rather than as a mere numerical curiosity.

2.4. Smart City Education and the SDG Context

Smart city education has been positioned in policy and curricular discourse as a vehicle for integrating AI literacy, civic engagement, and sustainability thinking. Curricula that engage students with smart city concepts expose them to real data pipelines, sensor networks, urban AI applications, and the governance challenges these entail—providing an authentic context for human–AI collaboration in a problem-solving mode. This aligns directly with the United Nations 2030 Agenda for Sustainable Development [13]: SDG 4's vision of quality education that promotes sustainable development (target 4.7), SDG 10's call to reduce inequalities of opportunity, and SDG 11's ambition to make cities inclusive, safe, and sustainable. Research on smart city education in European secondary schools [4] has shown positive effects on science, technology, engineering, and mathematics (STEM) motivation and on students' understanding of data-driven governance but has rarely examined the infrastructure conditions that determine whether such curricula are accessible to all students equally.

A key gap in the literature concerns the measurement of preconditions. The majority of studies evaluating AI or smart city curricula assume that participating schools have adequate infrastructure, either by design (only well-equipped schools are selected) or by omission (infrastructure is not measured). This selection effect means that positive outcome findings may reflect the characteristics of the school environment as much as the curriculum itself. The present study addresses this gap by treating infrastructure variation as a substantive object of inquiry rather than a nuisance variable.

3. Materials and Methods

3.1. Study Design and Sample

This study uses a cross-sectional survey design. Data were collected in 2025 from $N = 419$ Slovak secondary-school students via an online questionnaire hosted on the SmartCityExplorer.sk platform. Recruitment followed a multi-channel convenience-sampling procedure: invitations were distributed through (i) the Ministry of Education of the Slovak Republic, (ii) regional school authorities (self-governing regions, acting within their educational competencies), and (iii) individual cooperating secondary schools and teachers. This multi-institutional distribution channel was designed to reach schools across Slovakia's administrative regions regardless of prior engagement with smart-city educational initiatives; the SmartCityExplorer.sk platform served only as the technical hosting environment for the questionnaire and was not used as a recruitment community. To encourage student participation, respondents who completed the questionnaire were offered a small gamified incentive (a "wheel of fortune" prize draw upon submission). Multiple secondary schools across Slovakia participated, spanning grammar schools (gymnázia), vocational secondary schools (stredné odborné školy), and business academies. The survey was fully anonymous: no direct personal identifiers (names, addresses, personal identification numbers) were collected, and school-level identifiers were used solely for aggregated group comparisons. Informed consent was obtained at two levels—school management authorised the administration of the survey within the school environment and informed parents and legal guardians where appropriate, and individual respondents provided active consent at the start of the questionnaire after being informed of the study's purpose, the anonymous nature of participation, and their right to withdraw at any point without consequence. The study posed minimal risk to participants: the questionnaire collected no sensitive personal data, no direct identifiers, and was fully anonymous from the outset. The research design and informed-consent procedures were reviewed by the ethics liaison of the Faculty of Social Sciences, University of Ss. Cyril and Methodius in Trnava; under Slovak research practice, anonymous educational surveys involving non-sensitive data and posing minimal risk do not require separate formal institutional review board approval.

Participants were upper-secondary students, predominantly enrolled in years 1–4 of mainstream secondary education (typical age range 15–19), attending schools located across multiple regions of Slovakia. The sample is regionally and institutionally diverse, although it is not statistically representative of the Slovak upper-secondary population given the convenience-sampling design. The study was conducted in accordance with the ethical guidelines of the Faculty of Social Sciences, University of Ss. Cyril and Methodius in Trnava, and adhered to the principles of voluntary participation, anonymity, informed consent, and aggregate-only reporting. Datasets are stored on an access-restricted drive available only to the author. Earlier thematically related work on Slovak municipal readiness for smart-city development [14] situates the present study within a broader research line, although it draws on a different dataset and analytical focus. For the present 2025 data wave, item-level missingness was addressed by listwise deletion: the analytic sample retained for the logistic regression is $n = 383$, with varying denominators for descriptive statistics as reported. Data were collected through the Smart City Explorer online platform (SmartCityExplorer.sk), developed at the University of Ss. Cyril and Methodius in Trnava. A parallel territorial sub-analysis on the same dataset, examining whether settlement size (log-population) and self-rated local internet quality predict students' perceived absence of smart-city elements in their own municipality, was conducted and is reported separately in a companion poster [15]. That analysis (analytic $n = 412$ after listwise deletion for the alternative outcome) found that students in smaller municipalities were significantly more likely to report no perceived smart-city elements ($OR = 0.67$ per log-population unit,

$p = 0.015$), with a marginal protective association for local internet quality ($OR = 0.75$, $p = 0.062$). The present article reports the curriculum-exposure analysis only; the difference in analytic n between the two analyses (383 vs. 412) reflects different outcome variables and consequently different listwise-deletion patterns.

3.2. Measures

Internet quality was assessed using separate single-item self-rated questions for three contexts: school, home, and municipality (local area). Each item used a five-point Likert-type scale from 1 (very poor) to 5 (excellent). Self-rated measures of internet quality are widely used in digital inequality research [16] and capture the experienced quality of connectivity, including reliability, speed, and availability, rather than nominal infrastructure parameters that may not reflect classroom reality.

