ECONOMIC INNOVATION GROUP

Measuring the Economic Effects of AI

A path forward

By Nathan Goldschlag

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How many firms are using Artificial Intelligence? What are they using it for? How many workers are using AI, and how are they using it?

To track and understand the effects of AI on the economy, researchers will need accurate, detailed, comprehensive answers to these fundamental questions.

Partial answers won't do — not at a time when policymakers are struggling to catch up with the sweeping consequences of AI for workers and businesses. Without improved measurement, they risk getting the policy response wrong.

Fortunately, the statistical infrastructure is already in place to help get it right. But that infrastructure needs an upgrade, fast, to match the scale of the challenge.

In this essay, I outline the necessary investments in the U.S. statistical agencies that will give them the ability to answer the most pressing and vital questions about the impact of AI on the American economy.

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Measurement Momentum

A widespread consensus in favor of better measurement of AI has formed across the policy-making and scholarly landscapes.

The Trump administration's AI Action Plan has called on the major statistical agencies — the Bureau of Labor Statistics, the Bureau of Economic Analysis, and the Census Bureau — to study AI's impact on the labor market. Both this plan and two bills in Congress aim to consolidate AI measurement in an AI Workforce Research Hub, which would coordinate this work.[1]

Things are moving outside of government as well:

- The American Economic Association's Committee on Economic Statistics (AEAStat) published a summary of a January 2025 working session focused on measuring the economic effects of AI, with numerous insights about the state of AI measurement and potential improvements.
- American for Responsible Innovation organized a letter signed by numerous economists urging the Department of Labor to improve the measurement of AI's impact on the labor market.
- Christos Makridis and Erik Brynjolfsson, scholars studying technological change, outlined measurement improvements aimed at avoiding the underestimation of AI's impact on the national income.
- In her testimony to the U.S. House Committee on Education and Workforce, Revana Sharfuddin, a Research Fellow at the Mercatus Center, outlined the current state of AI measurement with several concrete recommendations to improve it.
- Similarly, Sam Manning, a Senior Research Fellow at GovAI, outlined first steps the AI Workforce Research Hub could take to improve AI measurement and ways to improve federal survey data on AI's Workforce Impacts.

Challenges in Measuring AI

Before reviewing available data, it's worth pausing to stress just how difficult it is to measure AI's impact on the economy. There are at least six primary challenges to overcome, and more could arise in time.

1. The definition matters.

In the case of surveys, highly technical definitions may not be intelligible to the typical respondent. Definitions that are too vague, too broad, or too narrow can result in over- or under-measurement of AI use.

2. Some workers who use AI may not even know that they are using it.

AI or machine learning, for example, may be embedded in specialized software without the user's awareness. When a survey question asks workers if they are using AI, the answers may underestimate diffusion if AI is embedded because respondents don't realize that they are using AI.

3. The *intensity* of AI use can vary significantly.

Use of AI can be formal, explicitly integrated into production processes; or informal, used by workers in an ad hoc or inconsistent manner. And in both cases, the share of tasks done using AI can vary dramatically. Definitions of AI and usage need to account for these different types of usage.

4. The speed of AI progress complicates economic measurement.

A survey respondent's understanding of what AI means can change over time as the technology itself evolves and diffuses. Definitions or questions may need to be updated periodically to account for the evolution of technical capabilities.

5. Increased diffusion will make questions about AI's effects more difficult for respondents to answer over time.

The longer a firm uses AI, the harder it will be for the firm to disentangle even qualitative impacts. The Annual Business Survey (ABS), for example, includes questions about the effects of adopting AI on the number of workers employed at a given business. If the business makes complementary investments after incorporating AI, are subsequent employment changes the direct result of AI or of those complementary investments? Self-assessments of AI's impacts are useful during the transition period, where causal links are easier to see, but their efficacy is likely to deteriorate over time.

6. The type of statistic we want needs to be mapped to the appropriate unit of observation.

Worker-level surveys, like the Current Population Survey (CPS), will be more informative on questions related to the worker's view of economic activity. They are poorly suited to questions about the reason for layoffs and hires.

7. Causal inference, determining whether AI is actually impacting workers and/or firms, is hard.

The types of public-use statistics described in this document are valuable and informative. But without additional statistical machinery, they cannot by themselves say how AI is impacting workers and firms. Even if a particular occupation is highly "exposed" to AI and employment declines in that occupation, a number of other factors could explain that pattern. Perhaps work-from-home policies that correlate with AI exposure, for example, caused the employment changes, as suggested by Lambert and Schindler (2026).

Public-use statistics can be combined with analytic techniques to establish causal estimates of AI's impact, but research using microdata often provides more variation to exploit, making causal inference easier. Any work to improve the quality and quantity of public-use statistics about AI's impacts should be paired with support for microdata research.

Federal Statistics

Federal statistics on the impact of Artificial Intelligence can be separated into surveys of firms and surveys of workers.

The two most important firm surveys for AI measurement are the Annual Business Survey (ABS) and the Business Trends and Outlook Survey (BTOS), both published by the Census Bureau.[2]

Within these two surveys, the primary sources of federal statistics on business AI use are:

- Periodic “modules” in the ABS
- A limited set of core questions about AI use in the BTOS
- A periodic supplement to the BTOS with additional questions

The two surveys of workers sometimes used to indirectly measure the impacts of AI are the Current Population Survey (CPS) and the Occupational Employment and Wage Statistics (OEWS), both published by the Bureau of Labor Statistics. These data are indirect because they do not include questions about AI use. Instead, researchers combine CPS and OEWS data with occupation-level AI exposure data to characterize the labor market impacts of AI.

In this section, I describe the pros and cons of each survey’s current approach to measuring AI use. I also include a table summarizing the conclusions about AI’s effects that researchers have gleaned from the surveys.

1. Annual Business Survey (ABS)

The ABS is a large firm-level survey collected annually. Its sample covers about 300 thousand to 850 thousand businesses, depending on the year.

The ABS also uses a relatively long survey form, supporting highly detailed questions. Questions about AI and AI-related technologies specifically have been included in the ABS as periodic “modules” of additional questions added to the main form. These questions were initially about AI-related technologies (e.g., machine learning and machine vision) in the 2018 and 2021 survey years, and about AI itself in the 2019 and 2023 survey years.

> **Pros: The ABS is sampled from the Census Bureau’s frame of all non-farm employer businesses, allowing for nationally representative statistics about firms’ use of AI. Survey content is subject to rigorous testing and review processes, and the methodology of the collection and tabulation is transparent.**

Cons: A significant drawback of the ABS is that AI questions are not fielded every year. The data also take a significant amount of time to process. Data about use in a given period will be two years old by the time they are released. (The AI questions in the 2023 survey, for example, asked about AI use from 2020–2022 and were released in fall 2024.)

2. Business Trends and Outlook Survey (BTOS)

The BTOS is a biweekly qualitative business survey designed to provide real-time measures of current and near-term economic activity. The sample includes about 1.2 million employer businesses, organized in panels of about 200,000 firms with response rates of about 10 to 15 percent — large samples but relatively small numbers of respondents.

Since 2023, a limited "core" set of questions about business use of AI have been included in each collection. Periodic AI supplements to the BTOS have also been fielded, containing richer, more contextual questions about why and how firms use AI and its impacts on the demand for workers.

In November 2025, the Census Bureau made a consequential change to the wording of the question on AI use, broadening the type of AI usage from "in the production of goods and services" to "in any business function." This change caused the percent of firms using AI to jump from 10 to 17 percent.

