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The Double Divide Revisited: Sector Composition, Within-Sector Adoption and Artificial Intelligence Use Among Minority- And Women-Owned U.S. Businesses

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ABSTRACT:

Purpose. Policy discussion often assumes that minority- and women-owned businesses face a "double divide" in artificial intelligence (AI) adoption, compounding their other disadvantages. This study tests that assumption. It asks how far owner-group differences in AI use reflect the sectors in which firms operate (composition) and how far they reflect differences in adoption among firms in the same sector.

Methodology. Drawing on mixed-embeddedness and resource-constraint theories of minority entrepreneurship, the study combines six published tabulations from the U.S. Census Bureau's Annual Business Survey (ABS) for reference years 2017 and 2022 with sector adoption rates from the Business Trends and Outlook Survey (BTOS) AI Supplement for 2025–26. Owner-group gaps are decomposed by indirect standardisation (a Kitagawa-type decomposition) into a sector-composition component and a within-sector component, and a size-composition component is estimated separately. Monte Carlo confidence intervals are derived from the published standard errors. A forward-looking exposure index applies 2025–26 BTOS sector rates to the 2022 sector composition and compares the result with 2017 rates over the same ten sectors.

Findings. Sector composition places Hispanic-, Asian- and minority-owned firms at a disadvantage: in 2017 their composition-implied AI use was 6–8% below that of the baseline group. Net of sector composition, however, minority-owned firms used AI more often than nonminority firms (+1.09 percentage points, 95% CI 0.81–1.38), and this advantage outweighed the composition penalty for every minority group. In 2022 minority-owned firms again reported higher use (3.8% vs. 3.1%, p = .002); the approximate 2022 within-sector component remained positive and significant for minority-, Hispanic- and Black-owned firms. Minority-owned firms were also 7.3 points less likely to report that AI was "not applicable" to their business. Women-owned firms show the opposite profile: a favourable sector mix but a within-sector shortfall in 2017 (−0.53 points) that was no longer statistically detectable in 2022. Compared over the same ten sectors, the relative composition penalty of Hispanic- and Asian-owned firms widens from about 9–10% under 2017 sector rates to about 12% under 2025–26 rates.

Originality. This is the first decomposition of owner-group AI-adoption gaps using official U.S. statistics. It shows that, at the level of published aggregates, the "double divide" for minority-owned firms is a sector-placement divide rather than a shortfall in within-sector adoption, and that the placement disadvantage is larger under current sector adoption rates than under earlier ones.

KEYWORDS: artificial intelligence; minority entrepreneurship; women-owned businesses; technology adoption; decomposition; Annual Business Survey
JEL codes: J15; J16; L26; O33

1. INTRODUCTION

Whether the gains from artificial intelligence (AI) will be shared widely across the business population, or will reinforce existing inequalities, is now a central question for entrepreneurship and small-business policy. A common assumption in that debate is that minority- and women-owned businesses face a "double divide". On this view, the same constraints that limit their access to capital, networks and markets (Blanchflower et al., 2003; Fairlie & Robb, 2008; Fairlie et al., 2022) also slow their adoption of new digital technologies, so that the AI transition compounds existing gaps. Wherever AI-readiness support is targeted by owner demographics, it implicitly rests on the same assumption.

The empirical basis for that assumption is thin and, so far, inconsistent. Firm-level studies of AI adoption in the United States document strong gradients by firm size, age, industry and location (Zolas et al., 2020; Acemoglu et al., 2022; McElheran et al., 2024; Bonney et al., 2024) but say

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much less about owner demographics. Recent non-official evidence points in different directions. Transaction data from small-business bank accounts show women-owned firms adopting AI tools more slowly than men-owned firms, with the gap widening after 2023 (Wheat et al., 2026). A national owner survey, by contrast, finds Latino owners using AI at more than twice the rate of White owners (Smith, 2026). Neither source separates where firms operate from how they behave given where they operate.

That distinction matters because minority- and women-owned firms are distributed very differently across industries. Hispanic-owned employer firms are concentrated in construction, Asian-owned firms in accommodation and food services and in retail, Black-owned firms in health care, and women-owned firms in health care and professional services. Because AI adoption also varies widely across industries, any raw comparison of owner groups mixes the two. They also have different policy implications. A placement gap calls for sector-focused programmes and for help in entering higher-adoption industries. A behavioural gap calls for owner-targeted assistance within industries.

This study separates the two. It asks three research questions:

- RQ_1. How much of the difference in AI use between minority-owned (or women-owned) and baseline firms is explained by differences in sector composition, and how much remains among firms in the same sectors?
- RQ_2. Do minority- and women-owned firms differ from baseline firms in how they relate to AI: in whether they consider it applicable, test it, or are unsure about it?
- RQ_3. Under the wider sector differences of the current diffusion wave, is the sector-composition disadvantage larger or smaller than under earlier sector rates?

To answer these questions, the study combines published Annual Business Survey (ABS) tabulations for two reference years, 2017 and 2022. These give the industry composition of employer firms by owner group, AI use by industry, and AI use and adoption status by owner group. Owner-group gaps are decomposed by indirect standardisation, the aggregate-data form of the Kitagawa (1955) decomposition (Das Gupta, 1993), into a sector-composition component and a within-sector component; a size-composition component is estimated alongside. Confidence intervals come from Monte Carlo simulation using the published standard errors. The analysis then applies the much wider sector differences recorded by the Business Trends and Outlook Survey (BTOS) AI Supplement for November 2025–February 2026 to the 2022 sector composition, comparing like with like over the same ten sectors.

The study makes three contributions. First, it provides the first decomposition of owner-group AI-adoption gaps based on official U.S. statistics. The result does not support the behavioural reading of the double divide: net of sector composition, minority-owned firms report using AI more often than nonminority firms, not less. Second, it documents a distinct gender pattern. Women-owned firms benefit from their sector mix but showed a within-sector shortfall in 2017 that was no longer statistically detectable in 2022, suggesting that gender and minority status operate through different channels. Third, it shows that the sector-composition disadvantage of Hispanic- and Asian-owned firms is larger under current sector adoption rates than under 2017 rates, which gives a placement-focused reading of the double divide a forward-looking justification.

Section 2 develops the theoretical framework and hypotheses. Section 3 describes the data and methods, and Section 4 presents the results. Section 5 discusses the implications for theory and policy. Section 6 sets out the limitations, and Section 7 concludes.

2. THEORETICAL BACKGROUND AND HYPOTHESES

2.1 Sector placement: mixed embeddedness and opportunity structures

A long tradition in the sociology and economics of entrepreneurship explains why owner groups cluster in particular industries. The interactive model of ethnic entrepreneurship (Aldrich & Waldinger, 1990) and its successor, the mixed-embeddedness framework (Kloosterman & Rath, 2001), attribute sector concentration to the interaction between group resources (co-ethnic networks, labour, information and capital) and the opportunity structure of local markets: barriers to entry, capital intensity and the presence of under-served demand. Low-entry-barrier sectors such as construction, food service, retail and personal services absorb a large share of immigrant and minority entrepreneurship. These sectors are also, for the most part, those in which AI is least used (McElheran et al., 2024; Bonney et al., 2024). Sector placement can therefore produce an owner-group gap in AI use even when firms in the same sector behave identically.

H1 (composition). Owner groups concentrated in low-AI-adoption sectors have lower composition-implied AI use than baseline firms.

2.2 Within-sector behaviour: constraint versus selection

Two competing explanations predict how minority-owned firms behave within a sector. The resource-constraint explanation emphasises tighter credit (Blanchflower et al., 2003; Fairlie et al., 2022), smaller inherited assets and business networks (Fairlie & Robb, 2008), and historically lower household access to digital technology (Fairlie, 2004). Each of these would raise the cost of adopting technologies that require complementary investment in data, software and skills. On this view, minority-owned firms adopt less AI than nonminority firms in the same sector.

The alternative selection-and-opportunity explanation combines two arguments. The first concerns firm age. In 2022, 50.0% of minority-owned employer firms had been in business for less than six years, compared with 35.3% of nonminority firms; among Black-owned firms the figure was 57.7% (U.S. Census Bureau, n.d.-f). Firm youth and owner education are among the strongest correlates of AI use (McElheran et al., 2024), and many minority-owned firms serve fast-changing, digitally intensive customer segments. The second is positive selection: if only the most capable or growth-oriented entrants overcome the barriers to forming an employer firm, survivors should adopt more readily. Both arguments predict equal or higher within-sector adoption, but they cannot be separated with aggregate data. Selection implies that the advantage should be largest where entry barriers are highest, which would require sector-by-owner AI tabulations to test; the firm-age argument implies that the advantage should shrink once firm age is held constant, which would require firm-level data (Section 6).