Household device inventory was assessed by asking students to report the number of devices in each of four categories: mobile devices (smartphones, basic phones), media devices (TVs, projectors), computing devices (tablets, PCs, notebooks), and Internet of Things (IoT) devices (smart appliances such as connected fridges, robot vacuum cleaners, etc.). A total household device count was computed by summing across all four categories ($n = 393$ with complete device data).

Curriculum exposure was assessed via the question: 'Have you ever encountered the concept of a smart city in your school curriculum?' Responses were: 'Yes, in detail' ($n = 20$), 'Yes, marginally' ($n = 128$), 'No, never heard it' ($n = 147$), and 'Not sure/Don't remember' ($n = 118$); 6 responses were missing. For logistic regression, exposure was coded as binary: any curriculum exposure (either 'in detail' or 'marginally') versus no confirmed exposure (combining 'never heard it' and 'not sure'). This conservative operationalisation assigns uncertain responses to the non-exposure category.

3.3. Digital Readiness Index

A composite digital readiness index was constructed in three steps. First, three constituent variables were standardised to z-scores: school internet quality (1–5 scale), home internet quality (1–5 scale), and total household device count. Second, the three z-scores were summed to produce a composite readiness score. Third, the composite was re-standardised to mean = 0, SD = 1 to facilitate interpretation of logistic regression coefficients as effects per one standard deviation increase. This approach treats school connectivity, home connectivity, and device access as equally weighted, additive contributors to digital readiness, a simplifying assumption noted in Section 7.

3.4. Statistical Analysis

Descriptive statistics (frequencies, means, medians) were computed for all variables. Curriculum exposure rates were cross-tabulated by readiness quartile, by school internet quality category (low: 1–2; mid: 3; high: 4–5), and by gender to examine unadjusted gradient patterns. Logistic regression with curriculum exposure as the binary outcome was estimated in two specifications: an unadjusted model including only the standardised readiness index and a model additionally adjusting for gender (male vs. female). Results are reported as odds ratios (OR) with 95% confidence intervals derived from the Wald approximation and two-sided p -values. Analyses were conducted in Python 3.11 using pandas 2.2 and statsmodels 0.14. All tests were two-tailed with a significance threshold of $\alpha = 0.05$. Model assumptions were assessed prior to interpretation. Variance inflation factors (VIF) for the three index components and for the predictors in the adjusted model were all below 1.01, indicating no multicollinearity. Model fit was evaluated via the Hosmer–Lemeshow goodness-of-fit test ($\chi^2 = 9.39$, $df = 8$, $p = 0.31$), indicating no evidence of lack of fit, and the area under the ROC curve was $AUC = 0.621$, indicating modest but above-

chance discrimination. Robustness was assessed through sensitivity analyses reported in Section 4.5. An a priori sensitivity calculation indicated that, given an analytic n of 383, an event rate of approximately 35%, and $\alpha = 0.05$, the study was powered ($\geq 80\%$) to detect odds ratios of approximately 1.30 or larger per one-SD change in standardised predictors.

4. Results

4.1. Internet Quality: A School–Home Divide

Table 1 presents the distribution of self-rated internet quality across three contexts. The contrast between school and home settings is stark (Figure 1). At school, nearly half of respondents (47.6%, 191/401) rated connectivity in the low range (1–2 on the five-point scale), with a mean of 2.59. Fewer than a quarter (23.2%) rated school internet in the high range (4–5). At home, the distribution is nearly inverted: 69.3% rated home internet as high quality, with a mean of 3.89, and only 12.6% rated it as low. Municipal internet quality showed a pattern closer to school internet, with 52.6% of respondents rating local connectivity as low (mean = 2.46, $n = 384$).

Table 1. Self-Rated Internet Quality Distributions (School, Home, Municipality).

Context	n	Low (1–2) %	Mid (3) %	High (4–5) %	Mean
School	401	47.6%	29.2%	23.2%	2.59
Home	404	12.6%	18.1%	69.3%	3.89
Municipality	384	52.6%	24.5%	22.9%	2.46

Note. Low = ratings of 1 or 2; Mid = rating of 3; High = ratings of 4 or 5. Scale: 1 (very poor) to 5 (excellent). n varies due to item-level missingness.