Pros: Like the ABS, since it is derived from Census sampling frames, it can produce nationally representative statistics. Unlike the ABS, the BTOS is much more timely. The BTOS data are released every two weeks, covering a collection period less than a month in the past.

Cons: Because the sample of firms for any given bi-week period is relatively small, detailed tabulations can be somewhat noisy or subject to disclosure suppressions, which the Census Bureau uses to avoid the release of confidential information. Even at a relatively high level of aggregation, such as the state-level BTOS tabulations, about 28 percent of observations are missing due to disclosure suppressions.[3]

3. Annual Integrated Economic Survey (AIES)

The Annual Integrated Economic Survey (AIES) was established in 2023 and replaced seven annual business surveys, including sector-specific surveys of business activity like the Annual Survey of Manufactures and Annual Retail Trade Survey in addition to the Annual Capital Expenditures Survey, which collected information on business investments in new and used structures and equipment.

The 2025 wave of the AIES is set to include a question about expenses for AI technologies across a broad set of sectors.

> **Pros: To the extent that AI questions remain on future waves of the AIES survey, they will provide consistent and useful information about the value firms spend on AI technologies. A portion of the AIES sample is collected at the establishment level, which would provide geographic information on AI spending.**
>
> **Cons: Like the ABS, the AIES data are published with a significant time lag. As of mid-2026, only the 2023 data are available.**

4. Current Population Survey (CPS)

The CPS is a monthly survey of more than 65,000 U.S. households that provides information about the nation's labor force, capturing data on the employed, unemployed, and those out of the labor force.

Occupation data available in the CPS public-use microdata files allows researchers to characterize the labor market outcomes of "AI-exposed" workers such as their rates of unemployment and labor force participation.[4]

> **Pros: CPS data are very timely and provide high-quality, longitudinally consistent information about the labor market outcomes of different segments of the labor market.**
>
> **Cons: The CPS does not directly capture information about AI use or worker impacts because it does not have questions on the survey instrument about AI. The relatively limited sample size of the CPS means that highly granular analyses are either very noisy or impossible. For example, the CPS is inappropriate for studying the outcomes of specific types of young, highly-AI-exposed workers (e.g., those ages 22–25 in occupations like software programmer).**

5. Occupational Employment and Wage Statistics (OEWS)

Another source of data with occupation and wage information is the OEWS. The OEWS is an annual survey that measures employment and wage rates for wage and salary workers in non-farm business establishments. Tabulations of employment and wage distributions are available by occupation, industry, and geography. As with the CPS, researchers combine OEWS data with information on occupation-level AI exposure to characterize the impacts of AI on the labor market.

> **Pros:** OEWS provides occupation detail across both geography and industry, allowing researchers to characterize outcomes for AI-exposed occupations in finer detail than the CPS.
>
> **Cons:** Similar to the CPS, the OEWS does not include questions about AI. The data are annual and published in March or April following the collection year (statistics for 2024 were published in April 2025). Annual frequency makes evaluating high-frequency changes in the labor market difficult.

Below I summarize empirical findings from a selection of studies using federal statistics from these surveys to understand AI's impact on the economy.

TABLE 1. Findings on AI's Impacts from Federal Statistics

ABS	Early waves of the ABS (2018 and 2019) found firm use rates of 3 to 6 percent, and remained at about 6 percent in the 2023 survey. AI use tends to be concentrated among large and young firms and is more common in the information sector, manufacturing, professional services, and healthcare. Firms that use AI also tend to have higher labor productivity, lower labor shares, and pay higher wages (Acemoglu et al. 2022). An analysis using multiple waves of ABS for the manufacturing sector finds a productivity J-curve, with short-term negative effects on labor productivity followed by subsequent growth and improved performance (McElheran et al. 2025).
BTOS	BTOS reported about 4 percent of businesses using AI in the production of goods and services in late 2023, rising to about 10 percent by September 2025. The use rate in any business function rose from about 17 percent in November 2025 to 18 percent in February 2026. The vast majority of firms (>95 percent) report that AI did not impact their employment, and among those that did, about half reported increases and half reported decreases. Worker augmentation is far more common than automation, which happens about as often as task creation. 44 percent of AI-using firms are augmenting workers, 10 percent use AI to replace tasks, and 11 percent created tasks. Conditional on automating tasks, 71 percent say it's for a "small number" of tasks (Bonney et al., 2026).

CPS	Some studies using the CPS combined with occupation exposure measures find little evidence of differences in employment outcomes by AI exposure (Eckhardt and Goldschlag 2025), while others find a correlation between AI exposure and reduced employment, higher unemployment rates, and shorter work hours (Dominski and Lee 2025). Another way CPS data are used to evaluate AI's impact on the labor market is by measuring the rate of churn across occupations. Significant labor market impacts of AI would likely coincide with large changes in how many workers are employed in each occupation. So far, there has been no significant change in the distribution of workers across occupations (Gimbel, Kinder, Kendall, and Lee 2025). CPS has also been used to show recent labor market weakness among both college and non-college young workers (Ozimek and Goldschlag 2026).
OEWS	OEWS was used by Felten, Raj, and Seamans (2021) to translate occupation-based AI exposure measures into industry-level and geographic-level AI exposure. Analyses of tasks likely exposed to AI automation, aggregated using OEWS data to the industry level, suggest that 25 percent of work tasks could be automated by AI, with particularly high exposures in administrative and legal professions and low exposures in physically demanding professions like construction and maintenance (Briggs and Kodnani 2023).

Researcher-Fielded Surveys and Polling Data

Academics have attempted to fill measurement gaps by fielding their own surveys of workers and firms. Similarly, polling firms have fielded surveys asking individuals about their use of AI.

In this section, I describe examples of each approach and, as with federal statistics, assess their pros and cons.

1. Researcher-Fielded Worker Surveys

Bick, Blandin, and Deming (2024), in partnership with the Federal Reserve Bank of Dallas, developed the Real-Time Population Survey (RPS), a national labor market survey designed to be similar to the Current Population Survey. In 2024, Bick and coauthors added several questions to the RPS about the use of generative AI at work and at home. The survey received 2.5 to 5 thousand responses across each of the three waves in 2024.[5]

Hartley, Jolevki, Melo, and Moore (2025) perform a similar exercise using the private survey company IncQuery. The first wave of the survey included about 4,300 respondents using a probabilistic draw of the sample from Dynata, a global market research firm.

> **Pros:** Researcher-fielded surveys can be more timely and flexible than federal surveys. In some instances, they can even prove the case for federal statistical programs to add or change survey content.
>
> **Cons:** Sample sizes tend to be quite small and the questions do not go through the same rigorous evaluation as federal surveys.

2. Researcher-Fielded Firm Surveys

Yotzov et al. (2026), as part of a collaboration between the Federal Reserve Bank of Atlanta, Bank of England, Deutsche Bundesbank, and Macquarie University in Australia, fielded survey questions about AI use to a sample of senior executives. The survey covered about six thousand CFOs, CEOs, and executives from stratified firm samples across the United States, United Kingdom, Germany, and Australia. Similar to early waves of the ABS, Yotzov and coauthors ask about AI and AI-related technologies, ranging from LLMs to robotics to autonomous vehicles.

Pros: One argument in favor of company leadership surveys is that they are more likely to accurately capture AI use because company leadership have a clearer view of technology adoption at the firm. Firm surveys from the statistical agencies, on the other hand, may go to junior employees less able to assess the firm's technology use. Researchers disagree on whether this claim is true.[6]

Cons: Firm-level researcher-fielded surveys suffer from the same limitations as the worker-level ones do: They have small samples and lack the rigorous statistical infrastructure within the federal statistical system.