H2a (constraint). Within sectors, minority-owned firms use AI less than nonminority firms.

H2b (selection/opportunity). Within sectors, minority-owned firms use AI as much as or more than nonminority firms.

The same two explanations apply to women-owned firms. The literature on women's entrepreneurship points to smaller average firm scale, lower external financing, a greater weight on non-financial goals and gendered networks as possible constraints on investment and growth (Jennings &

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Brush, 2013; Robb & Watson, 2012). Women-owned employer firms are also younger than men-owned firms (44.7% vs. 37.4% under six years in 2022; U.S. Census Bureau, n.d.-f), so the firm-age argument would predict an advantage for them as well. We therefore test H2a and H2b separately for women-owned firms, and treat the comparison between the gender and minority results as informative about the firm-age mechanism.

2.3 Firm size

Firm size is the most consistent correlate of technology adoption (Zolas et al., 2020; McElheran et al., 2024). Minority- and women-owned firms are, on average, smaller, so part of any gap may reflect size composition rather than sector or behaviour.

H3 (size composition). Differences in employment-size composition contribute to owner-group gaps in AI use.

2.4 Perceived relevance

Diffusion theory emphasises that adoption depends on whether potential adopters perceive a relative advantage (Rogers, 2003). If constraints operate partly through information, constrained groups should be more likely to report that AI is irrelevant to them, or not to know. The selection/opportunity explanation predicts the opposite for perceived relevance.

H4 (perceived relevance). Minority- and women-owned firms are more likely than baseline firms to report that AI is not applicable to their business.

3. DATA AND METHODS

3.1 Data

All ABS data come from published national tabulations of the U.S. Census Bureau's Annual Business Survey. The ABS is the Census Bureau's principal source of statistics on employer-business ownership by sex, ethnicity, race and veteran status. It is conducted jointly with the National Center for Science and Engineering Statistics (NCSES) and periodically includes a technology module (Zolas et al., 2020). Only the cells required for the analysis were extracted, from six tables:

1. Sector composition, 2017: employer firms by 2-digit NAICS sector and owner group (U.S. Census Bureau, n.d.-c; table AB1700CSA01).
2. Sector composition, 2022: the same breakdown for reference year 2022 (U.S. Census Bureau, n.d.-d; table AB2200CSA01).
3. AI use by sector, 2017: the share of reporting employer firms that used AI at low, moderate or high intensity ("total use") in each 2-digit sector (U.S. Census Bureau, n.d.-a; table AB1800TCB01A).
4. AI use by owner group and size, 2017: the same measure by owner sex, ethnicity and race, overall and for three employment-size classes (no paid employees during the reference period, 1–9 and 10 or more) (U.S. Census Bureau, n.d.-b; table AB1800TCB01B).
5. AI adoption status by owner group, 2022: the distribution of reporting firms across five responses to the ABS 2023 technology question (AI "not applicable"; applicable but not tested or used; tested but not used in processes; used as part of processes or methods; don't know) (U.S. Census Bureau, n.d.-e; table AB2200MCB01).
6. Firm age by owner group, 2022: employer firms by years in business (U.S. Census Bureau, n.d.-f; table AB2200CSA02).

Each table was retrieved through the Census Bureau's data platform. The extracted cells were checked against independently computed totals at the source, and every extract matched exactly. All estimates are published with standard errors, which are used throughout. The extracts, code and intermediate results are provided as a replication package.

The owner groups are women-owned (baseline: men-owned), Hispanic-owned (baseline: non-Hispanic-owned), and Black-, Asian- and American Indian and Alaska Native (AIAN)-owned firms (baseline: nonminority-owned, i.e. non-Hispanic White). The Native Hawaiian and Other Pacific Islander (NHPI) group is reported for 2022 only, because the 2017 technology estimates are suppressed. "Minority-owned" is the Census Bureau's composite of firms owned by Hispanic persons or by persons of any race other than White. Equally owned firms (for example, equally male/female) are excluded from the comparisons. Owner groups defined by race are not mutually exclusive of Hispanic ethnicity, so the race comparisons all use the nonminority group as baseline.

The technology questions were answered by a subset of employer firms, and coverage differs by owner group (Table 4). In 2017 the reporting firms represent 82.7% of all employer firms (86.9% of nonminority-owned and 82.7% of minority-owned firms). In the 2022 module coverage is lower and less even: 47.0% of all employer firms, 50.3% of nonminority-owned, 40.0% of minority-owned and 32.5% of Black-owned firms. All rates in this paper therefore refer to firms that answered the technology question, and the implications of differential coverage are discussed in Section 6.

To assess how sector composition interacts with the current wave of AI diffusion, the analysis also uses national sector adoption rates from the BTOS AI Supplement collected from 17 November 2025 to 8 February 2026 (U.S. Census Bureau, 2026). These rates are available for ten sectors, which account for 72–84% of each owner group's employer firms.

Table 1 summarises the six ABS tables and the BTOS AI Supplement that underpin the analysis, with the reference year of each and its role. The 2017 tables are the only year in which sector-level and owner-level AI use were published from the same survey, which allows an internally consistent decomposition. The two 2022 composition and adoption tables (AB2200CSA01 and AB2200MCB01) provide the current sector composition and AI adoption profile of each owner group.

Table 1: Data Sources

Table (data.census.gov ID)	Survey and reference year	Content used	Role in analysis
AB1700CSA01	ABS 2018, reference year 2017	Employer firms by 2-digit NAICS and owner group	Sector shares s_{gk}, 2017

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Table (data.census.gov ID)	Survey and reference year	Content used	Role in analysis
AB1800TCB01A	ABS 2018 technology module, 2017	% of reporting firms using AI, by 2-digit NAICS (with SEs)	Sector AI rates a_k, 2017
AB1800TCB01B	ABS 2018 technology module, 2017	% using AI, by owner group and employment-size class (with SEs)	Group AI rates A_g; size composition
AB2200CSA01	ABS 2023, reference year 2022	Employer firms by 2-digit NAICS and owner group	Sector shares, 2022
AB2200MCB01	ABS 2023 technology module, 2022	AI adoption status by owner group (with SEs)	2022 adoption profile; group rates
AB2200CSA02	ABS 2023, reference year 2022	Employer firms by years in business and owner group	Firm-age profile (mechanism)
BTOS AI Supplement	BTOS, Nov 2025–Feb 2026	Current AI use by sector (10 sectors)	Exposure index

Note. ABS = Annual Business Survey; BTOS = Business Trends and Outlook Survey; SEs = standard errors. U.S. totals only; veteran status = all firms. Author's compilation (2026) from the U.S. Census Bureau data sources listed.

3.2 Decomposition

Let A_g denote the share of group g's firms using AI, s_{gk} the share of group g's employer firms in sector k, and a_k the AI-use rate of all firms in sector k. The composition-implied AI-use rate of group g is

$E_g = \Sigma_k s_{gk} \cdot a_k$,

the rate group g would have if its firms adopted AI at the all-firm rate of each sector in which they operate. The gap between group g and baseline b is then split into two terms:

$A_g - A_b = (E_g - E_b) + [(A_g - E_g) - (A_b - E_b)]$.

This is indirect standardisation with the all-firm sector rates as the standard (Das Gupta, 1993). The full Kitagawa (1955) decomposition would require each group's AI-use rate in each sector, which the ABS does not publish; indirect standardisation is the form of that decomposition that can be computed from the published margins. The first term is the sector-composition component: the part of the gap due solely to the groups' different industry mixes. The second term is the within-sector component. Writing $A_g = \Sigma_k s_{gk} a_{gk}$, where a_{gk} is group g's (unpublished) rate in sector k, it equals

$\Sigma_k s_{gk} (a_{gk} - a_k) - \Sigma_k s_{bk} (a_{bk} - a_k)$,

that is, the difference between each group's average deviation from the all-firm rate of its own sectors, with each group's deviations weighted by its own sector shares. It therefore measures whether a group adopts more or less than other firms in the same sectors, but it is a residual: it absorbs any difference that is not explained by 2-digit sector, including differences in sub-sector mix, location, firm age and response behaviour. The decomposition is the aggregate-data analogue of an Oaxaca (1973) decomposition with a single categorical regressor, subject to this weighting. A size-composition component is computed in the same way, from each group's distribution across the three employment-size classes and the all-firm AI-use rate in each class.

