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Bridging the Digital Skills Gap: A Prisma 2020 Systematic Review of Technology Adoption, Stem Workforce Equity, and Small Business Competitiveness in the United States

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Abstract

Background: The US faces issues from overlapping inequalities in small business competitiveness, representation in the STEM workforce, and use of digital technology. Although the spread of technology has accelerated since 2020, company sizes, demographic groups, and geographical areas continue to exhibit systematic differences in the availability and application of digital and artificial intelligence (AI) capabilities. This offers a comparative perspective that influences this synthesis and is based on the author's study on digital commerce and the performance of SMEs in West Africa.

Objective: In order to characterize (1) the extent of the digital skills gap in US SMEs and underrepresented STEM workers; (2) the technology-specific mechanisms through which adoption does, or does not, lead to workforce up-skilling; and (3) the structural barriers that perpetuate the gap, this systematic review synthesizes evidence from empirical studies and government statistical releases from 2022–2026, guided by the PRISMA 2020 statement (Page *et al.*, 2021).

Methods: In August 2026, five databases and government data repositories were examined. Studies that were stratified by at least one equity variable and included quantitative estimates of the rate of broadband access, the composition of the STEM workforce, or the use of digital technologies were eligible. The ROBINS-I domains, adjusted for observational evidence synthesis, were used to assess bias risk.

Results: Twenty-four eligible sources were identified. National AI adoption was 17.9% overall, rising to 30.6% among firms with 250 or more employees versus 17.6% among micro-firms. Underrepresented minorities held 24% of STEM positions; rural broadband subscription lagged urban rates by 14.2 percentage points; and only 22.1% of AI-adopting firms reported increased STEM skills.

Conclusion: The digital-skills equity gap is large, multidimensional, and not self-correcting. Policy must combine geographically targeted broadband investment, AI-specific workforce training for mid-sized firms, and sustained expansion of federal monitoring instruments.

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Keywords: digital skills gap, STEM workforce equity, AI adoption, small business, systematic review, PRISMA 2020, broadband access, underrepresented minorities, SME digital adoption

1. Introduction

1.1. Background and Rationale

The competitive landscape of the US economy is undergoing rapid change due to digital transformation, making it impossible for the SME sector and its workforce to keep up. Cloud computing, artificial intelligence, and digital commerce platforms have, within a single decade, transitioned from competitive advantages to baseline business infrastructure. Yet the capacity to deploy

these technologies, defined here as 'digital skills', encompassing both firm-level adoption capacity and worker-level technical competency, remains sharply unequal across firm size, geography, race and ethnicity, and sex (Nambisan *et al.*, 2023; Faiz *et al.*, 2024; OECD, 2025a)^[14, 9].

Three converging structural forces define this inequality. First, the firm-size digital adoption gradient is steep: cross-national evidence from the OECD (2025a) documents that 40% of firms with 250 or more employees used AI across member countries in 2024, against only 11.9% of firms with 10–49 employees, a gap factor exceeding 3:1. In the United States specifically, the Census Bureau's Business Trends and Outlook Survey (BTOS) AI Supplement (U.S. Census Bureau, 2026)^[34] found overall national AI adoption of 17.9%, but with a 13-percentage-point spread between the smallest and largest employer-business size classes (Bonney *et al.*, 2026)^[5]. Second, despite making up a significantly larger portion of the working-age population, underrepresented racial and ethnic minority groups, such as Hispanic, Black, and American Indian/Alaska Native workers, held 24% of STEM jobs, while women accounted for 35% of the STEM workforce in 2021 (National Center for Science and Engineering Statistics [NCSES], 2023). Third, the broadband infrastructure upon which digital skills depend is geographically fragmented: Census Bureau American Community Survey estimates indicate that fixed broadband access in rural households stood at 64.4%, compared with 98.5% in urban areas (Federal Communications Commission [FCC], 2024; Conlow, 2023)^[10, 8].

These structural deficits interact in ways that compound disadvantage: the populations most underrepresented in STEM occupations disproportionately own small businesses, and those businesses are disproportionately located in rural and lower-income counties where broadband infrastructure is weakest (U.S. Census Bureau, 2023; Brynjolfsson *et al.*, 2025)^[32, 7]. Understanding these interactions is essential for designing policy that addresses the digital-skills gap systemically rather than serially.

1.2. Situating the Review within the Author's Research Programme

Considering it is based on a long-term empirical study of digital adoption, SME performance, and financial technology results in Sub-Saharan Africa and emerging economies, this review is not conducted from the standpoint of disciplinary neutrality. In addition to offering a comparative viewpoint, this work supports the synthesis framework with a number of experimentally supported claims.

The early work of the author created a baseline association for digital-commerce security and customer trust. Oni and Adeyeye (2020)^[23] demonstrated that platform-level security perceptions are a primary determinant of customer satisfaction in digital commerce environments in South West Nigeria, a finding that anticipates the data-security barrier now documented among U.S. SME non-adopters in OECD (2025b) surveys. Oni (2021a)^[20] extended this analysis to show that digital commerce adoption itself directly improves customer satisfaction outcomes, while Oni (2021b)^[21] examined the distributional geography of digital commerce penetration in Nigeria's Federal Capital Territory, documenting urban-concentration patterns structurally analogous to the 18:1 urban-rural ratio in U.S. minority-owned business locations reported by the Annual Business Survey (U.S. Census Bureau, 2023)^[3].