3. Polling Data

Apart from researcher-fielded surveys, Pew Research and Gallup have fielded questions about individual AI use multiple times over the past several years. These polls collect information on everything from the percent of workers using AI, to sentiment about data center construction, to use of AI by young adults, to how AI is shaping college degree selection.

Pros: Polling firms can produce timely statistics using highly flexible collection infrastructure. This flexibility covers not only which questions to ask, but also which samples of individuals to target (e.g., workers versus students). Unlike some of the researcher-fielded surveys, private polling firms do have longstanding statistical infrastructure and methodological expertise to ensure data quality.

Cons: Compared to statistical agencies, private polling firms tend to be less transparent about their collection methods and have smaller samples. As with researcher-fielded surveys, private polling firms are at best a complement to federal statistics when it comes to measuring the impacts of AI on the economy.

Below I summarize the empirical evidence from researcher-fielded surveys and private polling data.

TABLE 2. Findings on AI's Impacts from Researcher-Fielded Surveys and Polling Data

Researcher-Fielded Worker Surveys	Bick, Blandin, and Deming (2024) find that as of late 2024, about 27 percent of workers used generative AI at work in the past week. They also find that AI use generates time savings equivalent to 1.4 percent of work hours. Hartley, Jolevki, Melo, and Moore (2025) find similar patterns, reporting AI use rates for workers of 30 percent in December 2024, rising to 36 percent by December 2025.
Researcher-Fielded Firm Surveys	Yotzov et al. (2026) report that 78 percent of U.S. firms use at least one AI-related technology and 54 percent use LLMs for text generation. They also find that 89 to 91 percent of firms report no impact of AI on employment or productivity in the past three years, but only 39 to 42 percent expect no impact on employment or productivity over the next three years.
Polling Data	Pew Research reports that the share of workers using AI at work rose from 16 percent in 2024 to 21 percent in 2025. Gallup reported that the same percent rose from 12 percent to 19 percent over the same period. Gallup found that 42 percent of bachelor's degree students reported that AI had already caused them to give a "fair amount" of thought to their major, with 13 percent reporting they thought about it a "great deal."

Private Data

Perhaps the most direct measure of AI use by firms is whether or not they purchase AI services. Ramp, a fintech firm specializing in expense management, produces an AI index based on AI-purchased services.

Proprietary data can also be combined with other information to indirectly measure the impacts of AI. For example, the Automatic Data Processing corporation (ADP) provides HR and payroll services, generating significant amounts of data on private-sector employment. Brynjolfsson, Chandar, and Chen (2025) combined ADP data with measures of occupational AI exposure to calculate changes in employment between exposed and non-exposed workers.

Similarly, data derived from job postings (Lightcast) or career profiles (Revelio) have been used to understand the impacts of AI on workers. As with the payroll processing data, researchers typically combine job postings and career data with occupation-level AI exposure measures. For example, Iscenko and Curto Millet (2026) combine Lightcast data with occupational exposure to measure trends in job postings for AI-exposed workers. Frank et al. (2026) combine Revelio data with unemployment insurance claims to measure unemployment risk by AI exposure. Similarly, Hosseini and Lichtinger (2025) use job postings data from Revelio Labs to classify firms based on postings for “GenAI integrator” roles.

More recently, AI labs themselves have stepped into the AI measurement space. In 2025, Anthropic published its first Anthropic Economic Index, which leveraged internal usage data to analyze how users interact with their AI systems, using that information to characterize which types of tasks are automated versus augmented by AI (Handa et al. 2025). OpenAI also published an analysis of their internal data and how ChatGPT was used to perform different tasks (Chatterji et al. 2025). Researchers at Microsoft used conversations with Bing Copilot (now simply Copilot) to classify the activities, scope, and success of workers’ use of AI to compute an AI applicability score for each occupation (Tomlinson et al. 2025).

Mapping actual LLM-usage patterns to tasks provides an additional lens through which to see occupation-level exposure.

Pros: Compared to survey data, private administrative records like those from Ramp, ADP, Lightcast, and Revelio are often large enough to conduct highly granular analyses, allowing researchers to “zoom in” to focus on particularly interesting subsamples of the data. Private administrative data can sometimes offer unique insights because of the special nature of the data. Data on generative AI usage from within the AI labs, for example, provide a type of information that would be difficult to replicate with surveys.

Cons: The user base of a particular firm, like Ramp or ADP, is not going to be representative of the universe of businesses. Without being properly reweighted, especially for smaller, more-highly-selected samples like Ramp's user base, it cannot be informative of national AI use rate trends among businesses. Businesses also have different incentives than the federal government, which can threaten the reliability and longevity of the statistics. At any point, a firm may decide it is no longer profitable to produce public-use statistics.

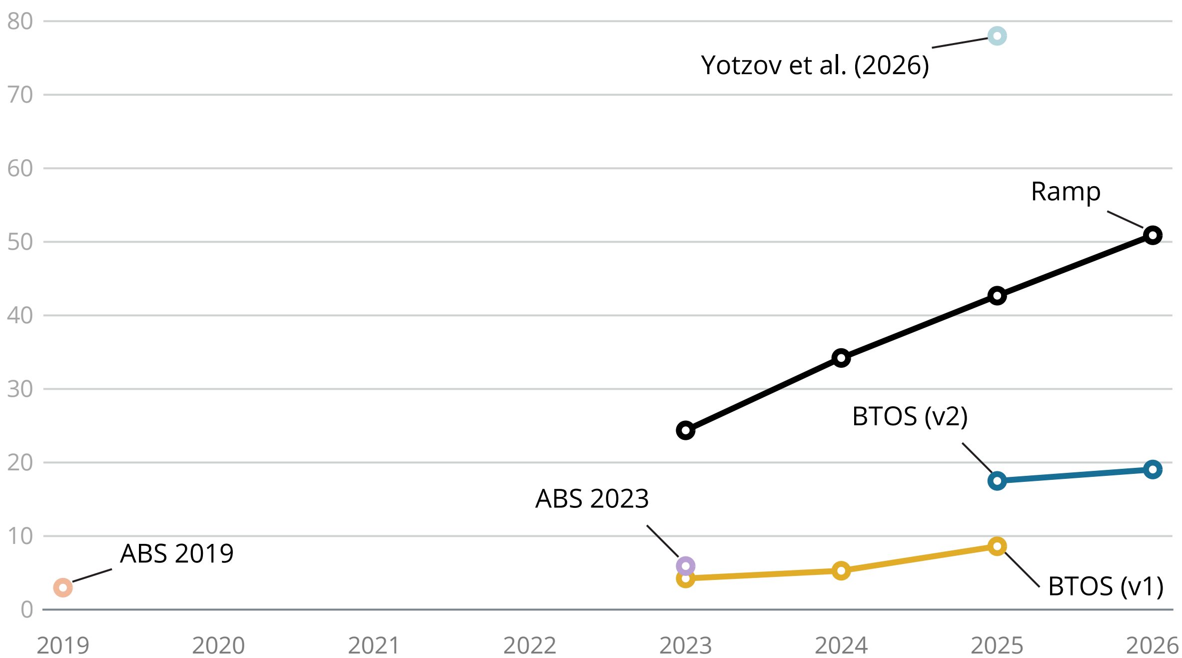
Below I summarize the empirical evidence on AI's economic impacts from private data sources.

