

The Firm-Size Digital Adoption Gap in the U.S. Small-Business Sector: Evidence from the Census Bureau's BTOS Artificial Intelligence Supplement

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DOI: <https://doi.org/10.47772/IJRISS.2026.100900050>

Received: 14 September 2026; Accepted: 19 September 2026; Published: 29 September 2026

ABSTRACT

Background: Artificial intelligence (AI) is a transformative general-purpose technology with important implications for business productivity and competitiveness. However, smaller firms tend to lag behind larger enterprises in AI adoption. This study examines the firm-size AI adoption gap, the depth of adoption, non-adoption barriers, and variations across industries and geographic areas.

Methodology: The study uses public-release tabulations from the U.S. Census Bureau's Business Trends and Outlook Survey (BTOS) AI Supplement, conducted between November 2025 and February 2026. The dataset provides national, employment-size, 2-digit NAICS sector, state, and metropolitan-area estimates. Unadjusted univariate and two-way descriptive comparisons were conducted using Census-published standard errors and 95% confidence intervals, with OECD, SBA Office of Advocacy, and Census Bureau publications providing contextual benchmarks.

Findings: Overall AI adoption was 17.9%, increasing from 17.6% among firms with 1–4 employees to 30.6% among firms with 250 or more employees. Employee-level generative AI use and planned adoption exhibited wider gaps of 19.6 and 19.2 percentage points, respectively. Sectoral adoption ranged from 5.1% in Agriculture to 37.6% in Information. Skills shortages and limited AI knowledge were particularly prominent barriers among medium-sized firms.

Conclusion and Recommendations: The findings indicate a substantial and multidimensional firm-size gradient in AI adoption, although descriptive tabulations cannot isolate firm-size effects from sectoral and geographic composition. Firms with 20–249 employees emerge as a plausible priority segment for AI-readiness support. Policy interventions should combine targeted workforce development for medium-sized firms, sector-specific AI demonstrations for micro-businesses, geographically targeted capacity-building, and monitoring of size-class adoption gaps alongside aggregate adoption. reduce to less than 250

Keywords: artificial intelligence adoption; firm size; small business; digital divide; workforce skills gap; Business Trends and Outlook Survey (BTOS); descriptive empirical study; cross-sectional survey analysis; U.S. Census Bureau

INTRODUCTION

Background and Rationale

The diffusion of digital technologies across firms has never been uniform. Several decades of economic and management research have established that larger, better-resourced firms adopt emerging technologies earlier and more extensively than their smaller counterparts (Davis, 1989; Rogers, 2003; Tornatzky & Fleischer, 1990). This pattern has been documented for information technology (Brynjolfsson & Hitt, 2003), e-commerce (Ghobakhloo et al., 2011), cloud computing (OECD, 2024), and, most recently, artificial intelligence (Acemoglu & Restrepo, 2018; Bonney et al., 2026).

Artificial intelligence represents the current frontier of this structural dynamic. As a general-purpose technology, AI has the potential to reshape productivity, operational efficiency, and competitive positioning across the economy (Acemoglu & Restrepo, 2018, 2022; Brynjolfsson et al., 2025). Evidence already documents substantial productivity gains among adopters. In a landmark study published in the *Quarterly Journal of Economics*, Brynjolfsson et al. (2025) found that generative AI tools increased the productivity of customer-support agents by 14% on average, with the largest gains accruing to less-skilled and less-experienced workers, who benefited most from AI-mediated access to best-practice knowledge. If, however, the productivity gains from AI accrue disproportionately to larger, already advantaged firms, the technology may compound existing competitive inequities rather than reduce them.

This concern is empirically grounded. Cross-national data from the OECD (2025a) show that, in 2024, 40% of firms with 250 or more employees in OECD member countries used AI, compared with only 11.9% of firms with 10–49 employees, a ratio of approximately 3.4, which exceeds the adoption gap documented for any earlier digital technology at a comparable stage of diffusion. In the United States, the SBA Office of Advocacy (2025) found that large businesses used AI at 1.8 times the rate of small businesses in early 2024. That estimate, however, relies on the earlier “producing goods or services” question wording and is therefore not directly comparable with the post-November 2025 BTOS estimates analysed here (see Section 3.4.8). Using linked Census Bureau microdata, Bonney et al. (2026) likewise found that AI use is heavily concentrated in large firms and knowledge-intensive sectors, with very large firms in Information, Professional Services, and Finance reaching 50–60% adoption on a firm-count basis. The economic stakes are considerable: small and medium-sized enterprises (SMEs) account for more than 99% of U.S. employer businesses and employ approximately 46% of the private-sector workforce (SBA Office of Advocacy, 2025), so their systematic exclusion from AI adoption could widen the productivity gap between small and large firms for years to come.

Despite growing descriptive evidence of a firm-size gap in AI adoption, comprehensive documentation based on government data has remained limited with respect to the gap’s precise magnitude, its multidimensional character, its sectoral and geographic embedding, and, critically, the specific barriers that drive it within different firm-size classes. The U.S. Census Bureau’s 2025–2026 BTOS AI Supplement, the first nationally representative, disclosure-reviewed federal instrument to cover AI adoption across all employer businesses, provides the data needed to address these gaps. This descriptive empirical study analyses that instrument in full and draws on contemporaneous evidence from the National Bureau of Economic Research (NBER), the OECD, and the Census Bureau’s own research publications.

This paper is a national descriptive empirical study based on secondary analysis of publicly released federal survey data (the BTOS AI Supplement). The unit of analysis is the published estimate for a size class, sector, state, or metropolitan area, not an individual study or report. Other publications are cited to benchmark and interpret the BTOS estimates; they were neither screened nor pooled.

Theoretical Framework

The analysis draws on three complementary theoretical traditions in the technology-adoption literature. First, Rogers’s (2003) Diffusion of Innovations (DOI) theory holds that adoption is shaped by five perceived attributes of an innovation (relative advantage, compatibility, complexity, trialability, and observability) and that larger organisations, by virtue of greater slack resources and more formalised decision-making, tend to adopt faster and more extensively. This prediction directly implies a firm-size gradient in AI adoption. Second, the Technology–Organisation–Environment (TOE) framework (Tornatzky & Fleischer, 1990; see also Chatterjee et al., 2021; Faiz et al., 2024; Hussain Shahadat et al., 2023) identifies three contextual domains that shape adoption decisions: the technological context (the characteristics of the innovation), the organisational context (firm size, human resources, and internal slack), and the environmental context (sectoral competition, the regulatory environment, and supply-chain pressure). The TOE framework predicts that firm size interacts with sector-level adoption norms to produce compounded, non-independent adoption gaps. The descriptive tabulations in Section 3.4 are consistent with this pattern but cannot test it, because testing an interaction requires a multivariate model. Third, complementary-assets theory (Acemoglu & Restrepo, 2022; Brynjolfsson & Hitt, 2003) holds that general-purpose technologies yield productivity benefits only when accompanied by sufficient complementary investment in skilled labour, organisational change, and data infrastructure, which smaller firms are less well

positioned to make. This framework offers one possible interpretation of the skills-barrier patterns reported in Section 3.4.4.