A parallel strand of the author's work examined digital banking adoption and its consequences for customer experience. Oni *et al.* (2019b)^[24] found that digital banking adoption in the Federal Capital Territory yielded measurable customer satisfaction improvements, but that adoption itself was moderated by awareness, trust, and skills, precisely the barriers most prevalent among U.S. SME non-adopters documented in this review's synthesis. This motivational dimension was also central to Adeyeye *et al.* (2019)^[3], whose analysis of opportunity-driven versus necessity-driven entrepreneurship among micro- and small businesses in Nigeria provides a typological framework for distinguishing voluntary from circumstantial non-adoption, a distinction with direct relevance to RQ5's analysis of why U.S. micro-firms cite AI inapplicability rather than cost or skills as their primary barrier.

At the workforce development level, Oni (2019a)^[19] evaluated the impact of Nigeria's N-Power Programme on youth enterprise and found that programme-linked digital-skills training produced measurable entrepreneurial outcomes, but only among participants with sustained access to connectivity and mentorship, a finding that directly parallels the Brynjolfsson *et al.* (2025)^[7] result that generative AI productivity gains require co-provision of employer-directed training. The author's work on green entrepreneurship (Oni, 2022)^[22] also details how technology adoption interacts with broader sustainability and social equity goals in SME performance, a topic the current review extends to the US context, through its focus on digital skills equity as a structural, not incidental, policy challenge.

All things considered, these early works offer the theoretical framework for the current PRISMA review, which holds that, in the absence of trust-building circumstances, incentive-compatible program design, and a deliberate investment in employees' skills, digital adoption will not always result in better firm or worker outcomes. The fact that this pattern was widely repeated in two very different national contexts the largest advanced economy in the world and a developing-market Sub-Saharan economy provides more proof that these are structural characteristics of the diffusion of digital skills more generally rather than particular institutional anomalies specific to any one nation. In order to explain where American policy is and is not functioning, this assessment applies that established paradigm to federal statistics in the United States.

Despite the growing amount of descriptive data available in the U.S. context, no published systematic review has synthesizes the entirety of adoption data, workforce representation, broadband infrastructure, and technology-specific up-skilling effects into a cohesive, PRISMA-formatted report. This review fills that gap.

1.3. Theoretical Framework

The review uses three sets of interacting theoretical frameworks to structure evidence and explain findings. First, Rogers' (2003)^[26] Diffusion of Innovations (DOI) theory establishes that adoption of any innovation is shaped by five perceived attributes: relative advantage, compatibility, complexity, trial ability, and observability, and that adoption curves characteristically leave resource-constrained adopters behind the innovator and early-adopter cohorts for extended periods. Applied to digital skills, DOI predicts that smaller firms and lower-skilled workers will consistently lag in both awareness and capability, a prediction borne out across

successive digital technology waves (Ghobakhloo *et al.*, 2011; Troise *et al.*, 2022) ^[11, 30] and corroborated in the author's own research on SME digital adoption in Nigeria (Oni & Adeyeye, 2020; Oni, 2021a) ^[20].

Second, the Technology–Organisation–Environment (TOE) framework (Tornatzky & Fleischer, 1990; Faiz *et al.*, 2024) ^[29, 9] identifies three contextual domains shaping technology adoption decisions: technological characteristics (ease of integration, perceived security), organisational factors (firm size, human capital, resource slack), and environmental pressures (competitive norms, regulatory requirements, infrastructure quality). Within a TOE lens, the digital-skills gap is not a single phenomenon but the product of interactive deficits across all three domains simultaneously, a finding with direct implications for the design of targeted interventions. This multi-domain interaction was empirically demonstrated in the author's digital banking adoption research (Oni *et al.*, 2019b) ^[24], where organisational readiness and environmental infrastructure (network connectivity and regulatory confidence) each exerted independent and interactive effects on adoption outcomes.

Third, complementary investments in skilled labor, organizational capital, and data infrastructure are necessary for the productivity-boosting impacts of general-purpose technology, according to the idea of complementary assets (Brynjolfsson & Hitt, 2003; Acemoglu & Restrepo, 2022) ^[6, 21]. Thus, the theory offers the microeconomic justification for the empirical regularity that small businesses' adoption of technology does not result in worker up-skilling. This claim is directly supported by the author's evaluation of Nigeria's N-Power digital-skills program (Oni, 2019a) ^[19]: rather than just program attendance, connectivity and mentorship were the complementary assets that determined whether training translated into entrepreneurial outcomes.

1.4. Research Questions

This systematic review examines five pre-specified research questions:

- **RQ1:** What is the magnitude and trajectory of the digital-skills adoption gap between small and large U.S. employer businesses, including AI, cloud computing, and specialised software?
- **RQ2:** To what extent does technology adoption among U.S. small businesses translate into STEM workforce up-skilling, and does the translation differ by technology type?
- **RQ3:** What is the current state of demographic representation in the U.S. STEM workforce, and how does this interact with small-business ownership patterns?
- **RQ4:** What is the magnitude and geography of the broadband connectivity gap, and how does it constrain digital-skills development among underrepresented populations?
- **RQ5:** What specific barriers sustain the digital-skills gap among non-adopting small businesses, and how do these vary by firm size in ways relevant to targeted policy?

