The Labor Market Effects of Generative Artificial Intelligence

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Abstract

In this paper we develop a new survey analyzing Generative AI use in the labor market to assist in measuring the economic effects of Generative AI. We find, consistent with other surveys that Generative AI tools like large language models (LLMs) are most commonly used in the labor force by younger individuals, more highly educated individuals, higher income individuals, and those in particular industries such as customer service, marketing and information technology. Overall, we find that as of December 2024, 30.1% of survey respondents above 18 have used Generative AI at work since Generative AI tools became public. We also estimate Generative AI use at the intensive margins, its efficiency gains and its use in job search. We also seek to examine the effects of LLMs on productivity and the labor market using a number of additional datasets. These results have several implications for policymakers, businesses, and researchers navigating the evolving landscape shaped by the integration of Generative AI into the global economy.

Keywords: Large Language Models, Artificial Intelligence, Employment Dynamics, Automation, Skills

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1 The Economics of Generative AI

"Yet there is no country and no people, I think, who can look forward to the age of leisure and of abundance without a dread" -John Maynard Keynes, Economic Possibilities for our Grandchildren (1930)

The advent of generative artificial intelligence (AI) tools such as large language models (LLMs), enabled by the rapid declines in the cost of computing (Nordhaus (2008), Nordhaus (2021)) creates new and uncertain possibilities for such tools to raise productivity and reshape demand for labor within and across firms and industries (Figure 1).

In the past decade there have been statements and analyses about the recent decline in productivity and economic growth being a result of running out of ideas (Gordon (2015), Bloom et al (2020)), or "secular stagnation" and the lack of public investment (Summers (2015)).

Meanwhile, others have suggested that we may be approaching a point in time (or "singularity") that unleashes new innovations and productivity in part through machine learning and artificial intelligence (Brynjolfsson and McAfee (2014), Nordhaus (2021)).

Much of the labor market effect of generative AI will hinge on whether it is a complement or substitute for existing tasks performed by workers of differing skill levels. Complements would see enhanced wages along with productivity gains while labor substitutes would see declining or stagnant wages along with productivity gains.

There is little currently known about the pervasiveness of Generative AI and its potential effects given the recent release of such associated tools. Several key moments in the advent of Generative AI include the public launch of OpenAI's ChatGPT (the first publicly accessible LLM) in November 2022 and GitHub's AI-powered Copilot Chat feature launched in public beta in July 2023.

The number of employees hired by Generative AI firms producing AI tools such as OpenAI, Anthropic, and Google DeepMind has also been increasing considerably according to LinkedIn data (there are approximately 3500 employees at Google DeepMind, 3000 at OpenAI and, 1000 employees at Anthropic [see Figure 5 in Appendix]). The demand for artificial intelligence for PhDs in AI has risen substantially in recent years with the advent of Generative AI. Software engineers at such firms are often paid between $500,000 and $900,000 in USD, with a long upper tail[1].

The extent of the use of such Generative AI tools in the economy such as LLMs like ChatGPT has grown slowly since their initial release. Pew Surveys conducted about the use of ChatGPT give us a glimpse into the use of ChatGPT in the United States. According to a 2023 Pew survey, about 1 in 5 teens have used ChatGPT for schoolwork. [2] Pew Survey data finds that as of February 2024, approximately 20% of the U.S. workforce have used ChatGPT at work at least once over the past year.[3] In particular, LLM use at work skews toward younger individuals with over 30% of those surveyed Aged 18-29 reported using ChatGPT at work at least once over the past year compared to only 10% of those aged over 50.

The Pew Surveys also find that ChatGPT use at work over the past year varies significantly across educational attainment with those with a postgraduate degree are four times more likely to use ChatGPT than workers with a high school diploma or less (Figure 3).

With respect to firm use of Generative AI, Bonney et al (2024) insert AI-related questions into the U.S. Census-run biweekly Business Trends and Outlook Survey (BTOS) of 200,000 firms, finding real-time estimates of current and expected future use of AI for business purposes. They find the AI use rate among firms rose from 3.7% in September 2023 to 5.4% in February 2024, and expect the AI use rate to increase to about 6.6% by early Fall 2024.

These trends will likely continue upward as Generative AI adoption continues.

[1] See Levels software engineer wage data for Software Engineer wages working in Generative AI: https://www.levels.fyi/companies/openai/salaries

[2] Sidoti, Olivia and Jeffrey Gottfried, "About 1 in 5 U.S. teens who've heard of ChatGPT have used it for schoolwork", Pew Charitable trusts https://www.pewresearch.org/short-reads/2023/11/16/about-1-in-5-us-teens-whove-heard-of-chatgpt-have-used-it-for-schoolwork/

[3] Pew Surveys: https://www.pewresearch.org/short-reads/2024/03/26/americans-use-of-chatgpt-is-ticking-up-but-few-trust-its-election-information/ https://www.pewresearch.org/short-reads/2023/08/28/most-americans-havent-used-chatgpt-few-think-it-will-have-a-major-impact-on-their-job/ https://www.pewresearch.org/short-reads/2023/05/24/a-majority-of-americans-have-heard-of-chatgpt-but-few-have-tried-it-themselves/

This paper aims to fill this gap by offering a thorough economic analysis of the productivity and labor market effects associated with the introduction of large language models. Many papers over the past decade attempt to analyze "AI" or artificial intelligence, vaguely and broadly defined, and its impact (Acemoglu et al (2022)). This paper is specifically interested in the economic effects of Generative AI, that is technologies related to the advent of transformer foundation models, massive neural network-based architectures designed to process and generate human-like text, which became public in late 2022.