Research Questions

This study addresses five descriptive research questions (RQs):

1. What is the magnitude and statistical significance of the difference in AI adoption rates between small and large U.S. employer businesses?
2. Does the adoption gap extend beyond organisational incidence to employee-level penetration of generative AI and to forward-looking adoption intentions?
3. How does the firm-size adoption gap vary across 2-digit NAICS industry sectors, and is the gap compounded or attenuated by sectoral concentration?
4. What is the magnitude of geographic variation in AI adoption at the state and metropolitan-area levels, and how does it relate to firm-size and sectoral patterns?
5. Which specific barriers do non-adopting firms report, and how do these vary systematically by firm size in ways relevant to targeted workforce-development policy?

Where the research questions ask how patterns “relate” or whether a gap is “compounded or attenuated” (RQ3 and RQ4), the analysis reports the co-occurrence of separately tabulated, unadjusted estimates. It does not estimate the independent effects of firm size, sector, or geography.

Methods

This study is a secondary, cross-sectional descriptive analysis of publicly released federal survey tabulations. It is reported in accordance with the STROBE guideline for cross-sectional studies (von Elm et al., 2007), which is used here as a transparency checklist.

Study Design, Population, and Criteria for Benchmark Sources

The study population comprises U.S. employer businesses within the scope of the BTOS AI Supplement. The single-period BTOS AI Supplement (November 17, 2025–February 8, 2026) is the sole source of estimates. Other publications serve only as contextual benchmarks and are not pooled with the BTOS estimates. The criteria below govern only the selection of these benchmark sources.

Inclusion Criteria

Contextual benchmark sources were included if they met all of the following criteria:

- **Population:** U.S. employer businesses of any sector or size.
- **Phenomenon:** Use of artificial intelligence in at least one business function.
- **Data type:** Nationally representative probability-sample survey estimates or government-disclosed aggregate statistics drawn from a census frame.
- **Disaggregation:** AI adoption rates reported by firm employment-size class, with at least three distinct size strata.
- **Reference period:** Coverage of, or estimates directly benchmarked to, November 2025–February 2026, or identification as a supplementary cross-national benchmark contemporaneous with this window.
- **Publication:** Published or publicly released before the August 2026 search date.

Exclusion Criteria

- Non-probability or convenience samples (e.g., vendor-commissioned surveys, industry-association polls, and opt-in panels).
- Case studies, qualitative narratives, or reports without quantitative AI adoption rates.
- Studies limited to a single sector or a single geographic unit without size-class disaggregation.
- Data predating January 2024 that had not been explicitly benchmarked or cross-validated against a post-2024 source.
- Studies of non-employer or self-employed-only populations without coverage of employer businesses.

Data Sources

The primary data source was the set of public-release BTOS AI Supplement workbooks. Contextual benchmark sources were located through targeted searches of the following repositories:

- U.S. Census Bureau BTOS data portal (<https://www.census.gov/hfp/btos/data>): the primary data source, searched in March 2026 and updated in August 2026.
- U.S. Census Bureau Center for Economic Studies (CES) working-paper series: searched in March 2026 and August 2026.
- National Bureau of Economic Research (NBER) working-paper repository: searched in March 2026 and August 2026.
- SBA Office of Advocacy research publications database: searched in April 2026 and August 2026.
- OECD iLibrary (<https://www.oecd-ilibrary.org>): searched in April 2026 and updated in August 2026.

Identification of Contextual Benchmark Sources

The following search string was applied to all portals: (“artificial intelligence” OR “AI”) AND (“small business” OR “firm size” OR “establishment size” OR “employer business”) AND (“adoption” OR “use” OR “utilisation” OR “diffusion”). For the Census Bureau portal, the search was supplemented by direct navigation to the BTOS AI Supplement download page and a systematic review of all linked data files, documentation, and associated publications. The full search string and a complete list of hits for each portal are available from the author on request. The search served only to locate benchmark literature; it was not designed to be exhaustive, and no claim of systematic coverage is made.

Analytic Sample and Selection of Benchmark Sources

The analytic sample consists of the six BTOS AI Supplement workbooks. Five contextual benchmark sources were selected by the author against the criteria above: Bonney et al. (2026), Grundy et al. (2026), OECD (2025a), OECD (2025b), and SBA Office of Advocacy (2025).^{2.5} Data Extraction.

All statistics were extracted by the author (a single extractor, without independent double extraction) from the Census Bureau’s six public BTOS download workbooks (Employment_Size_Class.xlsx, Sector.xlsx, National.xlsx, State.xlsx, Top_25_MSA.xlsx, and AI_Supplement_Table_2026.xlsx) and were checked cell by cell against the Bureau’s published standard errors. All estimates are the Bureau’s own publicly released single-period supplement tabulations (Project No. P-7529868; Disclosure Review Board approval number CBDRB-FY26-0278).

Metropolitan-area figures are simple averages, computed by the author, of the six biweekly BTOS collection cycles that fall within the supplement window (November 17, 2025–February 8, 2026), because the Bureau’s special supplement table does not publish a dedicated single-period breakdown by metropolitan statistical area (MSA). These averages are unweighted, are not accompanied by variance estimates, and combine cycles that may differ in sample size. Consequently, no confidence intervals or significance tests are reported for MSA figures, and MSA comparisons are descriptive only. If cycle-level standard errors were available, an approximate standard error for each average could be computed as $SE = \sqrt{(\sum SE_i^2) / k}$ across the $k = 6$ cycles, on the assumption that cycle estimates are independent. From the supplementary sources, population-level findings, standard errors or confidence intervals (where reported), and data on barriers were extracted into a standardised extraction form.

Data-Quality and Bias Considerations

Data quality and potential bias were appraised qualitatively across six domains. The domains were adapted from ROBINS-I (Sterne et al., 2016), a tool designed for non-randomised studies of interventions, and are used here only as a structured prompt, not as a formal risk-of-bias instrument. The domains are (1) sampling bias; (2) measurement bias, including the BTOS question-wording change of November 17, 2025, which was documented on December 3, 2025 and introduced as a new series from the December 4, 2025 release (U.S. Census Bureau, 2025); (3) non-response bias; (4) aggregation bias, specific to the author’s MSA averaging procedure; (5) publication and sponsor bias; and (6) confounding, that is, the inability to isolate firm-size effects from sectoral and geographic composition in aggregate data. The full assessments are presented in Table 2 (Section 3.3).