2. Methods

This review is reported in accordance with the PRISMA 2020 statement (Page *et al.*, 2021) ^[25]. The review protocol was pre-registered prior to data extraction, and all eligibility criteria, search strategies, and synthesis methods were specified in advance.

2.1. Eligibility Criteria

2.1.1. Inclusion Criteria

Sources were eligible for inclusion if they met all of the following criteria:

- **Population:** U.S. employer businesses of any sector, or the U.S. STEM workforce, or U.S. broadband-connected households.
- **Exposure/phenomenon:** Digital-technology adoption (AI, cloud computing, e-commerce, specialized software) OR STEM workforce participation OR broadband connectivity, measured quantitatively.
- **Equity dimension:** Results must be disaggregated by at least one of: firm employment-size class; race, ethnicity, or sex of business owner or worker; geographic category (rural/urban, state, metropolitan area).
- **Data type:** Nationally representative probability-sample survey estimates, statistics from the government-released census frame, or empirical analyses published in peer-reviewed work using these data.
- **Reference period:** Books published or released between January 2022 and August 2026.
- **Language:** English.

2.1.2. Exclusion Criteria

- Non-probability or convenience samples (vendor-commissioned surveys, opt-in panels, industry association polls without disclosed sampling methodology).
- Purely qualitative research without quantitative estimates of adoption, representation, or connectedness.
- Research that does not contain an equality comparison between groups and exclusively focuses on one sector or geographic area.
- Blogs written by practitioners, editorials, or opinion pieces without unique quantitative evidence.
- Research that looks at populations that are exclusively foreign, self-employed, or non-employed but do not include US comparisons.

2.2. Information Sources

Structured searches were conducted across the following five sources (final search date: August 15, 2026):

- Web of Science (all databases): peer-reviewed articles.
- Scopus: peer-reviewed articles and book chapters.
- EconLit (via EBSCOhost): economics and policy studies.
- U.S. Census Bureau publications portal (census.gov): government statistical releases, America Counts Stories, and BTOS data files.
- OECD iLibrary (oecd-ilibrary.org): cross-national policy analyses.

Grey literature sources inclusion: by direct navigation to obtain grey literature, NBER working-papers, SBA Office of Advocacy documents, and FCC Broadband Data Collection.

2.3. Search Strategy

The following search string was applied to Web of Science, Scopus, and EconLit:

('digital skills' OR 'digital technology adoption' OR 'artificial intelligence adoption' OR 'cloud computing' OR 'e-commerce') AND ('small business' OR 'SME' OR 'firm size' OR 'employer business') AND ('workforce' OR 'STEM' OR 'equity' OR 'broadband' OR 'digital divide') AND ('United

States' OR 'U.S.' OR 'American')

For the Census Bureau website and the gray literature repositories, searches were supplemented by browsing directly to pertinent program pages and by a review of linked data files, along with any associated publications. The entire search log can be obtained from the corresponding author on request.

2.4. Selection Process

Database searches produced duplicate entries, which the author reduplicated and screened in two successive stages. A second reviewer independently screened a random 20% sample, and disagreements were discussed until a consensus was established.

- **Stage 1** — Title and abstract screening: Based on the title, abstract, and source name, records were assessed for inclusion and exclusion criteria. The rationale behind the exclusion was recorded.
- **Stage 2** — Full-text eligibility assessment: All records passing Stage 1 were assessed in full. Records meeting all criteria were retained for data extraction.

2.5. Data Extraction

Data were extracted into a pre-piloted standardized extraction form capturing: (1) source type, author(s), year, and reference period; (2) population and sample characteristics; (3) digital-technology or equity dimension measured; (4) primary quantitative estimates and associated standard errors or confidence intervals; and (5) key findings relevant to each research question. All extraction was conducted by the author and verified by cross-referencing headline statistics against source documents.

2.6. Risk of Bias Assessment

Six domains from the ROBINS-I tool (Sterne *et al.*, 2016)^[28] were used to assess the risk of bias in the included sources:

1. selection bias;
2. measurement bias, including changes in question

wording between survey waves;

3. non-response bias;
4. aggregation bias in the context of secondary analyzes;
5. publication and sponsor bias; and
6. confounders technology-type or firm-size effects cannot be separated from sector and geographic composition at the aggregate level.

Each domain received a risk rating of Low, Moderate, or High along with a narrative explanation. Complete assessments are shown in Table 2.

2.7. Synthesis Methods

Synthesis is descriptive-comparative. To determine statistical significance, adoption, workforce participation shares, and broadband penetration rates by equity dimension are compared with reported standard errors. When 95% confidence intervals ($\pm 1.96 \times SE$) do not overlap, differences across size classes or demographic groups are considered significant. To find consistent directional trends, barrier data are cross-tabulated by size class and analyzed as response distributions. Due to outcome heterogeneity, no meta-analytic pooling was done; instead, data was supplemented for cross-national triangulation from other international sources. The synthesis methods' protocol pre-specification is mentioned.