Sector shares are measured on employer firms, and AI-use rates on firms answering the technology question. The two populations are not identical, so the decomposition assumes that reporting firms are representative of employer firms within each sector-by-group cell.

3.3 Inference

The published standard errors (SEs) of A_g, A_b and every sector rate a_k are propagated by Monte Carlo simulation. Each of 20,000 draws samples these quantities from normal distributions centred on their published values. The decomposition is recomputed for each draw, and 95% intervals are taken from the 2.5th and 97.5th percentiles. Sector shares are treated as fixed, because the sector-by-owner firm counts are measured precisely. In the 2022 table, in every sector holding at least 5% of a group's firms, the relative standard error is at most 2.8% for the minority, Hispanic, Asian, women-owned and baseline groups, and at most 4.3% for Black-owned firms. Precision is lower for AIAN- (up to 9.4%) and NHPI-owned firms, and their results are interpreted with corresponding caution.

The published tables do not report covariances. Because the baseline group accounts for a large share of the firms behind every sector rate, the sampling errors of A_b and a_k are likely to be positively correlated. The main analysis draws them independently; Section 4.5 reports a sensitivity analysis in which they share a common sampling factor. For the 2022 adoption-status comparisons, differences between disjoint groups are tested with two-sided z-tests, using $SE = \sqrt{(SE_g^2 + SE_b^2)}$, which likewise assumes zero covariance between the two estimates.

3.4 The 2022 decomposition and the exposure index

The ABS 2023 technology module does not publish AI use by sector. The 2022 decomposition therefore applies the 2017 sector rates, scaled by a common factor (1.09) so that they reproduce the 2022 national rate (3.3%). Its intervals combine the published SEs of the 2022 group rates with those of the 2017 sector rates. This approach assumes that relative sector differences in AI use were stable between 2017 and 2022. The BTOS evidence suggests the opposite: across the ten BTOS sectors, the ratio of the highest to the lowest sector rate rises from 4.5 in the 2017 ABS to 7.4 in 2025–26. If sector differences had already widened by 2022, the 2017 profile understates the composition penalty of groups concentrated in low-adoption sectors and, by construction, understates their within-sector component by the same amount. Section 4.5 bounds this bias by interpolating the 2022 sector profile between the 2017 and BTOS profiles. Because the assumption is strong, the 2022 within-sector component is reported as approximate.

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To address RQ3, a forward-looking exposure index applies the BTOS 2025–26 sector rates to each group's 2022 sector shares, renormalised over the ten sectors for which BTOS rates are available. The relative composition effect ($E_g/E_b - 1$) under BTOS rates is compared with the same quantity under 2017 ABS rates computed over the same ten sectors, so that the comparison reflects the change in sector rates rather than the change in sector coverage. The index is a counterfactual exposure measure: it shows how large the placement disadvantage would be if the 2022 sector mix were exposed to current sector adoption rates, not an observed change in group adoption.

3.5 Robustness

The proportion of firms answering "don't know" differs across owner groups. It was 8.7% among minority-owned and 4.5% among nonminority firms in 2017, and 25.7% versus 18.4% in 2022. In the main analysis, "don't know" responses are counted as non-use. Because "don't know" is more common among minority-owned firms, this choice works against finding a minority advantage. As a robustness check, all gaps are re-estimated with these responses excluded from the denominator. Further checks cover the covariance assumption (Section 3.3), the stability of the sector profile (Section 3.4) and the sector coverage of the exposure index.

4. RESULTS

4.1 Where owner groups operate

Table 2 shows the sector composition of each owner group's employer firms in 2022, alongside each sector's AI-use rate in 2017 and 2025–26. Owner groups are distributed very differently.

- Hispanic-owned firms: 18.8% are in construction (nonminority firms: 14.6%) and 12.3% in accommodation and food services (nonminority: 7.4%).
- Asian-owned firms: 22.1% are in accommodation and food services and 18.2% in retail trade.
- Black-owned firms: 25.6% are in health care and social assistance, about 2.7 times the nonminority share (9.5%). Their share in transportation and warehousing is also high (9.2%).
- Women-owned firms: 17.5% are in health care and 16.7% in professional, scientific and technical services, but only 5.1% in construction (men: 16.4%).

AI use also varies widely across sectors. In the ABS 2017 module it ranges from 1.5% (agriculture) and 1.7% (construction) to 5.6% (professional services) and 6.7% (information). By the BTOS 2025–26 collection, the differences between sectors are much larger: from 8.0% in accommodation and food services to 34.2% in professional services and 37.6% in information. Construction, accommodation and food services and retail, where Hispanic- and Asian-owned firms are concentrated, are well below the all-sector average in both periods. Health care and professional services, where Black- and women-owned firms are concentrated, are at or above it.

Sector composition also changed between 2017 and 2022 in ways that matter for exposure. The construction share of Hispanic-owned firms rose from 15.6% to 18.8%, and the health-care share of Black-owned firms fell from 31.9% to 25.6%.

Table 2: Sector Composition of Employer Firms by Owner Group (2022) and Sector AI-Use Rates

Sector (NAICS)	AI use 2017 (%)	AI use 2025–26 (%)	Nonminority	Minority	Hispanic	Black	Asian	Men	Women
Agriculture (11)	1.5	5.1	0.4	0.1	0.2	0.1	0.0	0.4	0.2
Mining (21)	1.9	—	0.3	0.1	0.2	0.0	0.0	0.3	0.1
Utilities (22)	2.8	—	0.1	0.0	0.1	0.0	0.0	0.1	0.0
Construction (23)	1.7	9.2	14.6	9.2	18.8	6.8	2.6	16.4	5.1
Manufacturing (31-33)	3.0	12.4	4.5	2.2	2.9	1.2	1.8	4.3	2.8
Wholesale trade (42)	2.2	—	4.5	4.1	3.6	1.5	5.2	5.0	3.0
Retail trade (44-45)	2.4	12.6	10.1	12.9	8.1	6.9	18.2	10.3	10.6
Transportation & warehousing (48-49)	2.5	—	3.5	5.4	7.0	9.2	3.3	4.6	2.2
Information (51)	6.7	37.6	1.5	1.1	0.8	1.2	1.2	1.6	1.0
Finance & insurance (52)	4.5	30.4	4.4	2.5	3.1	3.2	1.8	4.4	3.2
Real estate (53)	3.4	—	6.7	3.9	4.2	3.7	3.6	5.2	7.5
Professional, scientific & technical (54)	5.6	34.2	15.4	11.8	10.9	13.5	11.8	14.6	16.7
Management of companies (55)	4.5	—	0.3	0.1	0.1	0.1	0.1	0.3	0.2
Administrative & support (56)	2.7	—	6.5	5.7	9.5	8.3	2.2	6.3	6.0
Educational services (61)	2.9	—	1.2	1.2	0.8	2.0	1.3	0.8	2.3

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Sector (NAICS)	AI use 2017 (%)	AI use 2025–26 (%)	Nonminority	Minority	Hispanic	Black	Asian	Men	Women
Health care & social assistance (62)	3.3	20.7	9.5	13.6	8.6	25.6	13.7	8.5	17.5
Arts & recreation (71)	1.6	—	2.2	1.2	1.2	2.8	0.7	1.8	2.2
Accommodation & food services (72)	2.0	8.0	7.4	16.2	12.3	6.8	22.1	8.9	9.6
Other services (81)	1.8	9.8	6.7	8.8	7.5	6.7	10.4	6.1	9.6
Not classified (99)	3.9	—	0.1	0.1	0.1	0.3	0.1	0.1	0.1
All sectors	3.0	17.9	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Note. Group columns give each sector's share (%) of the group's employer firms (ABS 2023, reference year 2022; table AB2200CSA01). AI use 2017: share of reporting employer firms using AI (ABS 2018 technology module, reference year 2017; table AB1800TCB01A). AI use 2025–26: BTOS AI Supplement (November 2025–February 2026; available for ten sectors). Nonminority = non-Hispanic White. Author's computation (2026) using data from U.S. Census Bureau (n.d.-a, n.d.-d, 2026).

4.2 Decomposing the 2017 gaps (RQ1, H1–H3)

Table 3 and Figure 1 report the 2017 decomposition. For each owner group, Table 3 gives the observed AI-use rates of the group and its baseline, the total gap, and the split of that gap into sector-composition and within-sector components with 95% Monte Carlo intervals, together with the size-composition component.