Analytic Approach

The analysis is descriptive and comparative. Adoption rates across size classes, sectors, and geographies are compared using the Census Bureau’s published standard errors to assess statistical significance. Differences between size class A (1–4 employees) and size class G (250 or more employees) are assessed using 95% confidence intervals ($\pm 1.96 \times SE$); where the intervals do not overlap, the difference is treated as statistically significant. Sectoral and geographic estimates are assessed against the national average using the same procedure. Barrier data are cross-tabulated by firm size and analysed as response distributions to identify systematic directional patterns. No meta-analysis or pooling was performed, and contextual sources are used only for benchmarking. The analysis is limited to univariate and two-way descriptive comparisons of published aggregate estimates. Because no regression, standardisation, or other adjustment for sectoral or geographic composition was possible, firm-size differences are reported as unadjusted associations rather than as effects of firm size.

RESULTS

Data Sources and Analytic Sample

The analytic sample comprises the six BTOS AI Supplement workbooks (the primary source, drawn from a sampling frame of approximately 1.2 million employer businesses) and five contextual benchmark sources: Bonney et al. (2026), Grundy et al. (2026), OECD (2025a), OECD (2025b), and SBA Office of Advocacy (2025). One further cross-national source, an OECD (2026) press release, is cited only for trend context in Sections 3.4.7 and 4.1. Table 1 lists each source, its role in the analysis, and its level of disaggregation. Nine other candidate items identified in the search were excluded because they were non-probability vendor surveys ($n = 6$), single-sector sources without size-class disaggregation ($n = 2$), or pre-2024 data without post-2024 benchmarking ($n = 1$).

Table 1 Data Sources and Analytic Sample

Source	Role in this study	Coverage and disaggregation	Reference period
U.S. Census Bureau (2026). BTOS AI Supplement: six public workbooks (Employment Size Class,	Primary source of all estimates and standard errors	National; seven employment-size classes; 2-digit NAICS sector; state; top-25 MSAs (author-averaged across six biweekly cycles); generative AI and	Nov 17, 2025–Feb 8, 2026

Sector, National, State, Top_25_MSA, AI_Supplement_Table_2026)		barrier items. Sampling frame of approximately 1.2 million employer businesses	
Bonney et al. (2026), NBER Working Paper No. 35141 / CES Working Paper	Contextual benchmark: linked microdata (employment-weighted adoption; use by business function)	Firm-wide, business-function, and worker-task levels	Nov 2025–Jan 2026
Grundy et al. (2026), U.S. Census Bureau	Contextual benchmark: six-month BTOS trend by firm size	Firms with fewer than 20 employees vs. firms with 20 or more	Dec 2025–May 2026
OECD (2025a)	Cross-national benchmark for adoption by firm size	Firm-size classes; G7 and OECD economies (Eurostat and OECD survey data)	2024
OECD (2025b)	Cross-national benchmark for barriers to generative AI	Survey of more than 5,000 SMEs in seven OECD countries	2024
SBA Office of Advocacy (2025)	U.S. benchmark for the large-to-small firm ratio	Small vs. large businesses; BTOS data under the earlier “producing goods or services” wording	Feb 2024–Aug 2025
OECD (2026), press release	Cross-national trend context (not one of the five benchmark sources)	Large vs. small firms, OECD countries	2025

Author’s compilation, (2026) Note. BTOS = Business Trends and Outlook Survey; MSA = metropolitan statistical area; NBER = National Bureau of Economic Research; CES = Center for Economic Studies. Contextual sources are used for benchmarking only and are not pooled with BTOS estimates.

Characteristics of the Data Sources

The primary data source, the U.S. Census Bureau BTOS AI Supplement (2026), was fielded from November 17, 2025 to February 8, 2026 using a sampling frame of approximately 1.2 million U.S. employer businesses across all states, sectors, and firm sizes. The published aggregate estimates carry standard errors that permit interval estimation and are disaggregated at the national, employment-size-class, 2-digit NAICS sector, state, and MSA levels. The contextual benchmark sources are as follows:

- Bonney et al. (2026), NBER Working Paper No. 35141 / CES Working Paper No. CES-26-25: an analysis of linked BTOS microdata characterising AI diffusion at three levels (firm-wide, business function, and worker task). Sample: a nationally representative panel of employer businesses. Reference period: November 2025–January 2026.
- Grundy et al. (2026), U.S. Census Bureau, *America Counts*: a six-month trend analysis of BTOS data covering December 2025–May 2026. It documents a significant increase in AI use among firms with 20 or more employees but not among firms with fewer than 20 employees.
- OECD (2025a), *AI Adoption by Small and Medium-Sized Enterprises*: a discussion paper prepared for the G7 Presidency (Canada, 2025) using Eurostat and OECD survey data for G7 economies. It reports that 40% of firms with 250 or more employees in OECD countries used AI in 2024, compared with 11.9% of firms with 10–49 employees.

- OECD (2025b), *Generative AI and the SME Workforce*: a survey of more than 5,000 SMEs in seven OECD countries. It reports barriers to generative AI adoption, including unsuitability for the business (57% of non-adopters), copyright and legal concerns (54%), data-security concerns (52%), and a lack of employee skills (50%).
- SBA Office of Advocacy (2025), *AI in Business: Small Firms Closing In* (Research Spotlight, September 2025): an analysis of BTOS data through August 2025, finding that large businesses used AI at 1.8 times the rate of small businesses in February 2024 (under the earlier “producing goods or services” wording).

Data-Quality and Bias Considerations

Table 2 presents the qualitative appraisal of data quality across the six domains for the included sources.

Table 2 Data-Quality and Bias Appraisal Across Six Domains

Bias domain	Assessment	Risk level
Sampling bias	The BTOS is a probability sample drawn from a frame of approximately 1.2 million employer businesses, with disclosure controls approved by the Disclosure Review Board. Non-probability samples were not used as benchmark sources.	Low
Measurement bias (wording change)	The revision effective November 17, 2025 (documented December 3, 2025) broadened the AI-use question from “producing goods or services” to “any business function.” The Census Bureau reports a level shift at the change, so estimates are not comparable with cycles using the earlier wording. Whether the shift differed by firm-size tier is untested (Section 3.4.8); it could either widen or compress the size gap.	Moderate (direction by size tier unresolved)
Non-response bias	BTOS non-response patterns by firm size are not published. Systematic under-response by very small firms could compress the estimated gap.	Low to moderate
Aggregation bias (MSA averages)	Author-computed unweighted averages across six biweekly cycles, with two San Antonio cycles suppressed. There are no variance estimates, and averages are not weighted by cycle sample size; MSA comparisons are therefore descriptive only.	Moderate for MSA comparisons
Publication and sponsor bias	The primary data source is the U.S. federal statistical agency, which has no commercial interest. Supplementary sources are peer-reviewed or government-reviewed.	Low
Confounding	Aggregate data prevent multivariate isolation of firm-size effects from sector and geography; this is acknowledged as the primary limitation. Univariate and two-way tabulations cannot separate firm-size effects from composition, so the findings are associational.	High for any causal interpretation of firm size (moderate for descriptive gaps)

Author’s compilation, (2026) Note. Risk levels reflect a combined assessment across all included sources and are qualitative judgements by the author. The measurement-bias domain is rated “moderate (direction by size tier unresolved)” because the Census Bureau reports an overall level shift at the wording change but provides no size-specific assessment.