3. Results

3.1. Study Selection

312 records were found through database searches (Web of Science: 118; Scopus: 124; EconLit: 70). After deduplication, 241 distinct records underwent Step 1 screening; 197 were eliminated based on abstract and title. After 44 records were examined in full, 13 studies were found to be eligible. Grey literature and government repository searches identified an additional 11 eligible sources. A total of 24 sources were included in the synthesis (Table 1 presents the PRISMA 2020 flow summary).

Table 1: PRISMA 2020 Study Selection Flow

PRISMA Phase	Description and Record Counts
Identification	Database searches: Web of Science (n = 118), Scopus (n = 124), EconLit (n = 70). Total retrieved: 312. After deduplication: 241 unique records. Grey literature repositories: U.S. Census Bureau publications portal, OECD iLibrary, NBER working-paper repository, SBA Office of Advocacy database, FCC Broadband Data Collection (n = 11 eligible sources identified by direct navigation).
Screening	241 records screened at Stage 1 (title/abstract). Excluded: n = 197. Reasons: non-U.S. population without benchmarking (n = 62); no equity disaggregation (n = 58); no quantitative estimates (n = 41); pre-2022 without benchmarking to post-2022 data (n = 36). Retained for full-text: n = 44.
Eligibility	44 records assessed in full. Excluded: n = 31. Reasons: convenience sample or non-disclosed methodology (n = 14); single sector without cross-group comparison (n = 9); no quantitative adoption or equity estimates (n = 8). Eligible: n = 13 (peer-reviewed) + 11 (government/grey literature) = 24 total.
Included	24 sources included: 11 government statistical releases/data products (BTOS AI Supplement, ABS 2022–2024, NCSES Diversity and STEM 2023, ACS Broadband, FCC BDC); 8 peer-reviewed journal articles; 3 OECD cross-national reports; 2 NBER working papers.

Note: BTOS = Business Trends and Outlook Survey; ABS = Annual Business Survey; NCSES = National Center for Science and Engineering Statistics; ACS = American Community Survey; FCC BDC = Federal Communications Commission Broadband Data Collection; OECD = Organisation for Economic Co-operation and Development; NBER = National Bureau of Economic Research.

3.2. Characteristics of Included Sources

The 24 included sources are distributed across four types of evidence. 242). Government statistical reports (n = 11) constitute the main quantitative base, based on nationally representative probability samples of U.S. employer firms, households, or STEM workers. 1-ranked journals provide theoretical foundation and mechanism analysis with peer

reviewed journal articles (n = 8). OECD cross-national reports (n = 3) enable international benchmarking of the U.S. adoption gap. NBER working papers (n = 2) provide linked-microdata analyses of AI diffusion at firm, business-function, and worker-task levels. Reference periods span 2022 to 2026, with the most recent government data covering the Census Bureau's 2025–2026 BTOS AI Supplement.

3.3. Risk of Bias Assessment

Table 2: Risk of Bias Assessment of Included Sources (ROBINS-I Adapted Domains)

Source Type	Sampling	Measurement	Non-Response	Aggregation	Sponsor	Confounding
Govt statistical releases (n=11)	Low	Moderate*	Moderate	Low	Low	Moderate
Peer-reviewed articles (n=8)	Low-Mod.	Low	Low-Mod.	Low	Low	Low-Mod.
OECD reports (n=3)	Low	Low	Moderate	Low	Low	Moderate
NBER working papers (n=2)	Low	Low	Low	Low	Low	Low

Note. *Moderate measurement bias reflects the December 2025 BTOS question-wording change broadening the AI-use definition from 'producing goods or services' to 'any business function'. Confounding rated Moderate for aggregate government tabulations because firm-size effects cannot be isolated from sector and geographic composition without micro-data decomposition. Low = minimal systematic bias concern; Moderate = bias present but assessable; High = substantial uncontrolled bias.

3.4. Synthesis of Findings

3.4.1. RQ1: Magnitude and Trajectory of the Digital-Skills Adoption Gap

The BTOS AI Supplement (U.S. Census Bureau, 2026), the first nationally representative, disclosure-reviewed federal instrument covering AI adoption across all U.S. employer businesses, establishes overall AI adoption at 17.9% (95% CI: 17.1%–18.7%). The firm-size gradient is statistically robust at every employment-class step: adoption rises from 17.6% among micro-firms (1–4 employees) to 30.6% among firms with 250 or more employees, yielding a gap of 13.0

percentage points (pp) (Bonney *et al.*, 2026) ^[5]. When adoption depth is extended to employee-level generative AI penetration and forward adoption intentions, the gaps widen to approximately 19–20 pp. Grundy *et al.* (2026) ^[12] document a trend analysis for December 2025 through May 2026 in which AI use increased significantly among firms with 20 or more employees but showed no statistically significant increase among firms with fewer than 20 employees, indicating that the gap is widening rather than closing organically.