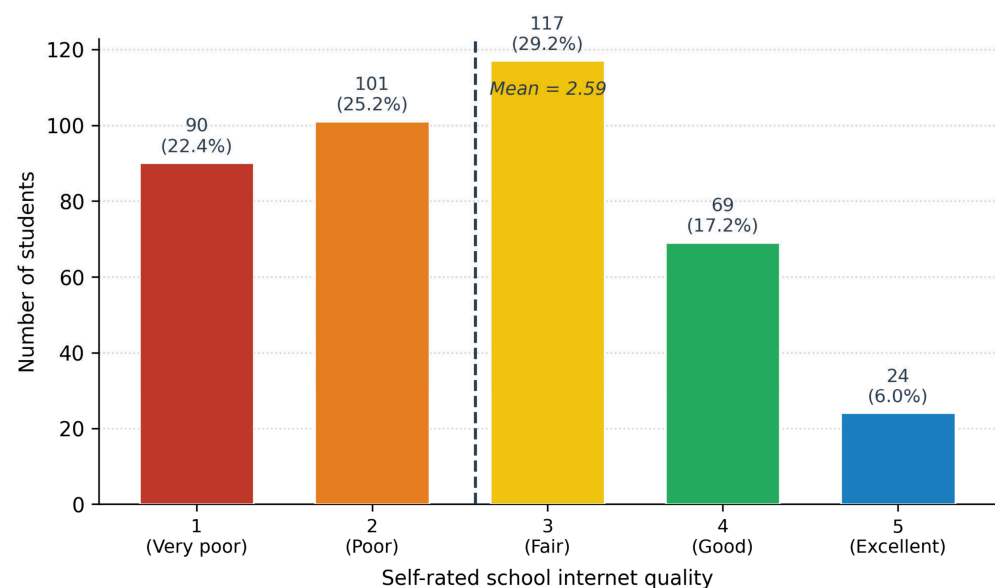


Figure 1. Self-reported quality of internet connectivity at school ($N = 401$). Bar chart shows the count of students at each rating on a 1–5 Likert scale (1 = very poor, 5 = excellent); the dashed line marks the sample mean (2.59).

4.2. Household Device Ecosystem

Table 2 summarises the distribution of household devices across four categories. Mobile devices were the most numerous category (mean = 4.72, median = 4), consistent with the ubiquity of smartphone ownership. Computing devices (tablets, PCs, and notebooks) showed a mean of 3.61 and median of 3, indicating that most households possess multiple computing platforms. IoT devices (mean = 3.30, median = 2) exhibited positive skew: the

mean exceeds the median, indicating that a subset of households with large IoT deployments pulls the distribution upward. Media devices were least numerous (mean = 2.03, median = 2). Total household devices had a median of 12.0 and mean of 12.9 ($n = 393$), reflecting the cumulative effect across categories.

Table 2. Household Connected Device Categories ($n = 393$).

Device Category	Examples	Mean	Median
Mobile	Smartphones, basic phones	4.72	4
Media	TVs, projectors	2.03	2
Computing	Tablets, PCs, notebooks	3.61	3
IoT	Smart fridges, robot vacuums, etc.	3.30	2
Total	Sum across all categories	12.9	12.0

Note. IoT mean exceeds median due to positive skew from high-device households. Total $n = 393$ with complete device data.

4.3. Curriculum Exposure to the Smart City Concept

Overall, 35.8% of students (148/413, excluding six missing responses) reported any curriculum exposure to the smart city concept—either ‘in detail’ (4.8%, $n = 20$) or ‘marginally’ (30.6%, $n = 128$). A further 35.1% ($n = 147$) stated they had never heard the concept in a school context, and 28.2% ($n = 118$) were uncertain or could not remember. Six responses were missing.

A notable gender gap was observed: male students reported any exposure at a rate of 42.2% (95/225), compared with 28.2% (53/188) for female students, a difference of 14.0 percentage points ($\chi^2 = 8.17$, $df = 1$, $p = 0.004$; Figure 2).

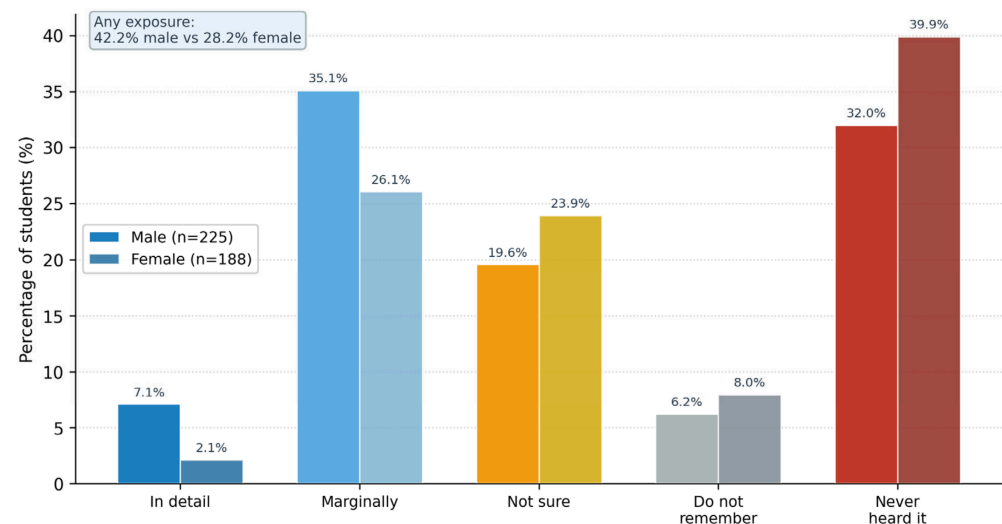


Figure 2. Smart-city curriculum exposure by gender ($n = 413$). Grouped bars show the percentage of male ($n = 225$) and female ($n = 188$) respondents reporting each level of curriculum contact with the smart city concept.