Overall, the sampling and sponsor risks associated with the primary data source are low, whereas the measurement (wording change), MSA aggregation, and confounding risks are not. The principal residual concern, namely the inability to conduct multivariate decomposition with aggregate data, limits this study to

descriptive, associational claims; statements about compounding, drivers, or binding constraints should be read as hypotheses.

Findings

National Baseline

Nationally, 17.9% of U.S. employer businesses reported using AI in any business function during the two weeks preceding the BTOS AI Supplement survey. On an employment-weighted basis, Bonney et al. (2026) report that 32% of U.S. private-sector employment is in firms that use AI, reflecting the concentration of adoption among larger, higher-employment firms. This baseline is broadly consistent with the OECD's (2025a) 2024 estimates for comparable economies, which lends cross-national plausibility to the U.S. finding.

RQ1 and RQ2: The Firm-Size Adoption Gap in Incidence, Depth, and Trajectory

Table 3 presents AI adoption on three measures by employment-size class. Adoption is highest in the largest size classes on all three measures, but the shape of the gradient differs by measure. Employee-level generative AI use rises at every step. Current use and planned adoption, by contrast, are essentially flat across the three smallest classes (17.0%–17.6% and 20.6%–21.9%, respectively, with the 5–9 employee class slightly below the 1–4 employee class on both measures) and rise from the 20–49 employee class upward.

Table 3 AI Adoption by Employment-Size Class across Three Measures (BTOS AI Supplement, November 2025–February 2026)

Employment-size class	Currently using AI (%)	SE (pp)	Employees using generative AI (%)	Planning to adopt in next 6 months (%)	95% CIs overlap (A vs. G, current use)
1–4 employees (A)	17.6	0.17	19.1	20.8	No
5–9 (B)	17.0	0.33	20.6	20.6	—
10–19 (C)	17.2	0.36	22.2	21.9	—
20–49 (D)	18.5	0.32	25.3	24.5	—
50–99 (E)	21.3	0.37	30.4	28.5	—
100–249 (F)	25.3	0.72	35.9	33.9	—
250+ employees (G)	30.6	0.87	38.7	40.0	No
Gap (G – A)	13.0 pp	—	19.6 pp	19.2 pp	—

Author's computation, (2026) Note. SE = standard error, as published by the U.S. Census Bureau, for current AI use; CI = confidence interval ($\pm 1.96 \times SE$); pp = percentage points. The final column indicates whether the 95% confidence intervals of the smallest and largest size classes overlap. Because standard errors were published only for current use, the test of statistical significance is restricted to that measure; the gaps in employee-level generative AI use and planned adoption are reported descriptively. Differences between adjacent smaller classes are small and were not tested.

For current AI use, the gap between size class A (1–4 employees; 17.6%) and size class G (250 or more employees; 30.6%) is 13.0 percentage points. Applying the Bureau's published standard errors, the 95% confidence interval is $17.6\% \pm 0.33$ pp (17.27%–17.93%) for size class A and $30.6\% \pm 1.71$ pp (28.89%–32.31%) for size class G. The gap far exceeds the combined margin of error, confirming that the difference is statistically significant at the 95% level and unlikely to be attributable to sampling variability. This result is consistent with,

and extends, the findings of Bonney et al. (2026), who use linked microdata to show that AI adoption is substantially higher in large firms, and with cross-national evidence from the OECD (2025a) showing a large-to-small ratio of approximately 3.4 across OECD economies. The test addresses sampling variability only. It does not show that firm size is the source of the difference, because the unadjusted comparison also reflects any differences in sectoral and geographic composition between size classes.

Two features of Table 3 are particularly noteworthy. First, the gap is wider on the depth and forward-looking measures than on current incidence: the planned-adoption gap (19.2 pp) exceeds the current-use gap (13.0 pp), and the gap in employee-level generative AI use (19.6 pp) exceeds both. This suggests that the gap is multidimensional. Larger firms are not merely more likely to have adopted AI at the organisational level; they are also more likely to have extended that adoption to individual workers' daily tasks and to report stronger intentions to expand adoption further. Second, planned adoption among the smallest firms (20.8%) is barely above their current use (17.6%), which, if stated intentions translate into behaviour, implies little near-term growth in the 1–4 employee tier (stated intentions are not observed adoption). This contrasts with the largest firms (250 or more employees), whose planned adoption (40.0%) substantially exceeds their current use (30.6%), suggesting possible continued growth at the top of the size distribution, subject to the same caveat.

These patterns are consistent with the six-month trend analysis of Grundy et al. (2026), who found statistically significant increases in AI use among firms with at least 20 employees between December 2025 and May 2026 but no significant change among firms with fewer than 20 employees. For a different measure and time window, this suggests that the gap may be widening. However, a significant change in one group combined with no significant change in another does not by itself demonstrate that the two changes differ from each other.

RQ3: Sectoral Variation

Table 4 presents AI adoption by 2-digit NAICS sector. The sectoral spread is pronounced, ranging from 5.1% in Agriculture, Forestry, Fishing and Hunting to 37.6% in Information. This 32.5-percentage-point range exceeds even the firm-size gap in magnitude.

Table 4 AI Adoption by 2-Digit NAICS Sector (BTOS AI Supplement, November 2025–February 2026)

Sector (2-digit NAICS code)	Currently using AI (%)	SE (pp)
Information (51)	37.6	0.95
Professional, Scientific, and Technical Services (54)	34.2	0.23
Finance and Insurance (52)	30.4	0.78
<i>Retail Trade (44–45)</i>	12.6	0.18
Manufacturing (31–33)	12.4	0.32
<i>Other Services (81)</i>	9.8	0.38
<i>Construction (23)</i>	9.2	0.29
<i>Accommodation and Food Services (72)</i>	8.0	0.30
Agriculture, Forestry, Fishing and Hunting (11)	5.1	0.82
National average	17.9	—

Author's computation, (2026) Note. Selected sectors, ordered by adoption rate. SE = standard error, as published by the U.S. Census Bureau; pp = percentage points. Sectors shown in italics are disproportionately

composed of firms with fewer than 250 employees (SME-dense sectors, as defined by the U.S. Small Business Administration).

Of central importance to this study's research questions, four of the five sectors furthest below the national average, namely Accommodation and Food Services (8.0%), Construction (9.2%), Other Services (9.8%), and Retail Trade (12.6%), are among the sectors most densely populated by small and independently owned businesses. The OECD (2025a) reports analogous patterns across G7 economies, with adoption in the information and communication technology (ICT) sector more than three times higher than in manufacturing, construction, and food services. This convergence of sectoral and size-class gradients means that the unadjusted firm-size gap documented in Section 3.4.2 cannot be separated from the sectoral distribution of small businesses; these data cannot show how much of the gap is attributable to firm size itself and how much to sectoral composition. A firm with 1–4 employees operating in Accommodation and Food Services may face overlapping size-related and sector-related barriers relative to a large firm in the Information sector, but because this study does not use size-by-sector cross-classifications, it cannot test that proposition. Bonney et al. (2026) additionally find that, among adopters, AI use is concentrated in sales and marketing (52% of adopters), strategy (45%), and information technology (41%), functions that require the kind of business infrastructure and human capital disproportionately available to larger, higher-revenue enterprises.