Table 3: AI Adoption Rates by Firm Employment-Size Class, United States, November 2025–February 2026

Firm Size Class	AI Adoption Rate	95% CI	Gap vs. Largest Class (pp)
1–4 employees	17.6%	16.5%–18.7%	–13.0
5–9 employees	22.2%	21.0%–23.4%	–8.4
10–19 employees	25.8%	24.5%–27.1%	–4.8
20–49 employees	27.1%	25.8%–28.4%	–3.5
50–249 employees	27.4%	25.9%–28.9%	–3.2
250+ employees	30.6%	28.8%–32.4%	Reference
National average	17.9%	17.1%–18.7%	—

Note. Source: U.S. Census Bureau (2026). BTOS AI Supplement, collected November 17, 2025–February 8, 2026. Confidence intervals computed as $\pm 1.96 \times$ published SE. pp = percentage points.

According to the 2023 (reference year 2022) ABS digital technology module, cloud technology had the highest pre-2022 adoption prevalence among small businesses (40.0%), surpassing specialized software (27.0%), while AI adoption was still in its infancy. They discovered that, for all five categories of technology AI, robotics, cloud computing, specialized software, and specialized equipment the majority of businesses saw no change in the total number of workers following adoption, suggesting that adoption by itself is not a significant factor in changing the size of the workforce (U. S. Census Bureau, 2023; Arledge, 2025) ^[4]. This finding was consistent with the author's earlier empirical research in Nigeria, where Oni (2021a) ^[20] discovered that adoption of digital commerce only affects consumer happiness when businesses spend in platform quality, rather than through the isolated act of online commerce adoption.

3.4.2. RQ2: Technology Adoption and STEM Workforce Up-skilling

A significant finding from the 2023 ABS technology module is that the adoption-Up-skilling relationship is both technology-specific and small in size. Of the firms that implemented AI, 22.1% indicated that the level of workers' STEM skills increased while 3.3% indicated a decrease,

resulting in a positive balance of 18.8 percentage points in terms of Up-skilling. Robots followed a similar trend (increased by 20.7 % vs. declined by 3.9%). However, cloud-based technology and professional grade software lead to much less reported up-skilling, with 40.9% and 41.6% of participants, respectively, stating these tools were 'not applicable' to STEM skills (U.S. Census Bureau, 2023). This technology-specific heterogeneity is consequential for policy. As Brynjolfsson, Li, and Raymond (2025) ^[7] document in a landmark Quarterly Journal of Economics study, generative AI tools increased worker productivity by 14% on average, with the largest gains accruing to lower-skilled workers, but only in contexts where employer-directed training was co-provided. Acemoglu (2025) ^[1] extends this analysis, arguing that without deliberate human-capital complementation, AI's productivity gains concentrate in large, high-skill firms. The author's evaluation of Nigeria's N-Power digital-skills programme corroborates this mechanism at the programme level: Oni (2019a) ^[19] found that training-linked digital up-skilling translated into enterprise outcomes only when sustained connectivity and mentorship were co-provided, mirroring the complementary-assets dynamic in the U.S. context.

Table 4: Effect of Technology Adoption on STEM Workforce Skills, U.S. Small Businesses, Reference Year 2022

Technology Type	No Impact (%)	Increased STEM Skills (%)	Decreased STEM Skills (%)	Net Up-skilling Margin (pp)
Artificial Intelligence	40.7%	22.1%	3.3%	+18.8
Robotics/Automation	56.6%	20.7%	3.9%	+16.8
Specialised Equipment	50.2%	15.4%	4.1%	+11.3
Cloud-Based Technology	44.4%	10.2%	3.8%	+6.4
Specialised Software	44.9%	9.8%	3.6%	+6.2

Note: Source: U.S. Census Bureau (2023). 2022 Annual Business Survey, technology module. Percentages do not sum to 100 because 'not applicable' and 'not sure' response categories are excluded. pp = percentage points.

3.4.3. RQ3: STEM Workforce Representation and Business Ownership Demographics

NCSSES' (2023) biennial Diversity and STEM report documents that women comprised 35% of the 2021 STEM workforce (up from 32% in 2011). Underrepresented minorities, Hispanic, Black, and American Indian or Alaska Native workers collectively, held 24% of STEM positions (up from 18% in 2011), yet remained substantially underrepresented relative to their share of the working-age population. Persons with disabilities comprised only 3% of the STEM workforce. Underrepresented minority STEM workers disproportionately held positions not requiring a bachelor's degree, with a corresponding earnings penalty, a structural pattern Faiz *et al.* (2024) ^[9] link to differential access to formal digital-skills training within and across firms.

The 2022 ABS release documents the parallel pattern in business ownership: of approximately 5.9 million U.S. employer firms, 21% were minority-owned and 22% were women-owned. ABS geographical data indicates that urban concentrations of minority businesses vastly outnumber rural (around 1.01 million urban compared to 56,900 rural) an 18:1 urban-rural ratio much higher than the overall urban-rural firm ratio (U.S. Census Bureau, 2023) ^[32]. This pattern of geographic concentration is almost identical with the urban focus of digital commerce adoption that the author identified in the Nigerian FCT (Oni, 2021b) ^[21], where digital-platform existence was city-based in a manner that left peri-urban and rural enterprise communities structurally marginalized not withstanding availability of devices. Nambisan *et al.* (2023) ^[14] describe a similar phenomenon in the U.S. context, observing that minority-owned urban SMEs are less likely to adopt technology than their non-minority urban counterparts by a gap that cannot be accounted for by location though it does suggest that urban proximity is a necessary yet not sufficient condition for digital-skills equity.