4.4. Curriculum Exposure by School Internet Quality and Readiness Quartile

Table 3 displays curriculum exposure rates stratified by school internet quality category and by readiness quartile. A clear positive gradient is visible across both stratifications. Among students who rated their school internet as low-quality (1–2), 28.3% reported exposure; this rose to 35.0% for mid-quality ratings and 52.7% for high-quality ratings. Similarly, exposure rates increased monotonically across readiness quartiles: 25.0% in Q1 (lowest readiness), 34.7% in Q2, 37.6% in Q3, and 49.0% in Q4 (highest readiness). The

24-percentage-point gap between the lowest and highest quartiles is substantively large: the descriptive exposure rate in Q4 (49.0%) is roughly twice that in Q1 (25.0%). This is a descriptive comparison of unadjusted proportions, not an estimated odds ratio.

Table 3. Curriculum Exposure to Smart City Concept by School Internet Quality, Readiness Quartile, and Gender.

Stratum	Subgroup	<i>n</i> (Subgroup)	Exposed <i>n</i>	Exposure %
School Internet Quality	Low (1–2)	191	54	28.3%
	Mid (3)	117	41	35.0%
	High (4–5)	93	49	52.7%
Readiness Quartile	Q1 (lowest)	96	24	25.0%
	Q2	98	34	34.7%
	Q3	93	35	37.6%
	Q4 (highest)	96	47	49.0%
Gender	Male	225	95	42.2%
	Female	188	53	28.2%

Note. Exposure = any curriculum contact with the smart city concept ('in detail' or 'marginally'). Denominator *n* varies by stratum due to item-level missingness.

4.5. Logistic Regression: Readiness and Curriculum Exposure

Table 4 presents logistic regression results predicting curriculum exposure (*n* = 383). The composite digital readiness index was positively associated with curriculum exposure in both the unadjusted model (OR = 1.337 per 1 SD, 95% CI: 1.081–1.654, *p* = 0.0075) and after adjustment for gender (OR = 1.328, 95% CI: 1.072–1.644, *p* = 0.0095), with male students showing significantly higher odds than female students (OR = 1.794, 95% CI: 1.166–2.762, *p* = 0.0079). However, component-level decomposition revealed that this composite signal originated almost entirely from one of its three constituents. When the three index components were entered as separate predictors in the same model, only school internet quality remained an independent predictor (OR = 1.532, *p* < 0.001); home internet quality (OR = 1.038, *p* = 0.74) and household device count (OR = 0.977, *p* = 0.83) showed essentially no independent association with curriculum exposure. A model with school internet quality alone produced the strongest effect (OR = 1.564 per 1 SD, 95% CI: 1.261–1.939, *p* < 0.001), exceeding that of the composite index. The composite index is therefore best interpreted as a noisier representation of the school-connectivity signal rather than as a multidimensional construct in which the three components contribute equally. The substantive finding is that school-level connectivity—not home infrastructure or device count—is the infrastructure dimension associated with curriculum exposure to the smart-city concept in this sample. Model discrimination was modest (AUC = 0.621), indicating that infrastructure is far from a sufficient predictor of individual exposure; the quantity of substantive interest is the associational gradient (the odds ratio), not classification performance.

Table 4. Logistic Regression: Predictors of Curriculum Exposure to Smart City Concept (*n* = 383).

Model	Predictor	OR	95% CI	<i>p</i> -Value
Unadjusted	Readiness index (per 1 SD)	1.337	1.081–1.654	0.0075
Adjusted for gender	Readiness index (per 1 SD)	1.328	1.072–1.644	0.0095
	Male vs. Female	1.794	1.166–2.762	0.0079

Note. OR = odds ratio. CI = confidence interval (Wald approximation). Readiness index: composite of standardised school internet quality, home internet quality, and total household devices; standardised to mean = 0, SD = 1. Reference category for gender: female. *n* = 383 after listwise deletion.

Two further sensitivity analyses supported the school-connectivity interpretation. Re-weighting the readiness index by principal-component loadings yielded a comparable adjusted association (OR = 1.443 per 1 SD, 95% CI: 1.160–1.795, $p = 0.001$), confirming that the result is not an artefact of equal weighting. Tightening the outcome definition to “in detail” only (excluding “marginally” exposed students) preserved the direction of the association but reduced precision (OR = 1.463 per 1 SD, 95% CI: 0.958–2.236, $p = 0.08$), consistent with the small number of “in detail” cases ($n = 20$). A test for a readiness $\times$ gender interaction yielded a marginal effect (OR = 0.641, $p = 0.064$), tentatively suggesting that the connectivity gradient may be steeper among female students. This exploratory finding is discussed further in Section 5.3; if replicated, it would imply that improvements in school connectivity could disproportionately benefit female students’ curriculum access.