RQ5: Barriers to AI Adoption by Firm Size and the Skills-Gap Finding

Table 5 presents the BTOS AI Supplement's module on non-adoption barriers, cross-tabulated by employment-size class. This cross-tabulation, which constitutes the study's main analytical contribution, shows that the composition of reported non-adoption barriers differs across size classes and follows a descriptive gradient as firm size increases.

Table 5 Barriers to AI Adoption by Employment-Size Class, Non-Adopting Firms Only (BTOS AI Supplement, November 2025–February 2026)

Size class	"AI not applicable" (%)	"Lack of knowledge of AI capabilities" (%)	"Lack of skilled workforce" (%)	"Too expensive" (%)
1–4 (A)	63.3	21.2	6.4	6.7
5–9 (B)	60.7	23.3	7.8	7.3
10–19 (C)	59.7	23.0	8.1	7.3
20–49 (D)	58.1	23.4	8.6	7.0
50–99 (E)	51.4	25.0	9.2	7.6
100–249 (F)	47.9	24.5	9.2	8.5
250+ (G)	42.2	20.0	8.1	9.0
Pattern (A → G)	Declines steadily	Rises to a peak at E, then declines	Rises to a peak at E–F, then declines	Generally rises

Author's computation, (2026) Note. Figures represent the percentage of non-adopting firms citing each reason; multiple responses were permitted. The pattern row indicates the directional trend of each response across size classes from A (1–4 employees) to G (250 or more employees). Additional response categories (e.g., regulatory and data-security concerns) are available in the full BTOS download files. No standard errors are reported for these estimates.

Among the smallest non-adopting firms (1–4 employees), 63.3% cite “AI is not applicable to this business” as a reason for non-adoption. This share declines steadily and substantially across size classes, falling to 47.9% among firms with 100–249 employees and to 42.2% among the largest non-adopting firms. The pattern is consistent with the OECD’s (2025b) finding, from its survey of more than 5,000 SMEs in seven countries, that unsuitability to their work was the most commonly cited barrier (57% of non-adopting SMEs). It is also consistent with the micro-logic of complementary-assets theory: very small firms, often operating in low-complexity settings, may genuinely lack viable AI use cases, so a uniform adoption-promotion policy might generate limited uptake in this tier. Nevertheless, “not applicable” is a self-reported perception that may partly reflect limited awareness or respondents’ interpretation of what counts as AI use (see Section 3.4.8).

More consequential for workforce policy is a countervailing pattern. The share of non-adopting firms citing a lack of knowledge of AI’s capabilities rises from 21.2% (1–4 employees) to a peak of 25.0% (50–99 employees) before declining modestly in the largest size classes. The share citing a lack of skilled workforce rises from 6.4% (1–4 employees) to 9.2% (50–99 and 100–249 employees). Both workforce-related barriers are therefore most prevalent in the 20–249 employee range, precisely where the “not applicable” response is declining. This is consistent with, but does not demonstrate, the interpretation that human-capital and awareness constraints, rather than a mismatch between business models and available AI tools, contribute to non-adoption in this range. The OECD (2025b) supports this reading at the cross-national level: 50% of non-adopting SMEs in its 2024 survey cited a lack of employee skills as a barrier. The reported reasons are self-reports by non-adopters, are not mutually exclusive, and were not analysed net of sector. Because Table 5 reports no standard errors, differences of one to three percentage points between adjacent size classes should be read as directional only. It should also be noted that a lack of knowledge (20.0%–25.0%) is cited far more often than a lack of skilled workforce (6.4%–9.2%).

A tentative policy implication follows. Digital-skills interventions, whether delivered through SBA technical assistance, Department of Commerce capacity-building grants, or state workforce-development programmes, may have the greatest marginal impact in the 20–249 employee band, where firms appear to be at or near a viability threshold for AI adoption but are held back by skills and awareness gaps rather than by any fundamental irrelevance of the technology. This remains an untested hypothesis. It also suggests, pending evidence on programme effects, that a uniform national promotion campaign may be less well targeted.

RQ4: Geographic Variation at the State Level

Table 6 presents selected state-level estimates of AI adoption. Across states, adoption spans 14.5 percentage points, from 23.5% in Colorado to 9.0% in North Dakota. Western and Sun Belt states (Colorado, Arizona, Nevada, Oregon, and Florida) cluster at the top of the distribution, whereas North Dakota, Alaska, West Virginia, and Arkansas, spanning the Great Plains, Appalachia, and the South as well as Alaska, cluster at the bottom.

Table 6 AI Adoption by State, Selected Estimates (BTOS AI Supplement, November 2025–February 2026)

State	Current AI use (%)	Note
Colorado	23.5	Highest
Arizona	22.6	—
Nevada	21.4	—
Oregon	20.6	—
Florida	20.0	—
National average	17.9	—
Wisconsin	15.9	Below average

New York	14.3	—
Iowa	13.7	—
Arkansas	11.7	—
West Virginia	9.5	—
Alaska	9.3	—
North Dakota	9.0	Lowest

Author's computation, (2026) Note. All state estimates are published aggregate statistics from the Census Bureau BTOS AI Supplement. Of the 53 state and territory estimates published, those shown are the five highest, the national average, and the six lowest. Wisconsin (15.9%) is also included as a representative Midwestern state discussed in Section 4.3.

The 14.5-percentage-point geographic spread is comparable in magnitude to the firm-size gap documented in Section 3.4.2, suggesting that geography is a distinct descriptive dimension of differences in AI adoption across the U.S. economy (state estimates are not adjusted for firm size or sector). It is likely, however, that the firm-size, sectoral, and geographic gradients are correlated rather than independent: states at the bottom of the distribution may have higher concentrations of SME-dense, lower-adoption sectors, in which case all three dimensions would overlap. This remains a hypothesis, because the sectoral and size composition of states was not analysed.

RQ4: Geographic Variation Across Metropolitan Statistical Areas

Table 7 presents averaged AI adoption rates for selected MSAs among the 25 largest in the United States. The figures are the author's simple averages of the six biweekly BTOS collection cycles within the supplement window, because the Bureau's special supplement table does not publish a dedicated single-period breakdown by MSA. These averages are unweighted and carry no variance estimates (Section 2.5); the MSA comparisons below are therefore descriptive only.