3.4.4. RQ4: Broadband Connectivity and the Digital-Skills Pipeline

The infrastructure prerequisite for the adoption and study of digital skills, cloud technology, and AI training is basic broadband internet connectivity. 64.4% of rural households and 98.5% of urban households have fixed broadband at the government benchmark speed in 2024, according to the FCC's Broadband Data Collection (2024), indicating a 34.1 percent access difference. Conlow (2023) ^[8] shown that adoption draws adoption swiftly after access is established, demonstrating that lack of access, not user preference, is a bottleneck, even though telecommunication subscription inequalities are lower (58.8% rural vs. 73.0% urban, 14.2 pages). Regardless of urbanicity, lower-income counties trail below the national average by about 13 percentage points. The geographical overlap of deficient broadband and minority small-business desert is substantial: the rural areas

with the worst broadband are also places where minority ownership of business is comparatively rare, as the ABS geographic module shows (U.S. Census Bureau, 2023) ^[33]. The FCC (2024) shows rural broadband access is lowest in the states of the Southeast Central Appalachia, and the Great Plains, geographies which also show up in the bottom tiers of the BTOS state breakout for AI adoption. The author's work on digital banking demonstrated the connectivity-adoption trend, with customers' network dependability also moderating the impact of digital banking provision on customer satisfaction (Oni *et al.*, 2019b) ^[24]. As a result, even among customers with device access, connectivity deficits diminished the benefits of adoption. The claim that connectivity is a load-bearing input to digital skills programs rather than just a background condition is supported by the structural similarities across these various nations.

3.4.5. RQ5: Barriers Sustaining the Digital-Skills Gap

In ways that are relevant to policy, the causes of non-adoption typically differ systematically with firm size. The primary cause of the barrier known as "perceived inapplicability" for micro-firms with one to four employees is significantly higher for non-adopting micro-firms in the BTOS AI Supplement (63.3%) than it is elsewhere (U.S. Census Bureau, 2026) ^[34]. OECD (2025b) cross-national evidence reports that 'unsuitability to business' was cited by 57% of non-adopting SMEs across seven OECD countries. This barrier profile is consistent with the typological distinction the author drew between opportunity-driven and necessity-driven entrepreneurs in Nigeria: Adeyeye *et al.* (2019) ^[3] found that necessity-driven micro-entrepreneurs systematically underestimated the relevance of digital tools to their operations, attributing this to low digital self-efficacy rather than genuine operational inapplicability, a finding that suggests the inapplicability barrier among U.S. micro-firms may be partially amenable to targeted awareness and demonstration interventions.

Among medium-sized firms (20–249 employees), workforce skills and awareness gaps emerge as the dominant and rising barriers: the BTOS Supplement documents that skills-gap citations increased across successive collection cycles within the supplement window for this size band, consistent with the widening-gap trend reported by Grundy *et al.* (2026) ^[12]. OECD (2025b) found that lack of skills among employees was cited by 50% of non-adopting SMEs, and data security concerns by 52%. Hussain Shahadat *et al.* (2023) ^[13], in a peer-reviewed multi-country empirical study, confirm that technological context factors, especially perceived security and integration complexity, constitute the primary barrier in emerging adopter cohorts. The data security dimension resonates with Oni and Adeyeye's (2020) ^[23] finding that security perceptions were the primary predictor of customer trust in digital commerce platforms in Nigeria, underscoring

that security anxiety is a structural barrier to digital adoption that recurs across very different institutional settings and must be addressed directly in programme design.

4. Discussion

4.1. Principal Findings

Four principal findings emerge from this synthesis. First, the firm-size digital adoption gradient is large, statistically robust, and dynamically widening: a 13 pp AI adoption gap between the smallest and largest employer-business size classes, expanding to approximately 19–20 pp when employee-level penetration and forward intentions are incorporated (Bonney *et al.*, 2026; Grundy *et al.*, 2026)^[5, 12]. Second, the most widely adopted digital technologies, cloud computing and specialised software, are systematically less associated with STEM workforce up-skilling than AI and robotics, creating a structural misalignment between the technologies driving current adoption growth and those most capable of closing the skills gap. Third, STEM workforce representation, while improving, remains substantially below parity for women and underrepresented minorities, and earnings and occupational-level penalties compound the long-run supply constraint on STEM-skilled workers available to SMEs. Fourth, broadband infrastructure deficits in rural and lower-income areas constitute a binding constraint on digital-skills pipeline development that neither technology-adoption nor workforce-training policy can address alone.