In our own survey, we find that (as of December 2024) 30.1% of survey respondents above 18 have used Generative AI at work since Generative AI tools became public consistent with other surveys. Among those who report to use Generative AI at work, about one third claim to use it every workday, while selectively using it for a limited number of hours per week. We also seek to examine the effects of LLMs on productivity and the labor market using a number of additional datasets. These results have several implications for policymakers, businesses, and researchers navigating the evolving landscape shaped by the integration of Generative AI into the global economy.

Understanding how Generative AI shapes productivity and labor markets will be crucial for understanding potential regulatory policies in the space. This research contributes to this ongoing dialogue through creating a new survey that tracks the extent of Generative AI use in the U.S. labor force across time. The ultimate goal with such surveys is to measure the labor market impact of Generative AI and LLMs and how the wage structure is impacted.

The rest of this paper is as follows. Section 2 describes the literature. Section 3 discusses the survey and its results. Section 4 concludes.

2 Literature Review

2.1 Generative AI Capabilities

The scope of applications of such Generative AI technologies is massive, giving much credence to the idea the LLMs and related Generative AI technologies are General-Purpose Technologies (or GPTs), that is technologies that can affect an entire economy (Bresnahan & Trajtenberg (1995)).

A significant amount of the economics and machine learning literature on Generative AI is focused on its capabilities in doing specific tasks better than humans which has direct implications for productivity. Brown et al (2020) is one of the early papers in this literature to compare transformers (specifically ChatGPT-3) to human performance across a number of tasks finding transformer outperformance.

One literature examines how well LLMs can perform on exams of various aptitude levels. For instance, Geerling et al (2023) finds that ChatGPT can complete microeconomics and macroeconomics standardized exams (Test of Understanding in College Economics (TUCE)) in the highest percentiles of human performance. Greska (2024) finds that LLMs can outperform humans in Kaggle competitions.

Within academic economics, a new literature has developed analyzing the extent to which LLMs can better assist economists and academics. Korinek (2023) analyzes how LLMs can assist research economists in six areas: ideation and feedback, writing, background research, data analysis, coding, and mathematical derivations. Charness, Jabarian & List (2023) discuss how LLMs can improve experimental design (eg. elicitation wording, coding experiments, and producing documentation), experimental implementation (consistent experiences, instruction comprehension, and participant engagement monitoring) and analyzing experimental data (pre-processing, data cleaning, and assisting reviewers and replicators in examining studies). Horton (2023) analyzes the use of LLMs to create simulated economic agents and run classic economic experiments traditionally run with human subjects finding similar results.

While broader literatures on Generative AI capabilities are extensive, giving a significant number of examples of Generative AI capabilities, this project is focused squarely on understanding the large-scale productivity, labor market and macroeconomics effects of such tools.

2.2 Measuring The Micro Productivity Effects of Generative AI

Since the public release of ChatGPT 3.5 in December 2022, a number of well-identified studies (RCTs as well as observational studies) have specifically analyzed the productivity effects of Generative AI transformers, large language models (LLMs) and their derivative technologies.

Brynjolfsson, Li and Raymond (2023) analyze the staggered rollout of a generative AI-based conversational assistant among 5,179 customer support agents finding positive effects on customer sentiment and employee retention as well as fewer requests for managerial interventions enhancing productivity. Anecdotal evidence also supports stories of firms replacing customer service agents with Chatbots.[4]

Noy and Zhang (2023) in an experimental setting analyze the productivity effects of using the chatbot ChatGPT—in the context of mid-level professional writing tasks finding that ChatGPT substantially raises average productivity (time taken decreases by 0.8 SDs and output quality rises by 0.4 SDs).

In another experimental setting, Dell'Acqua et al (2023) randomizes GPT-4 tools to Boston Consulting Group consultants and measures the effects on productivity. Randomly assigned consultants to one of three conditions: no AI access, GPT-4 AI access, or GPT-4 AI access with a prompt engineering overview. They find that in each one of of 18 tasks, consultants using the AI tool were significantly more productive relative to the control group in the number of tasks completed and the number of time it takes to complete a task as well as producing significantly higher quality results.

Peng et al. (2023) experimentally investigates how GitHub Copilot affects the productivity of software developers finding significantly positive productivity effects.

One important trend worth highlighting is that in all cases of the above studies, less skilled workers did better (inequality between workers decreases).