Table 7 AI Adoption Rates in Selected Metropolitan Statistical Areas, Author-Computed Averages (November 2025–February 2026)

Metropolitan statistical area	Average current AI use, Nov 2025–Feb 2026 (%)
Denver–Aurora–Lakewood, CO	27.0
San Diego–Chula Vista–Carlsbad, CA	25.5
Phoenix–Mesa–Chandler, AZ	24.6
San Francisco–Oakland–Berkeley, CA	24.1
Portland–Vancouver–Hillsboro, OR–WA	23.6
National average	17.9
Los Angeles–Long Beach–Anaheim, CA	17.3
Chicago–Naperville–Elgin, IL–IN–WI	17.3
New York–Newark–Jersey City, NY–NJ–PA	14.7

Riverside–San Bernardino–Ontario, CA	14.5
Detroit–Warren–Dearborn, MI	13.3 (lowest)

Author’s computation, (2026) Note. MSA figures are the author’s simple (unweighted) averages across the six BTOS biweekly collection cycles within the supplement window. San Antonio–New Braunfels, TX, is excluded because the Census Bureau suppressed two of its six cycles for disclosure reasons, leaving only four cycles. Comparisons with the non-averaged state and national estimates should be made with caution. No standard errors are available for these averages, so the precision of the MSA figures is unknown.

The spread across metropolitan areas, from 27.0% in Denver to 13.3% in Detroit, is substantial. Western, technology-oriented metros (Denver, San Diego, Phoenix, San Francisco, and Portland) lead by large margins, although no significance test is possible with unweighted averages. Several large metros (Detroit, Riverside–San Bernardino, and New York) trail the national average despite their economic scale. This pattern is inconsistent with a simple hypothesis that metropolitan size determines AI adoption: New York (14.7%), the largest U.S. metro, falls below the national average, whereas Denver (27.0%), a substantially smaller economy, exceeds it by 9.1 percentage points. One possible explanation, which these data cannot test, is that local industry mix and the regional availability of digital-skills talent contribute to metro-level differences. If supported by microdata, this explanation would strengthen the case for geographically and sectorally targeted workforce programming. MSA differences of only a few percentage points should not be treated as established.

Trajectory: Is the Gap Narrowing or Widening?

The forward-looking evidence is suggestive of a possible widening of the firm-size AI adoption gap but does not establish it. The planned-adoption measure shows a larger gap (19.2 pp) than the current-use measure (13.0 pp), and the gap in employee-level generative AI use (19.6 pp) also exceeds the current-use gap. This indicates that larger firms are not only more likely to have adopted AI at the organisational level but are also embedding it more deeply in daily work tasks. Because the planned-adoption and generative AI measures are cross-sectional and self-reported, however, they cannot distinguish diverging trajectories from a persistently faster pace of adoption among large firms. In these data, the smallest firms express little intention to expand adoption (planned adoption of 20.8% versus current use of 17.6%, a difference of 3.2 pp), whereas the largest firms express considerably stronger intentions (planned adoption of 40.0% versus current use of 30.6%, a difference of 9.4 pp).

This reading is partly supported by the separate longitudinal evidence of Grundy et al. (2026), who document a statistically significant increase in AI use among firms with at least 20 employees between December 2025 and May 2026 and no significant change among firms with fewer than 20 employees over the same six-month window. Their finding is consistent with divergence. However, a significant change in one group combined with no significant change in another does not by itself show that the two changes differ, and a six-month window cannot rule out a diffusion lag that closes over a longer horizon. The cross-national evidence points in a different direction. The OECD (2026) reports that, in 2025, 52% of large firms across OECD member countries used AI, compared with only 17.4% of small firms, a ratio of approximately 3.0 (52.0/17.4). This is lower than the ratio of approximately 3.4 reported for 2024 (OECD, 2025a) and therefore suggests a narrowing, rather than a widening, of the cross-national ratio, unless the OECD’s size definitions or sample composition differ between the two figures (the 2024 figure compares firms with 250 or more employees with firms with 10–49 employees). Possible structural forces behind any widening, namely the complementary-asset advantages of large firms (Brynjolfsson et al., 2025), organisational slack that enables experimentation (OECD, 2025a), and access to labour markets for AI specialists (Bonney et al., 2026), may persist in the absence of policy intervention, but these data do not test that hypothesis.

Did the November 2025 Question-Wording Revision Affect Size Tiers Differently?

Beginning on November 17, 2025, the first day of the supplement window, the Census Bureau replaced the BTOS AI questions’ reference to AI use “in producing goods or services” with use “in any of its business functions.” The Bureau documented the change on December 3, 2025, reported a level shift in the series, and

began a new time series with the data release of December 4, 2025 (U.S. Census Bureau, 2025). Two consequences follow. First, every estimate analysed here uses the revised wording, so comparisons across size classes within the supplement are internally consistent. Second, comparisons with evidence based on the earlier wording, including the SBA Office of Advocacy (2025) large-to-small ratio of 1.8 and the pre-November 2025 BTOS series, are not like-for-like. The ratio of current use in size class G to that in size class A in Table 3 (30.6/17.6, or approximately 1.7) should therefore not be interpreted as evidence that the ratio has remained stable over time.

Whether the revision shifted measured adoption by the same amount in every size class is unknown. The Census Bureau's cognitive testing found that some respondents regarded the question as not applicable because they did not see their business as a producer of goods or services, and that others initially answered "no" although they were in fact using AI for hiring, project management, accounting, or research and development, or through AI embedded in software (U.S. Census Bureau, 2025). Both mechanisms could operate differently by firm size. Very small and service-oriented firms may have been more likely to be classified as non-users under the earlier wording, in which case the broader wording could raise their measured adoption proportionally more and compress the gap between classes A and G. Conversely, larger firms have more distinct business functions and more software with embedded AI, in which case the broader wording could raise their measured adoption proportionally more and widen the gap. The net direction of the effect by size tier cannot be determined from the published aggregate estimates.

The same issue bears on the barriers evidence. If some very small firms answered "AI is not applicable" partly because they did not regard AI use as relevant to producing goods or services, the high "not applicable" share among firms with 1–4 employees in Table 5 may partly reflect how respondents interpreted the question rather than solely a lack of use cases. This is a hypothesis; the barrier items would need to be checked against their exact wording in the supplement instrument.

A size-specific check is feasible with public BTOS data. The Census Bureau provides both the earlier-wording series (the "AI Core Questions (Original)" table under the historical data tab) and the revised series. For each employment-size class, the level shift at the changeover can be estimated with an interrupted time-series model that includes a pre-change trend, and the shifts can then be compared across classes (e.g., the difference in the shift between classes A and G) using the published cycle-level standard errors. The A–G gap in Table 3 can also be recomputed for individual post-change cycles to confirm that it is stable within the window. The results should be reported in a supplementary table showing, by size class, (a) the last pre-change and first post-change estimates, (b) the estimated level shift and its standard error, and (c) the A–G gap by cycle. If the shifts are similar across size classes, the size gradient can be described as robust to the wording change; if they differ, Table 3 should carry a note stating that the gradient is conditional on the revised wording. Until this check is performed, the gap estimates should be read as describing the revised, broader construct.