Sector composition (H1). H1 is supported for Hispanic-, Asian- and minority-owned firms. Their composition-implied AI-use rates are significantly below those of the baseline group: the composition component is −0.23 points for Hispanic-owned firms (95% CI −0.29 to −0.18), −0.24 for Asian-owned firms (−0.33 to −0.14) and −0.19 for all minority-owned firms (−0.26 to −0.13). Relative to a national AI-use rate of about 3%, these penalties amount to 6–8%. For minority-owned firms as a whole, the penalty comes mainly from over-representation in accommodation and food services (−0.11 points) and under-representation in professional, scientific and technical services (−0.10 points). It is partly offset by under-representation in construction (+0.09 points). Black-owned and women-owned firms, by contrast, gain from their sector mix (+0.13 points each), largely because of their concentration in health care and professional services.

Within-sector component (H2a vs. H2b). The within-sector components are inconsistent with the constraint explanation (H2a) for every minority group and consistent with the selection/opportunity explanation (H2b). The component is +0.63 points for Hispanic-owned firms (95% CI 0.19 to 1.07), +1.37 for Black-owned (0.56 to 2.19), +1.24 for Asian-owned (0.95 to 1.53), +1.53 for AIAN-owned (0.14 to 2.93) and +1.09 for all minority-owned firms (0.81 to 1.38). Net of 2-digit sector composition, minority-owned firms were more likely to report using AI than nonminority firms. The within-sector component outweighs the composition penalty in every case. As a result, the net gap is positive for Asian- (+1.0 points), Black- (+1.5), AIAN- (+1.5) and all minority-owned firms (+0.9), and not significantly different from zero for Hispanic-owned firms (+0.4; 95% CI −0.04 to +0.83).

Women-owned firms show the opposite pattern. Their within-sector component is negative (−0.53 points; 95% CI −0.81 to −0.25), so H2a is supported for women-owned firms in 2017. This shortfall more than offsets their favourable sector mix and produces a net gap of −0.40 points (95% CI −0.68 to −0.13).

Size composition (H3). The size-composition components are small, between −0.02 and −0.04 points, and none differs from zero at the 5% level (the largest |z| is 1.7). One reason is that, in the ABS 2017 module, AI use differed only modestly across the three size classes available (3.0% among firms without employees during the reference period, 2.8% at 1–9 employees and 3.5% at 10 or more). Because the top class combines mid-sized and large firms, these classes cannot capture the steep size gradient documented in firm-level data (McElheran et al., 2024). H3 therefore cannot be assessed meaningfully at this level of aggregation.

Table 3: Decomposition of Owner-Group Gaps in AI Use, 2017 (Percentage Points)

Group (baseline)	AI use, group (%)	AI use, baseline (%)	Total gap	Sector-composition component	Within-sector component	Size-composition component
Women-owned (Men-owned)	2.7	3.1	−0.40 [−0.68, −0.13]	+0.13 [+0.08, +0.18]	−0.53 [−0.81, −0.25]	−0.03 (SE 0.021)
Hispanic-owned (Non-Hispanic-owned)	3.3	2.9	+0.40 [−0.04, +0.83]	−0.23 [−0.29, −0.18]	+0.63 [+0.19, +1.07]	−0.02 (SE 0.014)
Black-owned (Nonminority-owned)	4.3	2.8	+1.50 [+0.69, +2.31]	+0.13 [+0.04, +0.21]	+1.37 [+0.56, +2.19]	−0.03 (SE 0.018)
Asian-owned (Nonminority-owned)	3.8	2.8	+1.00 [+0.72, +1.28]	−0.24 [−0.33, −0.14]	+1.24 [+0.95, +1.53]	−0.03 (SE 0.018)

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Group (baseline)	AI use, group (%)	AI use, baseline (%)	Total gap	Sector-composition component	Within-sector component	Size-composition component
AIAN-owned (Nonminority-owned)	4.3	2.8	+1.50 [+0.10, +2.90]	−0.03 [−0.07, +0.00]	+1.53 [+0.14, +2.93]	−0.04 (SE 0.023)
Minority-owned (Nonminority-owned)	3.7	2.8	+0.90 [+0.62, +1.18]	−0.19 [−0.26, −0.13]	+1.09 [+0.81, +1.38]	−0.03 (SE 0.016)

Note. Total gap = sector-composition component + within-sector component (indirect standardisation with all-firm 2-digit sector AI-use rates as the standard; see Section 3.2). Sector composition from ABS table AB1700CSA01; AI use from AB1800TCB01A (sectors) and AB1800TCB01B (owner groups). 95% Monte Carlo intervals in brackets (20,000 draws from published standard errors). The size-composition component is estimated separately from three employment-size classes (no employees, 1–9, 10+) and is not part of the sum. Nonminority = non-Hispanic White. NHPI estimates suppressed in the source. Author's computation (2026) using data from U.S. Census Bureau (n.d.-a, n.d.-b, n.d.-c).

Figure 1 shows the decomposition in Table 3 graphically. For each comparison, the blue bar is the sector-composition component and the orange bar is the within-sector component, each with its 95% interval. The total gap, shown on the right, is the sum of the two. For every minority group the within-sector component dominates, more than offsetting a small composition penalty. Women-owned firms are the only group whose within-sector component is negative.

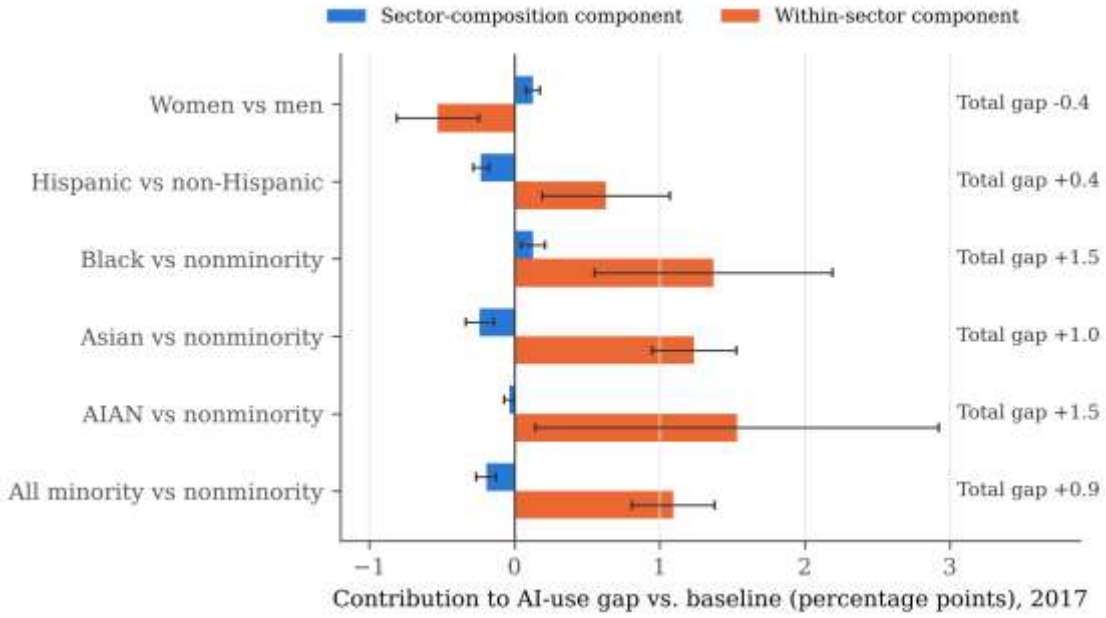


Figure 1. Decomposition of owner-group gaps in AI use, 2017. Bars show the sector-composition and within-sector components (percentage points) with 95% Monte Carlo intervals; the total gap is the sum of the two.
Source: Author's computation (2026) using data from U.S. Census Bureau (n.d.-a, n.d.-b, n.d.-c).

4.3 Adoption status in 2022 (RQ2, H4)

Table 4 gives the full distribution of AI adoption status in 2022 for each owner group, with published standard errors, and Table 5 expresses these profiles as differences from each group's baseline. Figure 2 plots the three most informative outcomes.

Use. The 2017 pattern persists. Minority-owned firms were more likely than nonminority firms to report using AI (3.8% vs. 3.1%; difference +0.7, $p = .002$). Black-owned firms reported the highest use of any group with precise estimates (5.6%; +2.5, $p < .001$). Hispanic-owned firms were marginally above non-Hispanic firms (+0.4, $p = .074$). Asian- and AIAN-owned firms did not differ significantly from nonminority firms. Women-owned firms did not differ significantly from men-owned firms (3.5% vs. 3.2%, $p = .18$).