4.2. Interpretation in Light of Theoretical Frameworks and Prior Research

Through the lens of DOI theory (Rogers, 2003)^[26], the widening adoption gap reflects a late-majority/laggard dynamic among micro-firms: having not adopted AI in the innovator or early-adopter waves, these firms face rising adoption costs relative to their resources as the technology matures. The OECD (2025a) finding that the firm-size AI gap exceeds any prior digital technology at a comparable diffusion stage is consistent with AI's higher complementary-asset requirements, as predicted by Brynjolfsson and Hitt (2003)^[6]. The author's own work adds longitudinal depth to this interpretation: the sequential pattern documented across Oni (2019a, 2021a, 2021b, 2022)^[19, 20], from digital commerce adoption to digital banking to green entrepreneurship, shows that late-adopter SMEs in Nigeria consistently faced the same compounding resource deficits at successive technological frontiers, never catching up to the leading edge, which is precisely the dynamic the widening BTOS trend data document in the U.S. context.

The TOE framework (Tornatzky & Fleischer, 1990; Faiz *et al.*, 2024)^[29, 9] illuminates the compounding nature of the gap: technological barriers (integration complexity, perceived security risk), organisational barriers (skills shortfall, resource constraints), and environmental barriers (broadband deficits, supply-chain pressure absence) interact multiplicatively in SME contexts. Multi-domain compounding explains why SME AI adoption has not converged despite overall growth in AI maturity and cost reduction. This framework was implicit in the author's digital banking research (Oni *et al.*, 2019b)^[24], where organisational readiness, network infrastructure, and regulatory environment each exerted independent and interactive effects, a pattern now visible at national scale in the BTOS

data.

Complementary-assets theory (Acemoglu & Restrepo, 2022; Acemoglu, 2025)^[2, 1] provides the clearest explanation for the up-skilling paradox documented in RQ2: cloud computing and specialised software are adopted primarily for operational efficiency, automating existing tasks rather than creating new ones, whereas AI tools, when appropriately deployed, create new task categories demanding higher-order STEM skills (Brynjolfsson *et al.*, 2025)^[7]. The policy implication is that encouraging AI adoption specifically, rather than digital adoption generically, is the more effective pathway to workforce up-skilling among SMEs. In ways that are relevant to policy, the causes of non-adoption typically differ systematically with firm size. The primary cause of the barrier known as "perceived inapplicability" for micro-firms with one to four employees is significantly higher for non-adopting micro-firms in the BTOS AI Supplement (63.3%) than it is elsewhere (U.S. Census Bureau, 2026)^[34].

4.3. Implications for Policy

Six evidence-based policy implications follow from the synthesis. The synthesis offers six policy recommendations. First, a geographic focus is necessary because broadband infrastructure investments, grants for digital skills training, and technical assistance for AI readiness should be provided in rural and lower-income counties where all three gaps overlap, rather than based on population density. The connectivity-adoption link documented by Oni *et al.* (2019b)^[24] in digital banking, and corroborated by Conlow (2023)^[8] and the FCC (2024) in the U.S. broadband context, makes co-investment a necessary rather than merely expedient policy design choice.

Second, firm-size differentiation is necessary: the barriers driving non-adoption among micro-firms (perceived inapplicability) differ fundamentally from those among medium-sized firms (skills and awareness gaps). Adeyeye *et al.*'s (2019)^[3] motivational typology of opportunity-driven versus necessity-driven entrepreneurs suggests that awareness and demonstration-based interventions will have the highest marginal return among micro-firms, while structured training and subsidized technical assistance will be more effective in the 20–249 employee band.

Third, technology-specificity matters: workforce development programmes should prioritize AI-specific training over generic digital skills curricula, given AI's superior documented up-skilling potential (U.S. Census Bureau, 2023; Brynjolfsson *et al.*, 2025)^[33, 7].

Fourth, accessible generative AI tools offer a near-term equalizer: OECD (2025b) documents that 39% of skills-constrained SMEs report that generative AI partially compensates for their skills deficit, consistent with the author's finding that platform-level quality improvements can partially substitute for underlying skill deficits in the short run (Oni & Adeyeye, 2020)^[23].

Fifth, monitoring must track the gap, not just aggregate adoption: a national AI adoption rate that increases while the firm-size gap widens represents distributional policy failure. Sixth, the STEM supply pipeline requires sustained investment: the representation deficits documented by NCSES (2023) translate directly into a supply constraint on STEM-skilled workers available to SMEs in underserved geographies, making STEM equity investment a prerequisite for long-run digital-skills gap closure.

4.4. Limitations

There are five primary limitations to this review. First, multivariate decompositions that separate the impacts of business size from sector and geographic composition cannot be carried out since the official statistical evidence is based on aggregate tabulations rather than micro-data at the level of individual enterprises. Table 2 grades co-founding as moderate. Second, a break in the series will result from the December 2025 BTOS rewording, which defines AI-use as "involved in any business function" rather than "engaged in generating goods or services." This will make it hard to compare pre- and post-revision data precisely. Third, the synthesis is cross-sectional because most of the sources that are included give data from a single collection wave, which restricts the ability to draw inferences about the direction of effects between broadband availability and adoption or between digital adoption and up-skilling. Fourth, the inclusion criteria reduce but do not completely eliminate the variation in the quality of gray literature among included papers. Fifth, because the research is limited to English-language sources, some relevant foreign information about digital skills policies may have been left out. The sixth is that the statistics from the U.S. government that make up the major evidence gathered here are not symmetrical with the author's earlier study, which is based on empirical Nigerian and West African contexts. The cross-national comparisons that are used throughout this review are structural rather than causal in nature; they function as theoretical lenses and guidelines for interpretation, but they do not replace direct assessments of U.S.-based programs, which must be the main focus of future research.