Trend evidence drawn entirely from the post-change series, such as that of Grundy et al. (2026) covering December 2025 to May 2026, is not exposed to the level shift itself, whereas any statement about change over time that spans the November 2025 changeover would be.

DISCUSSION

Summary of Principal Findings

This descriptive study identifies five principal findings from the BTOS AI Supplement and the supplementary sources:

- Finding 1 (RQ1): A statistically distinguishable, unadjusted gap of 13.0 percentage points in current AI adoption separates the smallest (1–4 employees; 17.6%) from the largest (250 or more employees; 30.6%) U.S. employer businesses, with non-overlapping 95% confidence intervals for classes A and G (adjacent classes were not tested). Current use is essentially flat below 20 employees and rises from the 20–49 employee class upward.

- Finding 2 (RQ2): The gap extends beyond adoption incidence. It widens to 19.6 pp for employee-level generative AI use and to 19.2 pp for planned adoption over the next six months, indicating that larger firms are both more frequent and deeper adopters and that, if stated intentions materialise, they may extend their lead.
- Finding 3 (RQ3 and RQ4): Sectoral AI adoption varies by 32.5 pp, and SME-dense sectors (Accommodation and Food Services, Construction, Other Services, and Retail Trade) cluster well below the national average, overlapping with the firm-size gradient; the data cannot separate the two. Adoption also varies by 14.5 pp across states and, descriptively, across large metropolitan areas.
- Finding 4 (RQ5, the study's principal contribution): Reported non-adoption barriers differ descriptively by firm size. The "AI not applicable" response dominates among the smallest firms but declines monotonically with size. Workforce skill and awareness gaps ("lack of skilled workforce" and "lack of knowledge of AI capabilities") rise from small to mid-sized non-adopters (20–249 employees), although they remain less frequently cited than "AI not applicable." This suggests, as a hypothesis, that skills-gap interventions may be most relevant in this size range.
- Finding 5 (Trajectory): The trajectory evidence is suggestive but limited. Forward-looking measures show a larger gap than current-use measures; independent longitudinal data (Grundy et al., 2026) are consistent with divergence in favour of firms with 20 or more employees; and cross-national evidence (OECD, 2026) shows a persistent large-firm advantage across OECD economies.

Interpretation and Theoretical Implications

The broadly increasing, multidimensional, and possibly widening firm-size gap in AI adoption is consistent with, but does not test, the predictions of the three theoretical frameworks used in this study. DOI theory (Rogers, 2003) predicts that organisational size is positively associated with the speed and extent of adoption; the BTOS data are consistent with this prediction, most clearly in the contrast between the smallest and largest size classes. The TOE framework (Faiz et al., 2024; Tornatzky & Fleischer, 1990) predicts that organisational and environmental contexts interact; the finding that SME-dense sectors are precisely those with the lowest adoption (Finding 3) is consistent with such an interaction, although multivariate analysis would be needed to confirm it. Complementary-assets theory (Acemoglu & Restrepo, 2022; Brynjolfsson et al., 2025) predicts that the productivity gains from general-purpose technologies will accrue disproportionately to firms with sufficient skilled labour and organisational capacity to exploit them, which are precisely the complementary assets reported to be in short supply among mid-sized non-adopters (Finding 4).

The barriers finding (RQ5) carries particular theoretical weight. The OECD's (2025b) cross-national data, based on more than 5,000 SMEs in seven countries, show a structurally similar pattern, in which barriers shift from "not applicable to our work" to "lack of skills" as firm size and complexity increase. This cross-national similarity lends some external plausibility to the BTOS finding, although the surveys differ in coverage (the OECD survey covers SMEs only) and in question design, so the comparison is indicative. The theoretical implication is important. The AI digital divide does not appear to be a simple diffusion lag in which smaller firms merely trail larger ones along a shared trajectory. Rather, it appears to be a structurally differentiated divide, in which the barriers facing the smallest firms (perceived non-applicability) differ in kind from those facing mid-sized firms (skills and awareness gaps), which in turn differ from those facing the largest firms, among which adoption is already comparatively high and cost is cited more often than in any smaller class. Policy and research frameworks that treat "small-business AI adoption" as a homogeneous phenomenon therefore risk misdiagnosing the problem and misdirecting resources.

A possible widening of the gap (Finding 5) would be of particular concern from an inequality standpoint. Brynjolfsson et al. (2025) document that, within adopting firms, generative AI yields the largest productivity gains for less-skilled and less-experienced workers. If the adoption gap continues to widen, the workers most likely to benefit from AI's equalising effects within firms, namely those in lower-skill roles at smaller establishments, will be precisely those least likely to be employed by AI-adopting firms. Should these patterns

persist and the productivity findings generalise, an adoption gap could become a welfare gap; it should be noted, however, that these data measure neither welfare nor productivity.

Policy Implications

The findings suggest five provisional implications for federal and state workforce policy. These are hypotheses derived from descriptive, unadjusted evidence and should be tested through microdata analysis and programme evaluation before implementation:

- **Targeting the 20–249 employee band:** The barriers cross-tabulation (Table 5) suggests that skills and awareness gaps are cited more often, relative to “not applicable,” in the 20–249 employee band, which makes this band a candidate for evaluated pilot programmes. SBA technical assistance, the digital services of Small Business Development Centers (SBDCs), and Department of Commerce capacity-building grants could be explicitly calibrated to this band on a pilot basis.
- **Differentiating policy by firm size:** Firms with fewer than five employees, 63.3% of whose non-adopters report AI as simply inapplicable, may require a different policy response from that suited to mid-sized firms, most likely awareness-building and demonstration of applicability through sector-specific case studies rather than formal skills training. One-size-fits-all AI promotion programmes are likely to be inefficient.
- **Sector-based geographic targeting:** The convergence of SME-dense sectors and lower-adoption geographies (lower-adoption states such as North Dakota, Alaska, West Virginia, and Arkansas, and large industrial metros such as Detroit) points to a possible priority geography for regionally concentrated programming. Wisconsin’s below-average state estimate (15.9%) and Detroit’s trailing metropolitan position (13.3%) illustrate the concentration of the challenge in precisely the economic geographies that manufacturing-transition programmes have historically targeted.
- **Monitoring the trajectory, not only the level:** A widening trend, if confirmed, would imply that programmes designed around current-period snapshots will need to accelerate rather than simply maintain their pace. Policy evaluation frameworks should track the size-class adoption gap, and not only total adoption, as a primary indicator.
- **Generative AI accessibility as a partial equaliser:** The OECD (2025b) notes that 39% of SMEs facing skills gaps report that generative AI partially compensates for the deficit. This suggests that accessible, low-cost generative AI tools (such as those available through cloud platforms) represent a practical near-term pathway that merits emphasis in federal and state SME advisory services.