5. Discussion

5.1. The School–Home Connectivity Gap

A substantively important feature of these data, reported descriptively in Section 4 and the abstract, is the inversion of connectivity quality between school and home. For many Slovak secondary students, the institutional setting in which structured AI-relevant learning would naturally occur is more connectivity-constrained than their home environment. The implication is significant for the vision of equitable technology-mediated and AI-supported education: pedagogical designs that assume high-bandwidth classroom connectivity (for interactive AI tools, streaming instructional content, or real-time data visualisation) will function well for home-based learners but fail in the classroom for the substantial share of students whose school connectivity is rated low.

Municipal internet quality, averaging 2.46, tracks closely with school quality and suggests that for students in lower-connectivity municipalities, the school–home gap may partially reflect residential location rather than school-specific under-investment. Disentangling these contributions would require individual-level geographic data not available in the present study. What the data establish is that the school cannot be assumed to function as a compensatory digital environment; for many students, it appears instead to constrain access.

5.2. The Readiness Gradient and Curriculum Exposure

The positive gradient between digital readiness and curriculum exposure is robust across two representations (quartile cross-tabulation and logistic regression) and survives adjustment for gender. Each additional standard deviation of readiness is associated with approximately 33% higher odds of having encountered smart city topics in the curriculum. The effect size, while modest, is consistent across specifications and achieves conventional statistical significance.

Interpreting this association causally is not warranted by the observational, cross-sectional design. Several mechanisms could plausibly underlie the correlation. Schools with better internet may invest more broadly in digital education, making both higher connectivity ratings and smart city curriculum exposure more likely. Students with more household devices may have greater informal exposure to technology topics, making them more likely to recognise and recall curriculum references to smart concepts. Alternatively, higher-resourced households may be concentrated in areas with better school infrastructure, creating an ecological correlation. All of these mechanisms are consistent with the data, and all point to the same underlying dynamic: digital capital, broadly construed, is unevenly distributed and co-varies with access to AI-relevant educational content.

5.3. The Gender Gap

The 14.0-percentage-point gender gap in curriculum exposure (42.2% male vs. 28.2% female) is consistent with documented patterns of gender-differential engagement with STEM and technology topics in European secondary education [17]. The logistic regression confirms that this gap is not explained by differential readiness: males and females in this sample do not differ substantially in their readiness index, yet males are significantly more likely to report exposure (OR = 1.794). This suggests that the gender gap operates through channels other than infrastructure—potentially through differential self-efficacy in technology topics, differential teacher attention, or gendered curricular tracking that steers male students toward technology-oriented subjects and female students away [17,18].

It is also possible that the gap reflects differential recognition or recall: male students may be more likely to identify a topic as relevant to technology or smart systems even when the curricular exposure was equivalent. Survey-based measures of curriculum exposure cannot fully distinguish between exposure and recognition.

A potentially important secondary finding is that the interaction between digital readiness and gender approached but did not reach conventional significance (OR = 0.641, $p = 0.064$). The direction of this estimate is interpretable: it tentatively suggests that the connectivity gradient may be steeper among female students than among male students, meaning that female students may benefit disproportionately from improvements in school connectivity. This pattern is consistent with prior evidence that female adolescents' engagement with STEM and technology topics is more sensitive to contextual cues, perceived self-efficacy, and the availability of institutional supports [17]. Although the result is not statistically robust at conventional thresholds and should not drive policy on its own, it is substantively important enough to flag as an exploratory finding warranting replication in larger samples. If confirmed, it would carry a direct policy implication: investments in school-level connectivity could simultaneously address the documented gender gap in technology-related curriculum exposure rather than merely shifting both groups upward in parallel.

Regardless of mechanism, the gender gap itself represents a concerning inequity that has direct implications for who develops competencies relevant to AI-supported and technology-mediated learning at the secondary level.

5.4. Smart City Curriculum as Proxy: Strengths and Limitations

The smart-city concept was chosen as the outcome variable because it is concrete, curriculum-verifiable, and observationally accessible: students can plausibly report whether the concept has appeared in their formal lessons in a way they could not easily report for an abstract construct such as "AI literacy." Smart-city topics also map onto specific technology-mediated applications students encounter in everyday urban life (traffic management, public service personalisation, environmental monitoring), several of which are increasingly AI-supported in practice. The smart-city outcome should therefore be read as one observable indicator of access to technology-mediated curricular content, not as a validated measure of AI literacy. The binary coding used here (any exposure vs. none/unsure) cannot distinguish between a one-sentence mention in a geography lesson and a project-based unit; consequently, the estimates capture the gradient in any exposure to such content, not in the depth or quality of engagement. Two implications follow. First, students may develop AI-relevant competencies through curricular channels not captured by this measure (coding, data science, robotics, civic technology). Second, validating smart-city exposure against established AI-literacy instruments in the Slovak secondary context is a necessary next step before the present findings can be extended into specific AI-pedagogy claims. The present article should therefore be read primarily as

evidence on digital infrastructure as a determinant of curriculum equity, with implications for AI-supported education that future research will need to confirm.