Perceived relevance (H4). H4 is rejected for minority-owned firms. They were substantially less likely than their baseline groups to report that AI was "not applicable" to their business: by 7.3 points for all minority-owned firms ($p < .001$), 7.3 points for Black-owned firms ($p < .001$), 10.2 points for Asian-owned firms ($p < .001$) and 1.7 points for Hispanic-owned firms ($p = .048$). Among firms that regarded AI as applicable, use was also higher in minority-owned firms: 24.4% used it, against 19.7% of applicable nonminority firms.

Women-owned firms did not differ significantly from men-owned firms on "not applicable" (+1.5, $p = .11$). They were, however, more likely to regard AI as applicable without having tested or used it (+0.8, $p = .027$). This is consistent with an implementation gap rather than a perceived-relevance gap.

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"Don't know" responses. Minority-owned firms answered "don't know" much more often: 25.7% versus 18.4% for nonminority firms, and 29.7% for Asian-owned firms. This points to uncertainty or information gaps among a substantial share of these firms, even as those that do engage with AI adopt it more readily. It may also reflect differences in how respondents interpret the question, a possibility taken up in Section 6.

Table 4: AI Adoption Status of Employer Firms by Owner Group, 2022 (% of Reporting Firms)

Owner group	Reporting firms	Coverage (%)	Used AI	Tested, not used	Applicable, not tested/used	Not applicable	Don't know	Use, known answers (%)
All firms	2,760,070	47.0	3.3 (0.2)	2.7 (0.2)	9.8 (0.3)	64.4 (1.0)	19.9 (0.3)	4.1
Nonminority-owned	2,128,474	50.3	3.1 (0.1)	2.7 (0.1)	9.8 (0.3)	66.1 (0.8)	18.4 (0.3)	3.8
Minority-owned	530,434	40.0	3.8 (0.2)	2.5 (0.1)	9.1 (0.2)	58.8 (0.5)	25.7 (0.4)	5.1
Hispanic-owned	178,944	38.5	3.6 (0.2)	2.4 (0.1)	9.1 (0.2)	63.0 (0.5)	21.9 (0.4)	4.6
Non-Hispanic-owned	2,500,028	48.7	3.2 (0.1)	2.7 (0.1)	9.8 (0.2)	64.7 (0.7)	19.7 (0.2)	4.0
Black-owned	63,220	32.5	5.6 (0.4)	3.4 (0.2)	11.6 (0.5)	58.8 (0.8)	20.6 (0.4)	7.0
Asian-owned	276,852	42.5	3.5 (0.3)	2.3 (0.1)	8.5 (0.3)	55.9 (0.6)	29.7 (0.5)	5.0
AIAN-owned	24,187	50.9	3.5 (0.3)	3.7 (0.3)	9.7 (0.8)	63.8 (0.8)	19.2 (0.8)	4.3
NHPI-owned	3,971	41.6	6.3 (1.9)	2.7 (0.8)	9.6 (2.2)	53.6 (4.5)	27.8 (3.6)	8.8
Men-owned	1,712,337	47.1	3.2 (0.2)	2.7 (0.1)	9.8 (0.3)	63.5 (0.8)	20.8 (0.2)	4.1
Women-owned	625,786	47.8	3.5 (0.1)	2.8 (0.1)	10.6 (0.2)	65.0 (0.5)	18.1 (0.2)	4.3

Note. ABS 2023 (reference year 2022), table AB2200MCB01. Standard errors in parentheses. Coverage = reporting firms as a percentage of employer firms in table AB2200CSA01. Use, known answers = AI use as a percentage of firms that did not answer "don't know"; this column and the conditional rates cited in the text are computed from the published firm counts. Author's computation (2026) using data from U.S. Census Bureau (n.d.-d, n.d.-e).

Table 4 shows that "not applicable" is the most common response in every owner group, ranging from 53.6% (NHPI-owned) to 66.1% (nonminority-owned firms). The differences that matter for the hypotheses lie at the margins of this distribution. Compared with nonminority firms, minority-owned firms are less likely to regard AI as not applicable (58.8% vs. 66.1%), more likely to answer "don't know" (25.7% vs. 18.4%) and more likely to report using AI (3.8% vs. 3.1%). The table also shows that coverage of the technology question is lower for minority-owned (40.0%) and especially Black-owned firms (32.5%) than for nonminority firms (50.3%), which is taken into account in interpreting the 2022 comparisons (Section 6). Table 5 tests whether each of these differences from the baseline group is statistically significant.

Table 5: Differences in AI Adoption Status Relative to Baseline, 2022 (Percentage Points)

Group (baseline)	Used AI	Tested, not used	Applicable, not tested/used	Not applicable	Don't know
Women-owned (Men-owned)	+0.3 (0.22)	+0.1 (0.14)	+0.8* (0.36)	+1.5 (0.94)	−2.7*** (0.28)
Hispanic-owned (Non-Hispanic-owned)	+0.4† (0.22)	−0.3* (0.14)	−0.7* (0.28)	−1.7* (0.86)	+2.2*** (0.45)
Black-owned (Nonminority-owned)	+2.5*** (0.41)	+0.7** (0.22)	+1.8** (0.58)	−7.3*** (1.13)	+2.2*** (0.50)
Asian-owned (Nonminority-owned)	+0.4 (0.32)	−0.4** (0.14)	−1.3** (0.42)	−10.2*** (1.00)	+11.3*** (0.58)
AIAN-owned (Nonminority-owned)	+0.4 (0.32)	+1.0** (0.32)	−0.1 (0.85)	−2.3* (1.13)	+0.8 (0.85)
NHPI-owned (Nonminority-owned)	+3.2† (1.90)	+0.0 (0.81)	−0.2 (2.22)	−12.5** (4.57)	+9.4** (3.61)
Minority-owned (Nonminority-owned)	+0.7** (0.22)	−0.2 (0.14)	−0.7† (0.36)	−7.3*** (0.94)	+7.3*** (0.50)

Note. Standard errors of differences in parentheses, computed as $\sqrt{(SE_1^2 + SE_2^2)}$ from published standard errors (groups are disjoint). Differences tested with two-sided z-tests. Author's computation (2026) using data from U.S. Census Bureau (n.d.-e).

†p < .10. *p < .05. **p < .01. ***p < .001.

Figure 2 plots, for each owner group, the share using AI, the share regarding AI as not applicable and the share answering "don't know", with 95% confidence intervals; the dashed line marks nonminority-owned firms. Minority-owned groups, especially Black-owned firms, sit to the right of the reference line on AI use and to the left of it on "not applicable". Asian-owned firms stand out for their high share of "don't know" responses.

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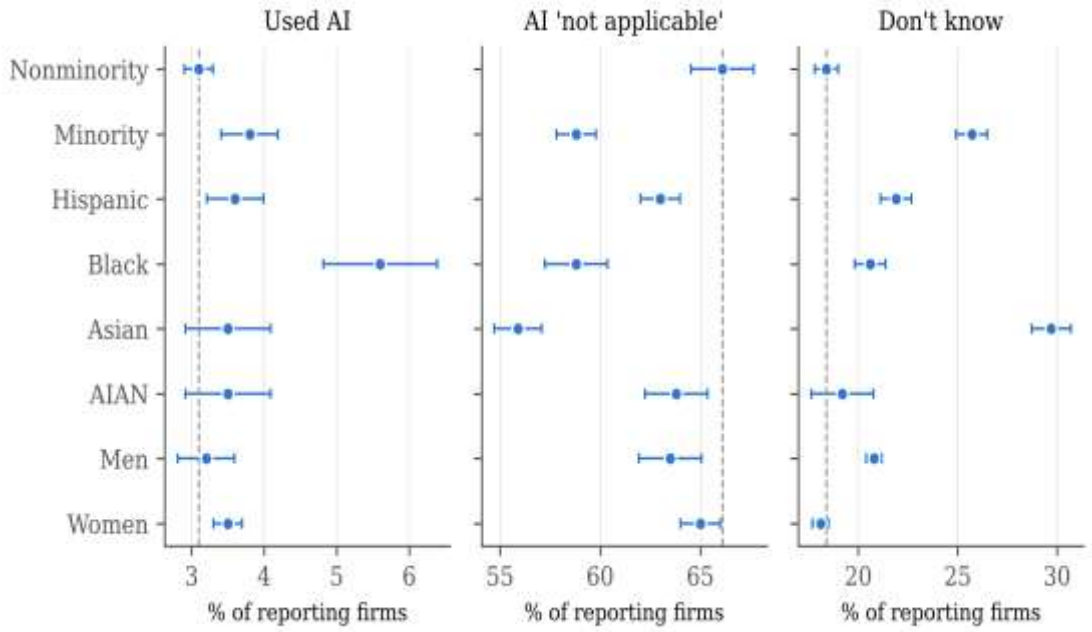


Figure 2. AI adoption status by owner group, 2022 (% of reporting employer firms, 95% confidence intervals). Dashed line: nonminority-owned firms.
Source: Author's computation (2026) using data from U.S. Census Bureau (n.d.-e).