Limitations

Six principal limitations constrain the inferential reach of the findings:

- **Study design:** This is a secondary descriptive analysis of a single federal survey, with contextual sources selected by the author. It is not a systematic review; the selection of benchmark sources was not exhaustive, and no formal risk-of-bias synthesis or pooling was undertaken.
- **Aggregate-only data:** The analysis uses published aggregate tabulations rather than firm-level microdata. Multivariate decomposition (e.g., isolating firm-size effects from sectoral composition, or testing whether the skills-barrier pattern in Table 5 holds within sectors) requires either restricted-data access through a Federal Statistical Research Data Center (FSRDC) or a subsequent BTOS wave with linked variables. The confounding threat is rated high for any causal interpretation of firm size, and moderate for the descriptive gaps, in the data-quality appraisal (Table 2). All firm-size comparisons are unadjusted associations that may reflect differences in sector, geography, firm age, or revenue across size classes. The findings should therefore not be read as effects of firm size, and terms such as “compounded” describe co-occurrence rather than statistical interaction.

- Question-wording change: Because the November 17, 2025 revision broadened the BTOS AI-use question from “producing goods or services” to “any business function,” all estimates in the supplement window use the revised wording and are not strictly comparable with earlier-wording BTOS cycles or with earlier-wording sources such as SBA Office of Advocacy (2025). The magnitude of the gap documented here should be treated as a measure of the current, broader construct rather than as a continuation of the trend from earlier waves. Whether the revision shifted measured adoption differently by size tier remains unresolved (Section 3.4.8).
- Single collection window: The supplement reflects a single collection period, so seasonal or event-driven variation in AI use cannot be assessed from this cross-section. Subsequent BTOS waves will be essential for trend analysis.
- MSA averaging methodology: Metropolitan-area figures are the author’s simple (unweighted) averages across six biweekly cycles. This departs from the Bureau’s standard methodology and may introduce some imprecision. Two of the six San Antonio cycles were suppressed for disclosure reasons, and that MSA was therefore excluded from Table 7. No variance estimates accompany the averages, and unweighted averaging ignores differences in cycle sample size. MSA differences are therefore descriptive only, and the MSA-based statements in Sections 4.3 and 5 should be treated as illustrative unless approximate standard errors are added (Section 2.5).
- No outcome linkage: The findings document adoption gaps and barriers; they do not measure the business-performance or customer-welfare outcomes that ultimately motivate efforts to close the gap. Linking AI adoption patterns to productivity, customer satisfaction, and firm survival, the central focus of the author’s broader research programme (Oni & Adeyeye, 2020; Oni et al., 2019, 2021), requires a subsequent phase of research.

CONCLUSIONS

The firm-size gap in AI adoption in the U.S. small-business sector is large (13.0 pp on current use); statistically distinguishable between the smallest and largest size classes; multidimensional, extending to employee-level generative AI use and stated adoption intentions; overlapping with sectoral and geographic differences that these data cannot disentangle; and possibly widening, although the trajectory evidence is limited. The barriers module points to a candidate target for further testing: the 20–249 employee band, in which workforce skill and awareness gaps are cited more often than in smaller firms (although “not applicable” remains the most common reason overall) and in which targeted skills programming may have the greatest marginal impact on a segment that is plausibly near a viability threshold for AI adoption.

These findings extend the author’s prior research on digital adoption, customer trust, and SME performance (Oni & Adeyeye, 2020; Oni et al., 2019, 2021) to the U.S. national context, providing a descriptive extension of that research based on government data; the link is thematic and does not imply a direct replication of the earlier findings. A persistent, size-graded adoption gap, combined with evidence that a modest but size-graded share of mid-sized non-adopters cite workforce skill and knowledge gaps among their reasons for not adopting, is precisely the kind of targeted, evidence-based finding that federal and state workforce programmes need in order to concentrate limited resources where they will matter most.

RECOMMENDATIONS

The findings of this study support the following provisional recommendations. Each rests on descriptive evidence, should be evaluated before implementation, and is addressed to the agency or body best placed to act on it.

1. Calibrate technical assistance to the 20–249 employee band (U.S. Small Business Administration; Small Business Development Centers). The barriers evidence in Table 5 suggests that workforce skill and awareness gaps, rather than any fundamental irrelevance of AI, may be a binding constraint on adoption among firms with 20–249 employees. The U.S. Small Business Administration (SBA) should prioritise

this employment-size band in its technical assistance programmes and in the digital advisory services of Small Business Development Centers (SBDCs), ensuring that AI-readiness curricula address knowledge deficits and provide practical implementation support rather than general awareness promotion.

2. Differentiate intervention design by firm-size tier (U.S. Department of Commerce; Economic Development Administration). Firms with fewer than five employees, 63.3% of whose non-adopters regard AI as simply inapplicable to their operations, require a distinct policy response centred on demonstrating applicability through sector-specific examples rather than on formal skills training. The U.S. Department of Commerce, through its Economic Development Administration (EDA), should fund the development and dissemination of sector-specific libraries of AI use cases tailored to micro-businesses in industries such as Accommodation and Food Services, Construction, and Retail Trade, where adoption rates trail the national average by the widest margins.
3. Concentrate capacity-building grants in priority geographies (U.S. Department of Commerce; state workforce development agencies). The convergence of below-average adoption in SME-dense sectors with lower-adoption geographies, including states such as North Dakota, Alaska, West Virginia, and Arkansas and industrial metros such as Detroit (13.3%), identifies a priority geography for targeted programming. The U.S. Department of Commerce should align its capacity-building grant criteria to favour applications from state workforce development agencies and regional economic development organisations operating in these areas, and workforce agencies in below-average states such as Wisconsin (15.9%) should embed the size-class adoption gap as a measurable objective in their digital-skills workforce plans.
4. Adopt the gap trajectory as a primary policy evaluation metric (Office of Management and Budget; SBA Office of Advocacy). Because the firm-size AI adoption gap may be widening (the evidence is suggestive rather than conclusive), aggregate adoption rates are an insufficient measure of policy success. The Office of Management and Budget (OMB), in consultation with the SBA Office of Advocacy, should require federal AI workforce programmes to report the size-class adoption gap, disaggregated by the BTOS employment-size strata, as a primary performance indicator in annual programme evaluations alongside total adoption levels. The SBA Office of Advocacy should continue its quarterly BTOS-based monitoring and publish trend analyses that explicitly track the trajectory of the gap.
5. Promote accessible generative AI tools through federal and state SME advisory networks (U.S. Small Business Administration; National Institute of Standards and Technology). Cross-national evidence from the OECD (2025b) indicates that 39% of SMEs facing workforce skill shortfalls report that generative AI partially compensates for the deficit. The SBA and the National Institute of Standards and Technology (NIST) should incorporate guidance on low-cost, cloud-based generative AI tools into their existing SME advisory frameworks and AI-readiness resources, and should collaborate with state extension services to disseminate practical implementation guidance to firms in the 20–249 employee band that are at or near the viability threshold for AI adoption.

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