5.5. Theoretical Contribution

This study extends the socio-cultural framing of human–AI partnership by foregrounding the material dimension of access. Vygotskian readings of AI as a cognitive scaffold are best understood as heuristic, given ongoing debate about how far current AI systems instantiate the responsive, dynamically calibrated guidance that the zone of proximal development originally presupposes; even taken as a heuristic, however, such readings tacitly assume that the scaffold is available—that the AI tool is accessible, responsive, and reliable. When school internet quality is rated as low by nearly half of students, the scaffold is either absent or unreliable. The present findings suggest that the first-level digital divide should be theorised as a constitutive element of the human–AI partnership relationship rather than as a background variable: infrastructure conditions whether the partnership can form at all.

This also has implications for how AI literacy frameworks are specified. Frameworks that define AI literacy purely in terms of knowledge and skills tacitly assume the availability of the infrastructure through which knowledge and skills are acquired and applied. A materially grounded AI literacy framework would include infrastructure access as a precondition dimension—recognising that equitable AI literacy requires both the competencies and the conditions.

5.6. Territorial and Educational Visibility Gaps

A companion territorial analysis on the same dataset [15] shows that students in smaller Slovak municipalities are also significantly more likely to perceive an absence of smart-city elements in their own municipality (OR = 0.67 per log-population unit, $p = 0.015$). Read together, the two findings suggest that educational visibility gaps (in curriculum exposure) and territorial visibility gaps (in lived civic environment) reinforce each other: students with weaker digital readiness are concentrated in places where smart-city services are also least visible. Addressing equitable human–AI partnership therefore requires policy attention to both school infrastructure and municipal-level digital visibility.

6. Policy Implications

The policy implications below are framed as recommendations consistent with the associational evidence reported in Section 4 and with established theoretical and international policy frameworks on digital equity, rather than as conclusions drawn from causal identification. Their primary purpose is to translate the observed readiness–curriculum gradient into actionable infrastructure and curriculum priorities for Slovak and comparable European contexts.

The findings of this study point to three interconnected policy priorities for making human–AI partnership in secondary education genuinely equitable.

First, school connectivity must be treated as a prerequisite for AI-oriented education, not as an optional enhancement. Current patterns, where 47.6% of students rate school internet as low-quality, represent a structural barrier that no curriculum innovation can overcome. National and regional digital infrastructure strategies, including the EU's 2030 Digital Compass for the Digital Decade [19] and Slovakia's Strategy of Digital Transformation 2030, together with its Integrated Regional Operational Programme [20], should include binding, monitored minimum connectivity standards for schools, with particular attention to rural and under-resourced municipalities where the school–home gap is likely most severe. Investment in school broadband infrastructure aligns directly with SDG

4's commitment to inclusive, quality education and with SDG 11's vision of connected, sustainable communities.

Second, pedagogical designs for AI-supported and smart city education must be developed that function under infrastructural constraints. This means designing for asynchronous and low-bandwidth modes—offline-first activities, downloadable AI tools, printed datasets, and peer-to-peer collaborative inquiry that does not rely on continuous streaming connectivity. Compensatory pedagogies of this kind are consistent with universal design for learning (UDL) principles [21] and with SDG 10's emphasis on reducing inequalities of access and opportunity. Teachers in under-connected schools should receive dedicated professional development that equips them to deliver meaningful AI literacy content without assuming constant high-bandwidth access.

Third, educational monitoring systems should integrate infrastructure and exposure equity indicators alongside standard learning outcome metrics. The present study demonstrates that a simple composite readiness index constructed from self-rated connectivity and device count data is associated with curriculum exposure in a consistent, statistically significant pattern. Incorporating similar measures into national education monitoring frameworks, building on existing digital competence survey instruments, would allow policy-makers to track whether infrastructure improvements translate into equitable curriculum access over time. Gender-disaggregated monitoring of AI-relevant curriculum exposure is also warranted given the 14.0-percentage-point gap documented here. Monitoring of this kind supports SDG 4.1 (inclusive and equitable quality education for all), SDG 10.2 (social inclusion irrespective of background), and SDG 11's broader vision of smart, equitable communities.

These three recommendations are mutually reinforcing: monitoring reveals gaps; compensatory pedagogy addresses them in the short term; and infrastructure investment closes them structurally. Together they constitute a precondition policy framework that prioritises equity at the foundation of the AI-in-education agenda rather than treating it as an afterthought.

7. Limitations

Several limitations should be noted when interpreting these findings. First, internet quality was measured through self-rated single items rather than objective speed tests or infrastructure audits. Self-rated measures capture experienced quality, which is arguably the variable most relevant to whether students can engage effectively with digital learning tools; however, they may be subject to reference-point bias and may not be directly comparable across individuals with different baseline expectations.

Second, the cross-sectional, observational design precludes causal inference. The association between digital readiness and curriculum exposure is consistent with several plausible causal mechanisms, as discussed above, but the data cannot identify which mechanism predominates or rule out unmeasured confounders. Longitudinal or quasi-experimental designs would be needed to establish causal relationships.

Third, the sample consists exclusively of Slovak secondary-school students, limiting generalisability. Slovakia has a specific policy and infrastructure context that may not apply to other Central European countries, to Western European contexts, or to non-European settings. The school-home connectivity gap, the device ecosystem patterns, and the curriculum exposure rates documented here should be understood as Slovak baseline data rather than as universal findings.