4.4 The 2022 decomposition and exposure under current sector rates (RQ3)

Table 6 reports the approximate 2022 decomposition. Applying the 2017 sector rates (scaled to the 2022 national level) to the 2022 sector mix yields composition components close to those for 2017. The within-sector component remains positive for every minority group. It is statistically significant for all minority-owned firms (+0.90 points; 95% CI 0.45 to 1.34), Hispanic-owned firms (+0.68; 0.23 to 1.12) and Black-owned firms (+2.42; 1.61 to 3.23). For Asian- and AIAN-owned firms the point estimates (+0.61 and +0.60) are similar to those of Hispanic-owned firms, but the intervals just include zero, and the NHPI estimate is too imprecise to interpret. For women-owned firms the within-sector component is small and not significant (+0.11; −0.33 to 0.55): the 2017 shortfall is no longer statistically detectable.

Table 6: Approximate Decomposition of Owner-Group Gaps in AI Use, 2022 (Percentage Points)

Group (baseline)	Observed gap	Sector-composition component	Within-sector component
Women-owned (Men-owned)	+0.30 [−0.14, +0.74]	+0.19 [+0.13, +0.25]	+0.11 [−0.33, +0.55]
Hispanic-owned (Non-Hispanic-owned)	+0.40 [−0.04, +0.84]	−0.28 [−0.35, −0.22]	+0.68 [+0.23, +1.12]
Black-owned (Nonminority-owned)	+2.50 [+1.70, +3.31]	+0.08 [−0.01, +0.18]	+2.42 [+1.61, +3.23]
Asian-owned (Nonminority-owned)	+0.40 [−0.22, +1.02]	−0.21 [−0.31, −0.12]	+0.61 [−0.02, +1.24]
AIAN-owned (Nonminority-owned)	+0.40 [−0.20, +1.02]	−0.20 [−0.26, −0.14]	+0.60 [−0.01, +1.22]
NHPI-owned (Nonminority-owned)	+3.20 [−0.46, +6.93]	−0.25 [−0.30, −0.19]	+3.45 [−0.21, +7.18]
Minority-owned (Nonminority-owned)	+0.70 [+0.26, +1.14]	−0.20 [−0.27, −0.13]	+0.90 [+0.45, +1.34]

Note. Group AI-use rates from AB2200MCB01; sector composition from AB2200CSA01. Sector rates are the 2017 ABS rates (AB1800TCB01A) scaled by 1.09 to reproduce the 2022 national rate (3.3%), which assumes stable relative sector differences between 2017 and 2022 (see Sections 3.4 and 4.5). 95% Monte Carlo intervals in brackets (20,000 draws from the published standard errors of the 2022 group rates and the 2017 sector rates). Author's computation (2026) using data from U.S. Census Bureau (n.d.-a, n.d.-d, n.d.-e).

Table 7 and Figure 3 compare composition effects under the two sets of sector rates. Because BTOS rates exist for only ten sectors, both columns of the comparison are computed over those ten sectors; the all-sector relative effects under 2017 rates are shown for reference. Under BTOS 2025–26 rates, the composition disadvantage of Hispanic-, Asian- and minority-owned firms is larger in both absolute and relative terms. Over the same ten sectors, the relative composition effect moves from −10.3% to −11.9% for Hispanic-owned firms (about −2.1 points at BTOS rates), from −8.6% to −12.1% for Asian-owned firms (about −2.2 points) and from −7.6% to −9.5% for all minority-owned firms (about −1.7 points). The

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favourable sector mix of Black- and women-owned firms also becomes more valuable: from +4.7% to +8.3% for Black-owned firms, and from +5.9% to +7.8% for women-owned firms.

The like-for-like comparison matters. Restricting the 2017 rates to the ten BTOS sectors already makes the composition effects more pronounced, because it removes sectors in which minority-owned firms are well represented and AI use was close to the middle of the distribution, such as transportation and warehousing (2.5%) and administrative and support services (2.7%). For the minority groups, between about two-fifths and one-half of the widening that a naive comparison with all-sector 2017 rates would suggest is due to this change in sector coverage rather than to the change in sector rates. The remaining widening, of 1.6 to 3.5 percentage points in relative terms for the disadvantaged groups, reflects the concentration of current adoption in professional services, information and finance, where Hispanic- and Asian-owned firms are under-represented. Sector placement matters more for these groups under current sector rates than it did in the earlier phase of diffusion.

Table 7: Composition-Implied AI Adoption Relative to Baseline Under 2017 ABS and 2025–26 BTOS Sector Rates (2022 Sector Composition)

Group (baseline)	Share of group's firms in BTOS sectors (%)	Relative effect, 2017 rates, all sectors (%)	Relative effect, 2017 rates, ten BTOS sectors (%)	Relative effect, BTOS rates, ten sectors (%)	Change, like for like (percentage points)	Composition component at BTOS rates (pp)
Women-owned (Men-owned)	76.4	+5.8	+5.9	+7.8	+1.9	+1.38
Hispanic-owned (Non-Hispanic-owned)	73.2	−8.5	−10.3	−11.9	−1.6	−2.14
Black-owned (Nonminority-owned)	72.1	+2.5	+4.7	+8.3	+3.6	+1.51
Asian-owned (Nonminority-owned)	83.6	−6.4	−8.6	−12.1	−3.5	−2.21
AIAN-owned (Nonminority-owned)	77.7	−6.1	−8.4	−9.3	−0.9	−1.69
NHPI-owned (Nonminority-owned)	74.7	−7.4	−9.9	−12.0	−2.1	−2.19
Minority-owned (Nonminority-owned)	78.2	−6.0	−7.6	−9.5	−2.0	−1.73

Note. Relative effect = group's composition-implied rate ÷ baseline's − 1, using 2022 sector shares (AB2200CSA01). BTOS rates are available for ten sectors; for the like-for-like columns, shares are renormalised over those sectors and the 2017 ABS rates (AB1800TCB01A) are restricted to the same sectors. The all-sector column is shown for reference only. Change = BTOS column minus ten-sector 2017 column. Author's computation (2026) using data from U.S. Census Bureau (n.d.-a, n.d.-d, 2026).

Figure 3 compares each group's composition-implied AI adoption, relative to its baseline, under 2017 ABS sector rates (grey bars) and 2025–26 BTOS sector rates (blue bars), both computed over the same ten sectors. Bars below zero indicate a placement disadvantage. For Asian-, Hispanic- and all minority-owned firms the blue bars are longer than the grey ones. Black- and women-owned firms benefit from their sector mix under both sets of rates.

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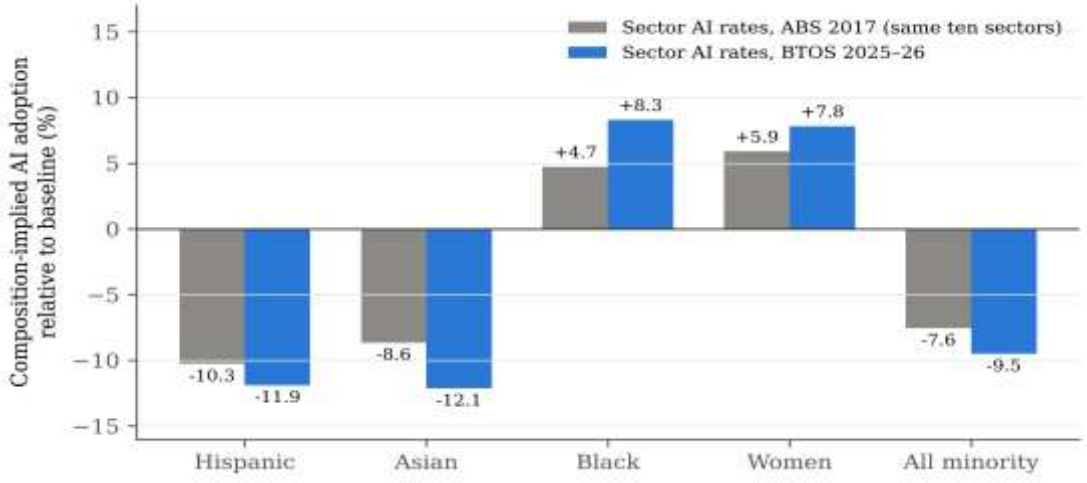


Figure 3. Composition-implied AI adoption relative to baseline under 2017 ABS and 2025–26 BTOS sector rates, computed over the same ten sectors (2022 sector composition). Baselines: non-Hispanic-owned (Hispanic), men-owned (women), nonminority-owned (others).