TABLE 3. Findings on AI's Impacts from Private Data

Ramp	Ramp's AI Index reports that 6.6 percent of businesses used AI at the beginning of 2023, rising to 26 percent by January 2025, then jumping another 13 percentage points over the following few months, reaching to 48 percent in February 2026. Stevens (2025), using Ramp data, found that businesses more reliant on online labor marketplaces (e.g., Upwork, Fiverr) decreased spending on those marketplaces as they increased spending on AI.
ADP	Brynjolfsson, Chandar, and Chen (2025), combining occupational exposure and ADP data, found that AI-exposed workers ages 22–25 saw 16 percent relative employment declines after controlling for firm-level shocks.
Lightcast and Revelio	Both Iscenko and Curto Millet (2026), using Lightcast data, and Frank et al. (2026), using Revelio data, find that the decline in AI-exposed jobs began prior to the November 2022 release of ChatGPT. Hosseini and Lichtinger (2025), using Revelio data, find that firms posting "GenAI integrator" roles reduced junior hiring. Lambert and Schindler (2026) use both Revelio and Lightcast data to compare the effects of the adoption of AI and work-from-home, finding that work from home policies are a more robust predictor of declines in early-career hiring than AI.
AI Lab Data	Handa et al. (2025), which describes the methodology for the initial Anthropic Economic Index, found that AI use is concentrated in a relatively small number of tasks, with software development and writing accounting for about half of usage. Even so, they also find widespread usage of AI across occupations: 36 percent of occupations use AI for at least a quarter of their associated tasks. Chatterji et al. (2025), using proprietary ChatGPT usage data, found that work-related chat messages have grown from 53 percent to more than 70 percent of all usage between 2022 and 2025, with writing being the most common task. Tomlinson et al. (2025) use data from Microsoft Bing Copilot chats to find that the most common and successful work activities being assisted by AI include the creation, processing, and communication of information. They use this data to predict which occupations are more likely to delegate tasks to AI versus assist existing workflows.

Figure 1 demonstrates the variability of even the most basic statistic — what percent of businesses use AI. Estimates for the percent of businesses using AI in 2025 range from 9 percent to 78 percent. As noted above, the quality of the data varies significantly across the measures.

FIGURE 1. Percent of Businesses Using AI



ABS 2019 is the count of AI using firms (low, moderate, or high use) divided by total reporting firms. ABS 2023 is the count of firms testing or using AI divided by total reporting firms. BTOS (v1) is the annual average percent of firms using AI in the production of goods or services. BTOS (v2) is the annual average percent of firms using AI in any business function. Ramp is the annual average of the share of businesses with paid subscriptions to AI models, platforms, and tools. Yotzov et al. (2026) is the percent of businesses using "Any AI Technology" (Figure 5 of Yotzov et al. (2026)).

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Recommendations

My recommendations for improving AI measurement would leverage the survey infrastructure and administrative records that already exist. Some recommendations will require lifting regulatory barriers for sharing data, and some will require additional resources to create new data infrastructure or process additional survey responses.

All of these recommendations are feasible — I would not make them otherwise — but the shape and execution would be down to the highly capable staff at statistical agencies, whose expertise would guide their implementation.

Even if every recommendation were someday implemented, it's important to recognize that different measurement methods will continue to answer different questions, each filling in a few pieces of the wider puzzle. But taken together, and with these improvements, the ability of the statistical agencies to track and make sense of AI's effects on the economy will be commensurate with the importance of the task.

1. Add AI questions to the ABS every year and run more-frequent AI Supplements in the BTOS.

Right now, truly deep measures of firm AI use and its impacts are only released every few years. AI supplements to the ABS and BTOS should instead run every year.

Multiple versions of tested and validated AI-related questions already exist. On and off since 2018, the ABS has been asking about AI use and its impacts on the demand for labor and skills. The first AI supplement to the BTOS — which asked about changes to labor demand, worker task substitution, and barriers to adoption — ran from December 2023 to February 2024. A second BTOS supplement ran in late 2025 and early 2026.

The best of these questions should be added to the ABS and BTOS annually. At a minimum, the ABS should include questions about AI use and impacts on the demand for labor and skill. Additional candidates would include questions about the intensity of use, how firms use AI, and barriers to adoption. As with the BTOS, the ABS should have a consistent set of "core" questions with periodic supplemental questions responsive to current measurement needs.

Asking questions about AI use on the ABS would provide direct estimates of the impacts of AI from a large sample with many complementary measures about firm characteristics. More-regular BTOS AI supplements would provide better real-time estimates of AI diffusion and its impact on firms' labor demand. Importantly, BTOS is a highly reactive survey, able to change content in response to evolving measurement gaps. Having regular BTOS AI supplements also provides space in the future for new types of questions about AI's impacts that we have yet to consider.

2. Add occupation to the Quarterly Workforce Indicators data.

Using data from surveys like the CPS to understand how occupations are expanding or contracting, in real time, is inherently limited by small samples. A better approach is to use administrative data, like that provided by the Quarterly Workforce Indicators (QWI), which would provide very large samples that can be reliably disaggregated, yielding a high-fidelity view of the evolution of work.

For background, the QWI publishes quarterly measures of employment, earnings, hires, and separations by industry, geography, and demographic characteristics. These data are derived from the administrative records of state-level unemployment insurance (UI) systems. Through agreements with individual states, the Census Bureau ingests state UI data and integrates them into a national employee-employer database called the Longitudinal Employer-Household Database (LEHD). Those data are then used to tabulate the QWI.[7]

Unlike surveys such as the CPS, the QWI is based on millions of administrative UI records. Those data are large enough to produce highly detailed tabulations. Given that the publication lag of the QWI is about three quarters, it is relatively timely as well, precluding the need for data partnerships between statistical agencies and private payroll processing firms such as ADP to get timely workforce data.[8]

QWI tabulations by occupation make it possible to have timely measures of which occupations are expanding and which are contracting. Changes by occupation could be combined with occupational AI exposure and task measures to help evaluate how AI is affecting specific types of work.

There are two primary ways to get occupation information onto the QWI.

First, occupation could be extracted from IRS 1040 forms. Bryant et al. (2024) already made significant advances in this direction. Once extracted, these occupation codes could be matched to the QWI microdata at the person level, allowing for tabulations of hires and separation by occupation.

Linking administrative data, especially when it involves unstructured text, is no small task. Beyond securing administrative approvals for access to the data, validating the scope of matched data takes time. But the work of Bryant et al. (2024) gives a headstart.

The second approach is to have occupation information collected within the state-level UI systems. Washington state, for example, has already begun requiring the reporting of occupation codes.

Integrating occupation fields flowing from state UI records is a relatively simple task that would require evaluation and validation. Coordinating and standardizing state-level processing, however, would be difficult.

3. Add AI questions to the Job Openings and Labor Turnover Survey.

Of the many effects AI may have on the labor market, increased churn, as workers move between jobs and occupations, is likely to be an important one. With relatively minor additions to an existing survey, we can see these impacts almost in real time.

The Job Openings and Labor Turnover Survey (JOLTS), published by the Bureau of Labor Statistics, provides monthly measures of job openings, hires, quits, and layoffs by ownership (private versus public), region, supersector, and select industry sectors. JOLTS provides measures of labor market tightness and dynamism (churn).

JOLTS data are collected using an establishment-level survey, where firms are asked to report the total number of job openings, hires, quits, and layoffs in a given month. Questions about AI should be added to the JOLTS form. Questions about whether the firm uses AI would allow for tabulations of labor dynamics by AI usage. Self-assessment questions could also be considered, subject to evaluations of the efficacy of those questions. For example, the form could ask the business for the count of hires and separations that were made due to its use of AI. Self-assessment questions are unlikely to be useful forever, but they could be informative in the short run.