Fourth, the use of smart city curriculum exposure as a proxy for AI literacy readiness is an acknowledged simplification. Students may develop AI literacy competencies through

other curricular channels not captured by this measure, and smart city exposure does not guarantee the critical AI engagement that AI literacy frameworks emphasise.

Fifth, gender is coded as binary in this dataset, precluding analysis of non-binary identities. Given evidence that non-binary students experience distinct patterns of STEM engagement and technology access [22], future surveys should use more inclusive gender measures.

Sixth, municipality-level internet quality data were available at the respondent level but not linked to school-level administrative data, preventing multi-level modelling that would separate individual, school, and community effects. Future work incorporating administrative infrastructure data and school-level covariates would substantially strengthen the analytical framework.

Seventh, the digital readiness index assigns equal weight to its three components (school internet quality, home internet quality, and household device count). Component-level analysis (Section 4.5) showed that school internet quality carried essentially all of the index's predictive signal, with home internet quality and household device count contributing no independent association. The index therefore functions in this sample as a noisier representation of school connectivity rather than as an independently validated multidimensional construct; alternative readiness instruments would require validation in an independent sample.

Eighth, although recruitment used multi-institutional distribution channels (Ministry of Education, regional authorities, and cooperating schools), schools that elected to participate may differ systematically from non-participating schools in their digital engagement or institutional readiness. This is a standard limitation of school-mediated convenience sampling and means the sample, while regionally diverse, is not statistically representative of the Slovak upper-secondary population.

Ninth, participation was incentivised through a gamified prize-draw mechanism upon questionnaire completion. While this raised response rates, it could also introduce mild self-selection toward students with higher interest in or comfort with digital participation—plausibly biasing the sample toward students more likely to encounter and recall technology-related curriculum content.

8. Conclusions

This study documents a substantial school-home connectivity gap among Slovak secondary students and shows that, of the three infrastructure dimensions examined (school internet quality, home internet quality, and household device count), school internet quality is the single dimension associated with curriculum exposure to the smart-city concept—used here as an observable indicator of access to technology-mediated curricular content, not as a validated measure of AI literacy. A composite readiness index combining the three components reproduces this association but at a weaker effect size, consistent with school connectivity carrying essentially all of the index's signal. The association is robust to gender adjustment, and gender itself emerges as an independent predictor, with male students reporting a 14.0-percentage-point higher exposure rate than female students; an exploratory readiness $\times$ gender interaction ($p = 0.064$) tentatively suggests that the connectivity gradient may be steeper for female students, a finding warranting replication.

The theoretical contribution of this work lies in extending the socio-cultural framing of human-AI partnership to include the material access dimension. The Vygotskian metaphor of AI as cognitive scaffold is only workable when the scaffold is available: when school internet is rated as low-quality by nearly half of students, the condition of possibility for AI-supported learning is structurally compromised. Digital inequality research has long distinguished first-level access divides from second-level skill divides; this study argues

that in the context of AI-oriented education, first-level divides at the school level are directly constitutive of second-level curriculum exposure gaps.

The policy implications follow from the correlational pattern documented here together with the broader literature on digital inequality, rather than from causal identification in a single cross-sectional dataset. Given the modest model discrimination ($AUC = 0.621$), infrastructure should not be treated as a sufficient determinant of individual curriculum exposure; the present evidence supports it as one structural condition among several. Even so, the alignment of the observed gradient with international evidence on digital divides in education suggests a clear direction: upgrading school connectivity to a standard adequate for technology-mediated and AI-supported learning, and monitoring whether such infrastructure investment translates into more equitable curriculum access, is directly consistent with SDG 4 (inclusive and equitable quality education) and SDG 10 (reduced inequalities); links to SDG 11 are more indirect and operate through the smart-city curriculum content rather than the infrastructure intervention itself. Until school connectivity gaps are addressed, the promise of technology-mediated learning—including AI-supported pedagogies—is likely to remain unevenly distributed: more readily available to the well-connected and less so to the rest. Confirming whether infrastructure investment translates causally into more equitable curriculum access will require longitudinal and quasi-experimental designs that move beyond the associational evidence reported here.

Funding: This research received no external funding.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki. Ethical review and approval were waived for this study because it involved anonymous, non-sensitive survey data and posed minimal risk to participants; under Slovak research practice, such educational surveys do not require formal institutional review board approval. The research design and informed-consent procedures were reviewed by the ethics liaison of the Faculty of Social Sciences, University of Ss. Cyril and Methodius in Trnava.

Informed Consent Statement: Informed consent was obtained from all participants involved in the study. School management authorised administration of the survey within the school environment and informed parents and legal guardians where appropriate, and individual respondents provided active consent at the start of the questionnaire.

Data Availability Statement: The data presented in this study are stored on an access-restricted drive and are available from the author on reasonable request. The data are not publicly available due to privacy restrictions, as the participants were minors.

Acknowledgments: The data were collected as part of the SmartCityExplorer project (SmartCityExplorer.sk) at the University of Ss. Cyril and Methodius in Trnava.

Conflicts of Interest: The author declares no conflicts of interest.