Source: Author's computation (2026) using data from U.S. Census Bureau (n.d.-a, n.d.-d, 2026).

4.5 Robustness

Table 8 summarises the robustness and sensitivity checks.

"Don't know" responses. Excluding "don't know" responses from the denominator widens rather than narrows the minority advantage. In 2017 the gap becomes +1.13 points for minority-owned firms, +1.67 for Black-owned and +1.29 for Asian-owned firms, while the women-owned gap is essentially unchanged (−0.45). In 2022, among firms giving a definite answer, use was 5.1% for minority-owned against 3.8% for nonminority firms (+1.3 points), and 7.0% for Black-owned firms (+3.3). Treating "don't know" as non-use therefore yields conservative estimates of the minority advantage.

Covariance of sampling errors. When the sampling errors of the baseline rate and the sector rates are allowed to share a common factor (correlation 0.5 or 0.9), the 2017 within-sector intervals barely change. For minority-owned firms the interval moves from [0.81, 1.38] to [0.87, 1.32] at a correlation of 0.9, and every interval that excludes zero in Table 3 continues to do so. Ignoring the covariance is therefore, if anything, slightly conservative.

Stability of the 2022 sector profile. If half of the widening in sector differences observed by 2025–26 had already occurred by 2022 (a geometric interpolation of the 2017 and BTOS profiles, rescaled to the 2022 national rate), the 2022 composition components change by at most 0.05 points and the within-sector components by at most 0.05 points. For the groups concentrated in low-adoption sectors the within-sector component rises slightly, because the composition penalty is larger. The approximate 2022 decomposition is therefore not sensitive to this assumption.

Sector coverage of the exposure index. As shown in Section 4.4, comparing 2017 and BTOS rates over the same ten sectors reduces the apparent widening of the composition penalty by about two-fifths to one-half for the minority groups, but leaves its direction and the ranking of groups unchanged.

Table 8: Robustness and Sensitivity of the Within-Sector Component (Percentage Points)

Group (baseline)	2017, main estimate		2017, "don't know" excluded: total gap	2017, correlated sampling errors (ρ = 0.9)	2022, main estimate		2022, half of 2017–2026 widening in sector profile
Women-owned (Men-owned)	−0.53	[−0.81, −0.25]	−0.45	−0.53 [−0.77, −0.28]	+0.11	[−0.33, +0.55]	+0.09
Hispanic-owned (Non-Hispanic-owned)	+0.63	[+0.19, +1.07]	+0.50	+0.63 [+0.21, +1.05]	+0.68	[+0.23, +1.12]	+0.70
Black-owned (Nonminority-owned)	+1.37	[+0.56, +2.19]	+1.67	+1.37 [+0.57, +2.17]	+2.42	[+1.61, +3.23]	+2.37
Asian-owned (Nonminority-owned)	+1.24	[+0.95, +1.53]	+1.29	+1.24 [+1.02, +1.46]	+0.61	[−0.02, +1.24]	+0.66
AIAN-owned (Nonminority-owned)	+1.53	[+0.14, +2.93]	+1.64	+1.53 [+0.17, +2.91]	+0.60	[−0.01, +1.22]	+0.61
Minority-owned (Nonminority-owned)	+1.09	[+0.81, +1.38]	+1.13	+1.09 [+0.87, +1.32]	+0.90	[+0.45, +1.34]	+0.93

Note. Main estimates from Tables 3 and 6. "Don't know" excluded: observed 2017 gap with "don't know" responses removed from the denominator. Correlated sampling errors: the baseline rate and all sector rates share a common sampling factor with correlation 0.9. Half of widening: 2022 sector rates set to the geometric midpoint of the 2017 ABS and 2025–26 BTOS sector profiles (ten BTOS sectors; other sectors at 2017 relative rates), rescaled to the 2022 national rate. 95% Monte Carlo intervals in brackets. Author's computation (2026) using data from U.S. Census Bureau (n.d.-a, n.d.-b, n.d.-c, n.d.-d, n.d.-e, 2026).

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Table 9 summarises the outcome of each hypothesis test against the evidence in Tables 3–8. The composition hypothesis is supported for Hispanic-, Asian- and minority-owned firms. The constraint hypothesis is rejected for all minority groups in favour of the selection/opportunity hypothesis. Size composition could not be assessed meaningfully with the size classes available, and the perceived-relevance hypothesis is rejected for minority-owned firms.

Table 9: Summary of Hypothesis Tests

Hypothesis	Prediction	Result
H1 Composition	Groups concentrated in low-AI sectors have lower composition-implied AI use	Supported for Hispanic-, Asian- and minority-owned firms; reversed (favourable) for Black- and women-owned firms
H2a Constraint	Lower within-sector AI use	Rejected for all minority groups; supported for women-owned firms in 2017 (not significant in 2022)
H2b Selection/opportunity	Equal or higher within-sector AI use	Supported for all minority groups in 2017 (+0.6 to +1.5 pp); in 2022 (approximate) positive for all, significant for minority-, Hispanic- and Black-owned firms (+0.7 to +2.4 pp)
H3 Size composition	Size mix contributes to gaps	Not detectable with the three size classes available (components −0.02 to −0.04 pp, none significant)
H4 Perceived relevance	More "not applicable" responses	Rejected for minority groups (−7.3 pp for all minority-owned firms); not supported for women-owned firms

Note. Author's compilation (2026) from Tables 3–8.

5. DISCUSSION

5.1 Theoretical implications

The findings recast the "double divide" in three ways.

For minority-owned firms, the measured divide is one of placement rather than within-sector adoption. The mixed-embeddedness framework (Kloosterman & Rath, 2001) is strongly supported as an account of where minority-owned firms operate. The opportunity structures that channel Hispanic- and Asian-owned firms into construction, food service and retail also place them in the sectors where AI is least used. The resource-constraint explanation (Blanchflower et al., 2003; Fairlie & Robb, 2008; Fairlie et al., 2022), however, finds no support in within-sector technology use. Net of sector composition, minority-owned firms report using AI more often than nonminority firms, are less likely to regard it as irrelevant and, once they consider it applicable, are more likely to use it. The direction of this result is consistent with recent survey evidence that Latino owners use AI more often than White owners after controlling for education, industry and other business characteristics (Smith, 2026). Because the within-sector component is a residual, it should be read as "not explained by 2-digit sector composition" rather than as a pure behavioural difference; Section 6 sets out the alternative explanations that the published aggregates cannot rule out.

Two mechanisms are consistent with this result. The first is firm youth. Half of minority-owned employer firms are less than six years old, compared with about a third of nonminority firms, and Black-owned firms (the youngest group, with 57.7% under six years) also report the highest AI use. Young firms are known to adopt AI more readily (McElheran et al., 2024). The second is positive selection: owners who overcome the documented credit and network barriers to forming an employer firm may be unusually capable or growth-oriented. The gender comparison qualifies the first mechanism. Women-owned firms are also younger than men-owned firms (44.7% vs. 37.4% under six years), yet they showed a within-sector shortfall in 2017. Firm youth alone therefore cannot account for the pattern, and either the minority advantage owes more to selection or the gender gap reflects constraints strong enough to offset the effect of youth. Separating these mechanisms requires firm-level data, but either way the results imply that constraints on entry and scale do not necessarily become constraints on technology use after entry.

Gender and minority status work through different channels. Women-owned firms have the opposite profile to minority-owned firms. They have a favourable sector mix but showed a within-sector shortfall in 2017. In 2022 they did not differ from men-owned firms in perceived relevance, but were more likely to regard AI as applicable without having tried it. This pattern fits an implementation constraint (time, finance or technical support at the point of adoption) better than an awareness constraint. It also sits alongside transaction-based evidence of a widening gender gap in spending on AI tools among small businesses after 2023 (Wheat et al., 2026). The two sources measure different things, self-reported use in production processes versus payments to AI providers, and cover different firm populations; together they suggest that the narrowing in the ABS 2022 estimate should not be read as evidence that the gender gap has closed. Treating "minority- and women-owned businesses" as a single policy category therefore conceals two different problems.