Relative to ABS and BTOS supplements, JOLTS data with questions about firm AI use and AI-induced job changes would provide more-direct measures of magnitudes of how AI affects labor dynamics. Whereas ABS and BTOS provide measures of whether firms increased, decreased, or did not change their employment due to AI, expanded JOLTS data could potentially provide the count of hires and layoffs due to AI.

A recent bipartisan Senate letter urged statistical agency heads to produce better measures of AI's economic impact, calling for a similar approach. In the letter, senators suggested the collection of "how many hires, job postings, and layoffs are directly related to the business' use of AI." (The letter also suggested that occupation be added to the JOLTS questionnaire in order to better understand shifting labor demand by occupation. The goal is an important one, but occupation detail on the JOLTS is not the way to achieve that. As described above, occupation on the QWI would provide much richer information with much larger samples that allow for far greater tabulation detail and would not impose significant burden on respondents.)

4. Add supplemental questions to the CPS.

Analyses of researcher-fielded surveys have demonstrated the value of worker-level surveys of AI use. They can tell us how many workers are using AI at home and at work, and they can provide insights into how individuals are using it.

The natural home for these inquiries within the federal statistical system is the CPS. The CPS is useful as a way to characterize individuals, both those in and out of the labor force. It has been used to measure the labor market outcomes of workers in highly-AI-exposed occupations, but it is unable to provide sufficient detail to identify patterns for smaller samples of workers, for example highly-exposed young workers with certain jobs.

Supplemental AI questions for the CPS could leverage the lessons learned from Bick, Blandin, and Deming (2024) by asking individuals about their use of generative AI at work and at home.[9] The CPS could also ask more-detailed questions about which types of tasks individuals use AI for, and how intensely they use it. The answers would not only improve our understanding of individual-level diffusion, but also help account for underestimation of AI's impact on national income through households and non-market production, as noted by Makridis and Brynjolfsson (2026).

5. Link firm-usage information from surveys like ABS and BTOS to employee-employer data.

Being able to combine occupation-level data from the QWI with occupation AI exposure as described in Recommendation 2 is useful, but we can do better than simply guessing who is impacted by AI using exposure measures.

Thanks to surveys like ABS and BTOS, we know which firms report using AI. By linking these surveys to the QWI microdata, we would be able to see how employment, hires, and separations differ between AI-using firms and all other firms by geography, industry, and, with the enhancement noted above, by occupation.

6. There should be more data-sharing agreements between AI labs and statistical agencies.

In 2019, then Deputy Director of the U.S. Census Bureau Ron Jarmin, in a reflection on the future of economic statistics, noted the importance of "private, academic, and government data providers find[ing] new ways to collaborate to leverage their different strengths." This sentiment is as true for AI as it is for any measurement problem.

Information on businesses that purchase AI services could be matched to administrative records within statistical agencies, under the strict privacy protections that govern the statistical use of information by the agencies. This matching could be done in much the same way that businesses listed on publicly available patent records are matched to data covering all non-farm employer businesses to create new statistical products. Those matched data could be used to characterize aggregate patterns for AI-using firms, and further linked to QWI data to characterize labor market outcomes as well.

7. Scale efforts to find AI business starts in the Business Formation Statistics.

An important way in which AI will have an impact on employment is through supply-side effects. New technologies generate new products and services, which are disproportionately introduced by startups. Indeed, radical changes in the relationship between labor and AI are likely to appear through new systems of production that are designed with AI from the ground up.[10]

It is important to track the formation of businesses introducing these novel implementations of AI. A prototype method for how to do this was introduced by Dinlersoz, Dogan, and Zolas (2024). Their method uses natural language processing techniques to identify AI-related startups among EIN applications that flow through to the Business Formations Statistics, a real-time public-use database of potential business starts. This approach should be scaled, improved, and translated into a public-use “Potential AI-startups” data series.

8. Scale efforts to link university records to QWI data.

How is AI influencing skill acquisition and early-career college graduates? Analyses using American Community Survey (ACS) or CPS data to study the labor market outcomes of recent college graduates are inevitably hampered by small samples (CPS) or slow data releases (ACS). Enhancing both existing data on university graduates and QWI could give us a much richer view of how college graduates are adapting to AI.

The Post-Secondary Employment Outcomes (PSEO) data provides tabulations of earnings and employment outcomes for college and university graduates by degree level, degree major, post-secondary institution, and state of institution. Coverage varies significantly by state and is reliant on establishing relationships with individual institutions. This effort could be scaled with additional resources to expand coverage and improve timeliness. These data would provide useful information about how skill acquisition is changing and about AI’s impacts on early-career college graduates.

9. Standardize the production of AI-usage data by large AI labs and augment with statistical agency expertise.

AI labs have already begun distilling their proprietary usage information into measures of AI’s impact on workers. Both Anthropic and OpenAI have translated human-AI conversation text into tasks performed and whether AI is augmenting or automating tasks. This task-level information can be aggregated to occupation codes, which then match directly to statistical products like the CPS, OEWS, and, if augmented as described in Recommendation 2, the QWI. A standardized methodology for translating usage data into task-level metrics would increase the value of statistical products derived from them.

Relatedly, New, Meyjes, and Carson (2025) propose normalizing usage information and linking it to North American Industry Classification System (NAICS) codes. Mapping business customer information into NAICS codes is a nontrivial task, in part because industry classification is fundamentally an establishment-level concept (a single, physical location where business is conducted) while customer information may be collected at the firm level (a collection of one or more establishments under common ownership or control).

It is unlikely that the AI labs would have the information necessary to link usage to industry codes. But data-sharing agreements could maximize the value of the statistics generated by the labs, which are based on distillations of AI usage data.

10. Augment Quarterly Workforce Indicators (QWI) data with data from the National Directory of New Hires (NDNH).

As noted in Recommendation 2, the QWI data have incredible potential to enhance our understanding of AI and the labor market. Adding occupation is one important enhancement, but linking it with additional information on hires and UI claims would provide higher-frequency measures of hires and separations.

The National Directory of New Hires (NDNH) data contains information on nearly all hires and UI claims. Housed within the enterprise data infrastructure of the Social Security Administration (SSA), it contains information on all new hires and re-hires, quarterly wages of existing UI-covered employees, and UI applications and claims. The NDNH data are also quite timely. Employers are required to report new hires to state directories within 20 days, and states transmit records to the NDNH at least twice per month.

The NDNH data could be combined with the microdata infrastructure for the QWI, providing higher-frequency measures of hires. If occupation were added to those data, this combination between NDNH and QWI could provide measures of hires and UI claims by detailed industry, geography, and occupation.

11. Encourage detailed econometric studies using matched microdata.

Finally, it is worth stating that tabular statistics provide only a first glimpse of AI's impacts on the economy. In some cases, researchers with clever identification strategies could help us understand the causal impact of AI diffusion. In other cases, deeper generalizable insights may only be possible using detailed microdata housed within the statistical agencies.

Policymakers should encourage this type of work by increasing funding and support for microdata research on AI within the Federal Statistical Research Data Center network.