5. Conclusions

This PRISMA 2020 systematic review is the first to synthesize 24 relevant sources in order to characterize the US digital-skills gap as extensive, multidimensional, exacerbated by structural inequities in representation in the STEM workforce and broadband infrastructure, and not self-correcting. National AI adoption is 17.9% and 30.6% among large firms; the gap is growing. Women and underrepresented minorities in the STEM workforce, though advancing, are still dramatically underrepresented. Rural broadband subscription lags urban by 14.2 pp. And AI, the technology most frequently linked to workforce up-skilling, is least available to small businesses, minority workers and rural households, all of which are most in need of skills development.

The combined evidence here advocates for a coordinated policy approach to broadband investment, AI-specific workforce training, and STEM incentive initiatives as a united regionally targeted challenge, not as three separate agency tasks. The theoretical claim that digital adoption in the absence of complementary skills development, security trust-building, and co-provision of infrastructure is systemically inadequate to promote equitable ends regardless of national context is strengthened by the structural similarities between these findings and the author's earlier empirical work on digital adoption and SME performance in Nigeria and West Africa (Oni & Adeyeye, 2020; Oni, 2021a, 2021b, 2022; Oni, 2019a)^[23, 21, 19]. The firm-size adoption gap should serve as a signal for federal agencies such as the SBA, the Department of Commerce, the FCC, and the NSF to co-

align program requirements and evaluation metrics. Maintaining the evidence base for surveillance requires ongoing modularization of the BTOS technology in conjunction with the NCSES Diversity and STEM series. Using restricted-access micro-data to separate firm-size effects from sector and regional variables and link adoption patterns to worker outcomes and productivity is a top focus for the research going forward.

6. Policy Recommendations

The recommendations aim to improve US economic competitiveness by raising the productivity of SMEs, enlarging the US workforce equipped with new technology, reducing national, regional, and demographic disparities, and enabling inclusive benefits of digital economy and AI.

Recommendation 1. Coordinate broadband investment with digital-skills development

The Federal Communications Commission (FCC) and National Telecommunications and Information Administration (NTIA) should coordinate broadband deployment with digital-skills programmes in rural and underserved U.S. communities. Linking infrastructure investment with workforce training would improve the capacity of SMEs to adopt digital technologies, increase productivity, and participate more effectively in the national digital economy.

Recommendation 2. Design technology-support programmes according to firm size

The Economic Development Administration (EDA) and the U.S. Small Business Administration (SBA) must modify their technology assistance programs to meet the requirements of various SMEs. While EDA Regional Technology and Innovation Hubs must provide scale-stage enterprises more sophisticated AI and digital transformation programs, SBDCs and SCORE must assist micro-firms with inexpensive AI instruction and demonstration programs. This kind of distinction can boost SMEs' competitiveness and improve the effectiveness of public investment.

Recommendation 3. Align workforce development with emerging AI skills

In federally funded workforce programs, the National Institute of Standards and Technology (NIST) and the U.S. Department of Labor (DOL) should integrate AI literacy, prompt engineering, data analysis, and practical AI tool use. In addition to helping businesses better innovate and boost efficiency, establishing national standards for AI competencies will assist the American workforce get ready for technological change.

Recommendation 4. Integrate cyber-security into SME digital transformation

As part of their SME technology adoption programs, the SBA, NIST, and the Cyber-security and Infrastructure Security Agency (CISA) ought to incorporate cyber-security and data-privacy education. SMEs would be able to accomplish safe digital transformation, safeguard their company assets, and lessen possible vulnerabilities that could cause disruptions in productivity and competitiveness if they were strengthened to better manage cyber and data risk.

Recommendation 5. Improve SME access to reliable generative-AI technologies

A list of reasonably priced and well assessed generative-AI solutions should be made publicly available by the SBA, NIST, and the Department of Commerce. SBDCs and SCORE mentors should provide SMEs with useful guidance on selecting and putting these solutions into practice. This would reduce information barriers and enable smaller businesses to use AI to increase efficiency without needing to develop a sizable internal technical competence.

Recommendation 6. Monitor SME AI adoption as an economic-performance indicator

SME AI adoption should be taken into account by the OMB and SBA Office of Advocacy as a measurable indicator of US digital economic performance. Federal programs should be routinely reviewed by the Government Accountability Office (GAO) to assess how well they support workforce development, SME productivity, technology adoption, and competitiveness. The science-based allocation of federal resources would be enhanced by regular monitoring.

Recommendation 7. Strengthen the U.S. STEM talent pipeline

NSF, U. S. Department of Education, and NCSES should enhance the pathways for STEM education and workforce for HBCUs, HSIs and other minority-serving institution. Increasing opportunities for STEM education, research infrastructure, and industry-connected training will enhance the pool of skilled workers for U.S. firms and support long-term innovation, productivity, and economic growth.

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