References

1. Luckin, R.; Holmes, W.; Griffiths, M.; Forcier, L.B. *Intelligence Unleashed: An Argument for AI in Education*; Open Ideas at Pearson Education: London, UK, 2016.
2. UNESCO. *Recommendation on the Ethics of Artificial Intelligence*; SHS/BIO/PI/2021/1; UNESCO: Paris, France, 2021. Available online: <https://unesdoc.unesco.org/ark:/48223/pf0000381137> (accessed on 12 June 2026).
3. Eurostat. *Urban–Rural Europe—Digital Society. Statistics Explained*; Publications Office of the European Union: Luxembourg, 2024. Available online: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Urban-rural_Europe_-_digital_society (accessed on 12 June 2026).
4. Russo, F.; Rindone, C. Smart city for sustainable development: Applied processes from SUMP to MaaS at European level. *Appl. Sci.* **2023**, *13*, 1773. [CrossRef]
5. Vygotsky, L.S. *Mind in Society: The Development of Higher Psychological Processes*; Cole, M., John-Steiner, V., Scribner, S., Souberman, E., Eds.; Harvard University Press: Cambridge, MA, USA, 1978.

6. Holmes, W.; Bialik, M.; Fadel, C. *Artificial Intelligence in Education: Promises and Implications for Teaching and Learning*; Center for Curriculum Redesign: Boston, MA, USA, 2019; ISBN 978-1-794-29370-0.
7. Kasneci, E.; Sessler, K.; Küchemann, S.; Bannert, M.; Dementieva, D.; Fischer, F.; Gasser, U.; Groh, G.; Günnemann, S.; Hüllermeier, E.; et al. ChatGPT for good? On opportunities and challenges of large language models for education. *Learn. Individ. Differ.* **2023**, *103*, 102274. [[CrossRef](#)]
8. Van Deursen, A.J.A.M.; Van Dijk, J.A.G.M. The digital divide shifts to differences in usage. *New Media Soc.* **2014**, *16*, 507–526. [[CrossRef](#)]
9. Long, D.; Magerko, B. What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*; ACM: New York, NY, USA, 2020; pp. 1–16. [[CrossRef](#)]
10. Carretero, S.; Vuorikari, R.; Punie, Y. *DigComp 2.1: The Digital Competence Framework for Citizens with Eight Proficiency Levels and Examples of Use*; EUR 28558 EN; Publications Office of the European Union: Luxembourg, 2017. [[CrossRef](#)] [[PubMed](#)]
11. Redecker, C. *European Framework for the Digital Competence of Educators: DigCompEdu*; EUR 28775 EN; Punie, Y., Ed.; Publications Office of the European Union: Luxembourg, 2017. [[CrossRef](#)]
12. Van Dijk, J. *The Digital Divide*; Polity Press: Cambridge, UK, 2020; ISBN 978-1-509-53446-3.
13. United Nations. *Transforming Our World: The 2030 Agenda for Sustainable Development*; A/RES/70/1; United Nations: New York, NY, USA, 2015.
14. Kóňa, A.; Horváth, P.; Brix, R. Slovakia on the way to the SMART future, the last opportunity for municipalities. *Adm. si Manag. Public* **2022**, *38*, 180–196.
15. Kóňa, A. Smart-City Visibility Gap across Settlement Sizes: Youth Perceptions and Local Connectivity in Slovakia. In *Proceedings of the 1st International Online Conference on Urban Sciences (IOCUS 2026)*; MDPI: Basel, Switzerland, 2026.
16. Warschauer, M. *Technology and Social Inclusion: Rethinking the Digital Divide*; MIT Press: Cambridge, MA, USA, 2003; ISBN 0-262-73193-5.
17. Sáinz, M.; Eccles, J. Self-concept of computer and math ability: Gender implications across time and within ICT studies. *J. Vocat. Behav.* **2012**, *80*, 486–499. [[CrossRef](#)]
18. Livingstone, S.; Helsper, E. Gradations in digital inclusion: Children, young people and the digital divide. *New Media Soc.* **2007**, *9*, 671–696. [[CrossRef](#)]
19. European Commission. *2030 Digital Compass: The European Way for the Digital Decade*; COM(2021) 118 Final; European Commission: Brussels, Belgium, 2021. Available online: <https://digital-strategy.ec.europa.eu/en/policies/europes-digital-decade> (accessed on 12 June 2026).
20. Ministry of Investments; Regional Development and Informatization of the Slovak Republic. *Strategy of Digital Transformation of Slovakia 2030 and Action Plan 2023–2026*; MIRRI SR: Bratislava, Slovakia, 2021. Available online: <https://mirri.gov.sk/sekcie/informatizacia/digitalna-transformacia/> (accessed on 12 June 2026).
21. Rose, D.H.; Meyer, A. *Teaching Every Student in the Digital Age: Universal Design for Learning*; Association for Supervision and Curriculum Development (ASCD): Alexandria, VA, USA, 2002; ISBN 0-87120-599-8.
22. Kersey, A.J.; Csumitta, K.D.; Cantlon, J.F. Gender similarities in the brain during mathematics development. *npj Sci. Learn.* **2019**, *4*, 19. [[CrossRef](#)] [[PubMed](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.