TABLE 4. Summary of Recommendations

	Recommendation	Benefit
1	**Add AI questions to the ABS every year and run more-frequent AI Supplements in the BTOS.**	ABS: More-regularly collected direct estimates of the impacts of AI from a large sample with many complementary measures about firm characteristics. BTOS: More-regular estimates of AI diffusion and its impact on firms' labor demand. Fast response to important measurement questions.
2	**Add occupation to the Quarterly Workforce Indicators data.**	Timely estimates of shifting labor demand — which types of jobs are growing and which are shrinking, and in which industries and geographies. If combined with occupational AI-exposure measures, could be used to evaluate how AI is impacting employment, hires, and separations.
3	**Add AI questions to the Job Openings and Labor Turnover Survey.**	Timely measures of the count of hires and layoffs at AI-using firms and potentially due to AI, based on the firm's self-assessment.
4	**Add supplemental questions to the CPS.**	The share of individuals and workers using AI, what they use it for, and how they see it impacting their work and home.
5	**Link firm-usage information from surveys like ABS and BTOS to employee-employer data.**	Estimates of employment, hires, and separations at AI-using firms by industry and geography. An important input into longitudinal analyses of causal effects of AI use on firms and workers.
6	**More data-sharing agreements between AI labs and statistical agencies.**	Estimates of the characteristics of businesses actually using AI services, including their employment dynamics and productivity from large samples within a nationally representative sampling frame. These statistics could be separated by intensity of use.
7	**AI business starts in the Business Formation Statistics.**	Timely counts of AI-related business applications with predictions of the number of AI-related employer business formations over the coming two years.
8	**Scale efforts to link university records to QWI data.**	Estimates of the changing demand for skill via the employment outcomes of college graduates by cohort and degree type.
9	**Standardized AI-usage data from large AI labs.**	More useful estimates derived from AI usage information that could be linked to data about workers and businesses.
10	**Combine National Directory of New Hires (NDNH) and Quarterly Workforce Indicators (QWI) data.**	Timely information on hires and UI claims by the characteristics stored within the QWI data, including demographics, industry, and geography.
11	**Encourage detailed econometric studies using matched microdata.**	More informative and detailed evidence about the impacts of AI on workers and businesses, potentially including causal estimates.

Final Thoughts

Much like the proverbial blind men groping an elephant, researchers should be careful not to overly rely on any single measurement or they risk coming away with an incomplete or, worse, false understanding of AI's impact on the economy.

At the same time, there is growing agreement on the need for policy responses, both to accentuate the upsides of the technology and to guard against its risks. Getting that policy right will be all but impossible without a clear view of AI's effects on firms and workers.

Luckily, all the raw materials exist to get it right: survey infrastructure that can be scaled, administrative data to combine, and the human capital within the federal statistical system to make good on the required investments, should policymakers be wise enough to make them.

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Appendix

AI Survey Definitions

ABS 2019 and 2023 Short

Artificial Intelligence: Artificial intelligence is a branch of computer science and engineering devoted to making machines intelligent. Intelligence is that quality that enables an entity to perceive, analyze, determine response and act appropriately in its environment.

ABS 2019 and 2023 Long

Artificial Intelligence: Artificial intelligence is a branch of computer science and engineering devoted to making machines intelligent. Intelligence is that quality that enables an entity to perceive, analyze, determine response and act appropriately in its environment. Systems with artificial intelligence perform functions including, but not limited to, speech recognition, machine vision, or machine learning:

- *Speech recognition transforms human speech into a format useful for computer applications (for example, a digital assistant)*
- *Machine vision uses sensors and software that allow images to be used as an input for computer applications (for example, systems that sort or inspect objects or support navigation in mobile equipment)*
- *Machine learning uses statistical software and data to "learn" and make better predictions without reprogramming (for example, recommender systems for websites, or sales and demand forecasting)*

Artificial Intelligence technologies also include virtual agents, deep learning platforms, decision management systems, biometrics, text analytics, and natural language generation and processing.

BTOS AI Supplement 2023–2024, Artificial Intelligence

Artificial Intelligence is computer systems and software that are able to perform tasks normally requiring human intelligence, such as decision-making, visual perception, speech recognition, and language processing. Types or applications of AI include machine learning, natural language processing, virtual agents, predictive analytics, machine vision, voice recognition, decision making systems, data analytics, text analytics, image processing, etc.
(see Bonney et al., 2024)

BTOS AI Supplement 2025–2026, Generative AI

Generative AI is a type of Artificial Intelligence that uses prompts or other inputs to create text, images, music, videos, or code. Some examples of Generative AI include ChatGPT, Gemini, Copilot, Claude, Dall E, MidJourney, and GitHub Copilot.

Bick, Blandin, and Deming (2024)

Generative AI is a type of artificial intelligence that creates text, images, audio, or video in response to prompts. Some examples of Generative AI include ChatGPT, Gemini, and Midjourney.

Survey Forms

Business technologies questions from the ABS 2018. Full survey form can be found here.

BUSINESS TECHNOLOGIES

In 2017, to what extent did this business use the following technologies in producing goods or services?

Select one for each row.

	No use	Testing but not using in production or service	In use for less than 5% of production or service	In use for between 5% - 25% of production or service	In use for more than 25% of production or service	Don't know
a. Augmented reality	☐	☐	☐	☐	☐	☐
b. Automated guided vehicles (AGV) or AGV systems	☐	☐	☐	☐	☐	☐
c. Automated storage and retrieval systems	☐	☐	☐	☐	☐	☐
d. Machine learning	☐	☐	☐	☐	☐	☐
e. Machine vision software	☐	☐	☐	☐	☐	☐
f. Natural language processing	☐	☐	☐	☐	☐	☐
g. Radio-frequency identification (RFID) inventory system	☐	☐	☐	☐	☐	☐
h. Robotics	☐	☐	☐	☐	☐	☐
i. Touchscreens/ kiosks for customer interface (Examples: self-checkout, self-check-in, touchscreen ordering)	☐	☐	☐	☐	☐	☐
j. Voice recognition software	☐	☐	☐	☐	☐	☐

Production technologies questions from the ABS 2019. Full survey form can be found here.

E.3 Production Technology for Goods and Services

During the three years 2016 to 2018, to what extent did this business use the following technologies in production processes for goods or services?

Artificial Intelligence

- ☐ Did not use
- ☐ Tested, but did not use in production or service
- ☐ Low use
- ☐ Moderate use
- ☐ High use
- ☐ Don't know

E.4 Motivation for Artificial Intelligence Technology Adoption and Utilization – Processes and Methods

During the three years 2016 to 2018, why did this business adopt or use **Artificial Intelligence**?

Select all that apply.

- ☐ To automate tasks performed by labor
- ☐ To upgrade outdated processes or methods
- ☐ To improve quality or reliability of processes or methods
- ☐ To expand the range of goods or services
- ☐ To adopt standards and accreditation
- ☐ Some other reason

E.5 Impact of Artificial Intelligence Technology on Workforce – Processes and Methods

During the three years 2016 to 2018, what were the effects of adopting or using **Artificial Intelligence** on the following?

A. The **number of workers** employed by this business

- ☐ Increased
- ☐ Decreased
- ☐ Did not change

B. The **skill level of workers** employed by this business

- ☐ Increased overall
- ☐ Decreased overall
- ☐ Did not change overall

C. The **scientific, technological, engineering, and mathematical skills of workers** employed by this business

- ☐ Increased overall
- ☐ Decreased overall
- ☐ Did not change overall
- ☐ Not applicable, we did not employ workers with scientific, technological, engineering and mathematical skills

E.6 Impact of Artificial Intelligence Technology on Worker Types – Processes and Methods

Indicate what effect **Artificial Intelligence** had on the following types of workers employed by this business during the three years 2016 to 2018.