Placement matters more as diffusion becomes sector-concentrated. In the early phase captured by the 2017 ABS, sector differences in AI use were small in absolute terms, and so was the composition penalty. In the current wave captured by the BTOS AI Supplement, adoption is heavily concentrated in professional services, information and finance. Over the same ten sectors, the same sector mix implies a composition penalty of about 12% for Hispanic- and Asian-owned firms under current rates, against about 9–10% under 2017 rates. Unless within-sector advantages keep pace, the placement divide will widen even if minority-owned firms continue to out-adopt their sector peers.

There is also a caution about information. The high rate of "don't know" responses among Asian-owned (29.7%) and other minority-owned firms shows that a sizeable share of these firms are uncertain whether or how AI applies to them. This group is distinct from both adopters and firms that have decided AI is irrelevant, and it is plausibly the group most responsive to outreach.

5.2 Policy implications and recommendations

The evidence argues against targeting AI-adoption support by owner demographics alone. It points instead to three distinct problems: sector placement, information gaps among uncertain firms, and implementation gaps among women-owned firms. Six recommendations follow, each

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assigned to the agency whose existing remit and delivery network best fit it. Because the evidence comes from aggregate tabulations, each programme should begin as an evaluated pilot.

Recommendation 1: Sector-specific AI demonstrations in low-adoption sectors. Construction, accommodation and food services, and retail account for 39.2% of Hispanic-owned and 42.9% of Asian-owned employer firms (Table 2), and these are the groups with the largest composition penalties (Tables 3 and 7). Practical, sector-specific demonstrations in these industries, such as estimating and scheduling in construction, and ordering, inventory and customer service in food service and retail, would reach the firms where the penalty is largest. The U.S. Small Business Administration (SBA) Office of Entrepreneurial Development should lead, working through Small Business Development Centers (SBDCs), with sector trade associations and community colleges as partners. Minority Business Development Agency (MBDA) Business Centers could also take part, subject to the agency's operating status, which remained subject to litigation in early 2026 (U.S. Government Accountability Office, 2026).

Recommendation 2: Multilingual, culturally adapted AI information. The high "don't know" rates among Asian-owned (29.7%) and other minority-owned firms (Tables 4 and 5) indicate an information gap that is distinct from both rejection and adoption. Plain-language guidance in the languages of the main business-owner communities, delivered through trusted community intermediaries, would help turn uncertainty into an informed decision. SBA resource partners (SBDCs, Women's Business Centers and SCORE) should lead, in partnership with ethnic chambers of commerce and, subject to its status, the MBDA.

Recommendation 3: Implementation support for women-owned firms. Women-owned firms were more likely than men-owned firms to regard AI as applicable without having tested or used it (Table 5), which points to a gap at the point of implementation rather than in awareness. Hands-on assistance, comprising help with tool selection, a supported pilot deployment and small technology grants or loans, targets that step directly. The SBA Office of Women's Business Ownership should lead through the Women's Business Center network, with SBDCs as partners. The proposed Small Business Artificial Intelligence Training Act of 2026 would, if enacted, strengthen this work by having the Department of Commerce develop AI training resources for delivery through SBA resource partners (U.S. Senate Committee on Commerce, Science, and Transportation, 2026).

Recommendation 4: Support movement into higher-adoption sectors. Composition penalties are larger under current sector adoption rates, which are concentrated in professional, technical, information and financial services (Table 7). Training, procurement-readiness and financing support that helps minority entrepreneurs enter these sectors would address the placement divide at its source. The SBA should lead through its entrepreneurial-development and lending programmes, with state economic development agencies and, subject to its status, the MBDA as partners.

Recommendation 5: Target by sector and firm characteristics, not owner demographics alone. Net of sector composition, minority-owned firms already report higher AI use than nonminority firms (Tables 3 and 6). Programmes that allocate AI-readiness funds solely by owner category would therefore direct resources away from the sector and information constraints that actually limit adoption. The SBA Office of Advocacy, in its research and regulatory-guidance role, should advise federal and state programme designers accordingly and commission firm-level evaluations.

Recommendation 6: Improve owner-level AI statistics. The U.S. Census Bureau (Economic Directorate), with the National Science Foundation's National Center for Science and Engineering Statistics (NSF NCSES) as co-sponsor of the ABS, should (a) publish ABS technology-module estimates of AI adoption by sector and owner group jointly; (b) retain the AI items in future ABS technology modules so that a time series can be built; and (c) explore linking BTOS respondents to ABS owner characteristics, to allow owner-group estimates at BTOS frequency. Each of these would allow the decomposition in this paper to be carried out without the approximations described in Section 6.

6. LIMITATIONS AND FUTURE RESEARCH

The study has eight main limitations.

1. The data are aggregate, and the within-sector component is a residual. The analysis uses published group-by-sector tabulations rather than firm-level microdata. The decomposition is exact for those aggregates, but it cannot control for sub-sector mix, firm age, owner education or location within sector-by-group cells. Location is a particular concern: minority-owned firms are concentrated in large metropolitan areas, where AI adoption is also higher (McElheran et al., 2024). The within-sector component may therefore partly reflect these correlated characteristics, as the firm-age evidence suggests. A decomposition by state, using the state-level ABS technology tabulations, is a priority extension.
2. Measurement of AI use. In 2017 AI was used by about 3% of firms and the term was less widely understood than it is today. Differences between groups in how respondents interpret "artificial intelligence", or in who answers the survey, could contribute to the within-sector component. The higher "don't know" rates among minority-owned firms show that response patterns do differ. A falsification test applying the same decomposition to the other technologies in the ABS module (cloud computing, specialised software, robotics and specialised equipment) would indicate whether the minority advantage is specific to AI or reflects a general response pattern.
3. Coverage of the technology questions differs by group. Reporting firms represent 83% of employer firms in 2017 but only 47% in 2022, and in 2022 coverage is lower for minority-owned (40%) and especially Black-owned firms (33%) than for nonminority firms (50%). If response is related to technology use, the 2022 comparisons could be affected. The 2017 results, on which the main decomposition rests, are less exposed.
4. The measurement windows differ. The 2017 ABS measured AI use early in its diffusion, and the question wording differs from the 2022 module and from BTOS, which asks about use in producing goods or services in the previous two weeks. Results across sources are compared in relative terms and should not be pooled.
5. The 2022 decomposition is approximate. It assumes that relative sector differences in AI use were stable between 2017 and 2022. The sensitivity analysis in Section 4.5 shows that the results are robust to a plausible degree of widening, but the true 2022 sector profile is unknown. The BTOS-based exposure index covers ten sectors representing 72–84% of each group's firms.
6. Size and sector are handled separately. Published tables do not cross size, sector and owner group jointly, so the two compositions cannot be decomposed simultaneously. The size classes available (no employees, 1–9, 10+) are also coarse.

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7. Inference ignores covariances that are not published. The sensitivity analysis suggests that this matters little, but exact intervals would require replicate weights or microdata.
8. Only employer firms are covered. The ABS excludes nonemployer businesses, which make up a large share of minority- and women-owned enterprises. The results therefore describe owners who have already formed employer firms, which is consistent with the selection interpretation in Section 5.1.

Future research using ABS microdata in a Federal Statistical Research Data Center could estimate the decomposition at firm level, with controls for firm age, size, location and owner characteristics, test the youth and selection mechanisms directly, and use the other technology items as a check on response behaviour.

7. CONCLUSION

Is there a "double divide" in AI adoption for minority- and women-owned U.S. businesses? For minority-owned firms, the answer from official statistics is no in within-sector adoption but yes in placement. Net of sector composition, minority-owned firms report using AI more often than nonminority firms and are less likely to regard it as irrelevant. Their industry mix, however, places them in sectors where AI is least used, and that disadvantage is larger under current sector adoption rates, which are concentrated in professional, information and financial services. For women-owned firms the pattern is reversed: they have a favourable sector mix but showed a within-sector implementation shortfall in 2017, which was no longer statistically detectable in 2022.

These findings imply that AI-adoption policy should be organised around sectors, information gaps and implementation support, not around owner categories alone. They also show that the official statistics needed to monitor the issue are within reach: the ABS and BTOS already collect what is required and need only be tabulated or linked jointly.

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