A. The number of **production workers**

- ☐ Increased
- ☐ Decreased
- ☐ Did not change
- ☐ Not applicable, we did not employ production workers

B. The number of **nonproduction workers**

- ☐ Increased
- ☐ Decreased
- ☐ Did not change
- ☐ Not applicable, we did not employ nonproduction workers

C. The number of **supervisory workers**

- ☐ Increased
- ☐ Decreased
- ☐ Did not change
- ☐ Not applicable, we did not employ supervisory workers

D. The number of **nonsupervisory workers**

- ☐ Increased
- ☐ Decreased
- ☐ Did not change
- ☐ Not applicable, we did not employ nonsupervisory workers

Technology use questions from the ABS 2022. Full survey form can be found here.

E.8 Use of Technologies

During 2021, to what extent did this business use the following technologies?

Select one for each row.

	A lot	Somewhat	A little	Not at all
a. Advanced computing (e.g., supercomputing, edge computing, cloud computing, data storage, advanced computing architectures)	☐	☐	☐	☐
b. Advanced sensing (e.g., machine vision, voice recognition, networked sensors and sensing, millimeter-wave radar, LIDAR, RFID, biointegrated sensors, electric grid measurement)	☐	☐	☐	☐
c. Artificial intelligence (e.g., machine learning, planning, reasoning, and decision making)	☐	☐	☐	☐

E.9.A. Impact of Artifical Intelligence Technology Use

During 2021, to what extent did this business's use of artificial intelligence technology impact your workforce for each of the following?

Select one for each row.

	Increase	Decrease	No impact	Don't know
a. Number of workers employed at this business	☐	☐	☐	☐
b. Skill level of workers employed at this business	☐	☐	☐	☐
c. The scientific, technological, engineering, and mathematical skills of workers employed by this business	☐	☐	☐	☐
d. Number of production workers	☐	☐	☐	☐
e. Number of nonproduction workers	☐	☐	☐	☐
f. Number of supervisory workers	☐	☐	☐	☐
g. Number of nonsupervisory workers	☐	☐	☐	☐

Technology use questions from the ABS 2023. Full survey form can be found here.

G.3 Production Technology for Goods and Services

During the three years 2020 to 2022, did this business adopt/use the following technologies?

Artificial Intelligence

- ☐ This technology is not applicable to this business
- ☐ Applicable, but did not test or use
- ☐ Tested, but did not use as part of the processes or methods
- ☐ Used as part of the processes or methods
- ☐ Don't know

G.4 Importance of Artificial Intelligence Technology - Processes and Methods

How important was **Artificial Intelligence** for the processes and methods used by this business?

- ☐ Not important
- ☐ Somewhat important
- ☐ Very important

G.5 Motivation for Artificial Intelligence Technology Adoption and Utilization - Processes and Methods

During the three years 2020 to 2022, why did this business adopt or use **Artificial Intelligence**?

Select all that apply.

- ☐ To automate tasks performed by labor
- ☐ To replace or upgrade already existing automated processes or methods
- ☐ To improve quality or reliability of processes or methods
- ☐ To improve quality or reliability of goods or services
- ☐ To expand the range of goods or services
- ☐ To adopt standards and accreditation
- ☐ Some other reason

G.6 Impact of Artificial Intelligence Technology on Workforce - Processes and Methods

During the three years 2020 to 2022, what were the effects of adopting or using **Artificial Intelligence** on the following?

a. The **number of workers** employed by this business

- ☐ Increased overall
- ☐ Decreased overall
- ☐ Did not change overall

b. The **skill level of workers** employed by this business

- ☐ Increased overall
- ☐ Decreased overall
- ☐ Did not change overall

c. The **scientific, technological, engineering, and mathematical skills of workers** employed by this business

- ☐ Increased overall
- ☐ Decreased overall
- ☐ Did not change overall
- ☐ Not applicable, we did not employ workers with scientific, technological, engineering, and mathematical skills

G.7 Impact of Artificial Intelligence Technology on Worker Types - Processes and Methods

Indicate what effect **Artificial Intelligence** had on the following types of workers employed by this business during the three years 2020 to 2022.

a. The ratio of **production** workers to **nonproduction** workers

- ☐ Increased
- ☐ Decreased
- ☐ Did not change
- ☐ Not applicable, we did not employ production workers
- ☐ Not applicable, we did not employ nonproduction workers
- ☐ Not applicable, we did not employ production **nor** nonproduction workers

b. The ratio of **nonsupervisory** workers to **supervisory** workers

- ☐ Increased
- ☐ Decreased
- ☐ Did not change
- ☐ Not applicable, we did not employ supervisory workers
- ☐ Not applicable, we did not employ nonsupervisory workers
- ☐ Not applicable, we did not employ supervisory **nor** nonsupervisory workers

G.8 Timing of Adoption for Artificial Intelligence Technology - Processes and Methods

Approximately what year did this business first adopt or use **Artificial Intelligence** in processes and methods?

- ☐ Prior to 1990
- ☐ 1991 - 1995
- ☐ 1996 - 2000
- ☐ 2001 - 2005
- ☐ 2006 - 2010
- ☐ 2011 - 2015
- ☐ 2016 - 2020
- ☐ 2021 - Present
- ☐ Don't know

G.9 Importance of Cloud-Based Computing Systems and Applications Technology - Processes and Methods

How important was **Cloud-Based Computing Systems and Applications** for the processes and methods used by this business?

- ☐ Not important
- ☐ Somewhat important
- ☐ Very important

G.10 Motivation for Cloud-Based Computing Systems and Applications Technology Adoption and Utilization - Processes and Methods

During the three years 2020 to 2022, why did this business adopt or use **Cloud-Based Computing Systems and Applications**?

Select all that apply.

- ☐ To automate tasks performed by labor
- ☐ To replace or upgrade already existing automated processes or methods
- ☐ To improve quality or reliability of processes or methods
- ☐ To improve quality or reliability of goods or services
- ☐ To expand the range of goods or services
- ☐ To adopt standards and accreditation
- ☐ Some other reason

Technology use questions from the BTOS 2023–2024 AI Supplement. Full survey form can be found here.

24. In the last six months, what types or applications of Artificial Intelligence (AI) did this business use in producing goods or services?
Select all that apply.

- Machine learning
- Natural language processing
- Virtual agents or chat bots
- Speech/voice recognition using AI
- Recommendation systems based on AI
- Large language models
- Text analytics using AI
- Data analytics using AI
- Neural networks
- Augmented reality
- Decision making systems based on AI
- Deep learning
- Image/pattern recognition
- Machine/computer vision
- Robotics process automation
- Biometrics
- Marketing automation using AI
- Other
- None

If the answer to 24 is anything other than "None", then ask 25-29 below:

25. In the last six months, did this business use Artificial Intelligence to perform tasks previously done by employees in producing goods or services?
a. Yes
b. No
c. Do not know

If yes to 25, ask 26:

26. In the last six months, how many tasks previously done by employees were instead performed by Artificial Intelligence?
- A small number
- A moderate number
- A large number

27. In the last six months, did this business use Artificial Intelligence to perform operations previously performed by existing equipment or software in producing goods or services?
- Yes
- No
- Do not know

28. In the last six months, how did the use of Artificial Intelligence affect this business's <u>total employment</u>? • Increased • Decreased • Did not change
29. In the last six months, to use Artificial Intelligence (AI), what changes did this business make? Select all that apply. • Trained current staff to use AI • Hired staff trained in AI • Purchased computing power or specialized equipment • Purchased cloud services or cloud storage • Changed data collection or data management practices • Developed new workflows • Used vendors or consulting services to install or integrate AI • Other • None
30. During the next six months, do you think this business will be using Artificial Intelligence (AI) in producing goods or services? (Examples of AI: machine learning, natural language processing, virtual agents, voice recognition, etc.) • Yes • No • Do not know If yes to 30, then ask 31-36 below:

Technology use questions from the BTOS 2025–2026 AI Supplement. Full survey form can be found here.

24. In the last six months, did this business use Artificial Intelligence (AI) in any of the following business functions?

	Yes	**No**	**Don't know**
Production of goods (e.g., making or assembling products, construction)			
Provision of services, products, or merchandise (e.g., providing services, products, or merchandise to customers)			
Strategy and business development			
Finance and accounting			
Sales and marketing			
Customer service			
Research and development			
Information technology			
Human resources			
Public relations and communication			
Management and administration			
Sourcing, supply chains, and purchasing			
Quality management and control			
Distribution			
Legal and compliance			

25. In the last six months, did this business use Artificial Intelligence (AI) to do any of the following? *Select all that apply*.
    - Perform a task previously done by an employee
    - Supplement or enhance a task performed by an employee
    - Introduce a new task not previously done by an employee
    - None of the above

26. In the last six months, how many tasks previously done by employees were instead performed by Artificial Intelligence (AI)?
    - A small number
    - A moderate number
    - A large number

27. In the last six months, did this business use Artificial Intelligence (AI) to perform operations previously performed by existing software or equipment?
    - Yes
    - No
    - Do not know

28. In the last six months, how did the use of Artificial Intelligence (AI) affect this business's total employment?
    - Increased
    - Decreased
    - Did not change

29. In the last six months, to use Artificial Intelligence (AI), what changes did this business make? *Select all that apply.*
    - Trained current staff to use AI
    - Hired staff trained in AI
    - Purchased computing power or specialized equipment or software
    - Purchased cloud services or cloud storage
    - Changed data collection or data management practices
    - Developed new workflows
    - Used vendors or consulting services to install or integrate AI
    - Other (*please describe*: ____________________)
    - This business did not make any changes to use AI

30. In the last six months, did this business's <u>employees</u> use Artificial Intelligence (AI) to assist in <u>any work-related tasks</u> that support business functions? *(e.g. software coding, writing emails, preparing visualizations, summarizing documents, gathering and processing information)*
    - Yes
    - No
    - Do not know

31. In the last six months, did this business's employees use Generative AI to assist in any work-related tasks? (*Generative AI is a type of Artificial Intelligence that uses prompts or other inputs to create text, images, music, videos, or code. Some examples of Generative AI include ChatGPT, Gemini, Copilot, Claude, Dall E, MidJourney, and GitHub Copilot*.)
    - Yes
    - No
    - Do not know

Skip to 33 if No or Do not know is selected for 31

32. In the last six months, what work-related tasks did this business's employees use Generative AI to assist with? *Select all that apply.*
    - Information processing, paperwork, or filing
    - Writing or editing documents, emails, or communications
    - Interpreting, analyzing, translating, or summarizing documents
    - Customer support
    - Developing or researching new projects, processes, or products
    - Searching for information or technical help
    - Software coding or debugging
    - Data analysis or visualization
    - Tutoring, training, or learning
    - Other tasks (*please describe*: ____________________)

JOLTS survey form for 2026. Full survey form can be found here.

3 Please provide data for the time period indicated for each item. Enter "0" if none. Enter "NA" if data are not available. See the back of this page for explanations of the terms below.

	EMPLOYMENT	**JOB OPENINGS**	**HIRES**	**SEPARATIONS**		
	Number of full- or part-time employees who worked or received pay for the pay period that includes the 12th of the month	A job is open if it meets **all three conditions**: • A specific position exists • Work could start *within 30 days* • You are actively seeking workers from outside this location to fill the position	A hire is any addition to your payroll, and: • May be a new hire or a previously separated rehire • May be permanent, short-term, or seasonal • May be a recall from layoff	**Quits** (Except retirements)	**Layoffs and Discharges** • Layoffs • Discharges • Terminations of permanent, short-term, or seasonal employees	**Other** • Retirements • Transfers from this location • Employee disability • Deaths
Report for month of:	**A** **Total Employment** ***for the pay period that includes the 12th of the month***	**B** **Number of Job Openings** ***on the last business day of the month***	**C** **Hires and Recalls** ***for the entire month***	**D** **Quits**	**E** **Layoffs and Discharges** - - - - - - ***for the entire month*** - - - - -	**F** **Other Separations**

Pew survey questions about AI and work. Full questionnaire can be found here.

QUE: AIWRKDONE1
ASK IF HEARD OF AI USE IN THE WORKPLACE (AIWRKHEARD=1,2):
[PN: ROTATE RESPONSE OPTIONS 1-5/5-1, HOLDING 6 AND 99 LAST; INCLUDE ROTATION IN DATA FILE]

Now thinking of the tasks you do in your job, how much of your work is done with AI?

[PN: IF CATI:] (READ LIST)

1 All
2 Most

3 Some
4 Not much
5 None
[PN: INSERT A LINE OF SPACE]
6 **[PN: IF WEB:]** Not sure **[PN: IF CATI:]** Or are you not sure?
99 **[PN: IF WEB:]** Web blank / **[PN: IF CATI:]** **(DO NOT READ)** Refused

Endnotes

1 See the AI Workforce PREPARE Act introduced by Senator Jim Banks and the Great American Artificial Intelligence Act introduced by Representatives Jay Obernolte and Lori Trahan.

2 The survey questions in the ABS and BTOS evolved over time and are nicely summarized by Dinlersoz et al. (2025).

3 This percentage is for the percent of businesses responding "yes" to using AI, pooling data for 2023 to 2025. Suppression of specific data points are made to avoid the disclosure of sensitive information about individuals and businesses.

4 AI exposure measures are mostly built by classifying the overlap between AI capabilities (actual or theoretical) and individual tasks, which are then aggregated to occupations to characterize whether workers in an occupation are "exposed" to AI or not. See the appendix of Eckhardt and Goldschlag (2025) for additional details, and Gimbel, Kendall and Kulsakdinun (2026) for a comparison of the different AI exposure measures.

5 In 2025, similar questions about AI use were included in the Federal Reserve's Survey of Household Economics and Decisionmaking (SHED).

6 Analyses done by Bonney et al. (2026) of different types of BTOS respondents, from top executives and owners to administrative support, suggest that this could only account for a modest difference in overall use rates. Moreover, the probability that firm leadership is responding to a firm survey increases as size decreases. This would suggest that the Census Bureau's surveys should be more accurate for small firms, which had use rates at about 18 percent in early 2026 compared to the 78 percent reported by Yotzov et al. (2026). Finally, as noted above, the Census Bureau has a "cognitive testing" protocol for new survey questions that involves fielding potential questions with individuals that would be filling out the forms. If those interviews suggest that respondents would be unable to answer the question, the question is either rewritten or not fielded.

7 The BLS uses state UI data to tabulate the Quarterly Census of Employment and Wages (QCEW) and the Business Employment Dynamics (BED) data.

8 See, for example, Manning (2025).

9 See example questions that could be added to the CPS, drafted by FAI, and building upon Bick, Blandin, and Deming (2024).

10 An example of this is the differential impact of ATMs versus smartphones on bankteller employment. ATMs allowed firms to do more of the same, while smartphones and mobile banking changed the business model entirely.