Some well-documented productivity enhancements in well-identified settings are less industry-specific but rather highlight potential productivity enhancements in broader labor market contexts. Wiles, Munyikwa and Horton (2023) run an RCT in a large online labor market treating jobseekers with algorithmic writing assistance on their resumes finding that treated jobseekers were hired 8% more often. Similarly, Wiles and Horton (2024) run an RCT using LLMs to create first drafts of job postings for firms finding that LLMs can significantly decrease time firms spend writing a job post and increase the number of job posts (the authors also find no difference in the number of hires between treatment and control firms). Spatharioti et al. (2023) conducts an RCT evaluating the effectiveness of LLM-based tools versus traditional internet search tools with various search tasks finding that LLMs outperform.

With respect to what industries have been most impacted by LLMs, some evidence points to industries involving writing, coding, or visual tasks such as customer service (Brynjolfsson, Li and Raymond (2023)), software engineering (Peng et al (2023)) and marketing (assisted by the advent of visual Generative AI assistants such as OpenAI's DALL-E).

These heavily-impacted industry areas are confirmed by evidence from the introduction of LLMs and Upwork. Upwork, an online task market and a frictionless spot labor market setting, offers a window into what the broader labor market effects of Generative AI may look like in the future. Research by Upwork finds a marked increase in overall freelancer earning per contract immediately after the release of ChatGPT (Liu, Deng and Monahan (2024)). However, they also find that aggregate earnings on Upwork are most negatively impacted in writing, translation, sales and marketing, and customer service sectors. In contrast, aggregate earnings improved most in areas such as Administrative Support, IT & Networking, Design and Creative, Software Development, and Accounting & Consulting. This suggests that LLMs may be substitutes for writing and visual tasks and more complementary to software related tasks. Hui, Reshef, and Zhou (2023) also analyze Upwork data following the November 2022 release of ChatGPT, finding that tasks involving writing are most impacted. Specifically, they find that the number of monthly jobs for more AI-exposed freelancers on Upwork declined by 2%, while their monthly earnings declined by 5.2%.

There is some suggestion that Generative AI could also transform industries plagued by productivity slowdowns and Baumol's cost disease such as healthcare. For instance, Baker et al (2024) finds using a randomized control trial that ChatGPT has the ability to improve documentation in medical settings.

[4]"ChatGPT provided better customer service than his staff. He fired them", *The Washington Post*, October 3, 2023

Such well-identified microeconomic effects may give some insight to more generalizable effects of generative AI on a more macro level.

2.3 The Prospective Macroeconomic Effects of Generative AI

Across the entire economy, it is not entirely clear what the long-run aggregate GDP gains will be from the advent of Generative AI. As discussed, some survey data of workers and firms have found some limited early evidence of Generative AI take-up so far.

Bonney et al (2024) using Census data finds the AI use rate among firms to have risen to 5.4% as of February 2024, and expect the AI use rate to increase to about 6.6% by early Fall 2024. The Pew Survey data finds approximately 20% of the U.S. workforce have used ChatGPT at work at least once over the past year (skewing toward younger and more educated individuals). These adoption rates are only likely to grow in the future.

Acemoglu, Autor, Hazell, and Restrepo (2022) analyze BurningGlass job vacancies finding substantial growth in AI-related vacancies over 2010–18 period but find undetectable shifts in the wage structure in in more exposed occupations and industries albeit finding some effects at the establishment level. It's worth noting that they study vacancies with AI related task keywords in job descriptions which can differ from Generative AI tasks. Effects on the wage structure from Generative AI will likely depend on their ability to be a complement versus substitute to existing labor.

Looking forward, the stock market provides some forward-looking indicator of expectations surrounding the effects of Generative AI. One sign of high expectations for the growth and prevalnce of Generative AI tools are the rapid gains in the stock price of Nvidia, a the leading GPU chipmaker providing the Generative AI industry necessary tools for matrix multiplication used in transformers. Nvidia is now one the largest companies in the world by market capitalization.

Eisfeldt, Schubert and Zhang (2023) analyze Generative AI mentions during public company conference calls and construct AI-exposure sorted stock portfolios, finding that such more AI-exposed portfolios have high positive expected returns. Alderucci et al (2024) merge census data on firms with patent data in an event study approach finding that firms granted patents containing with AI related text firms experience outsized revenue, employment growth, output per worker growth and less within firm wage inequality relative to firms without AI-related innovations.

Several papers have also attempted to forecast which tasks in the future will be automated by AI often using rubrics, experts or models (eg. a statement of 18 tasks on a scale of 1 to 5 of how much they are automatable). Specifically these papers analyze task data from O*Net. Brynjolfsson, Mitchell, Rock (2018) and Webb (2020) identify tasks automatable by machine learning. Eloundou et al (2023) and Felten et al. (2023) analyze how tasks automatable by LLMs.

These sorts of task grades have the ability to lend themselves to attempts to analyze how the demand for labor across different occupations and industries along with their wage structure, may be affected by LLMs, artificial intelligence and machine learning, a critical question for the future of labor markets.

Several papers also attempt to forecast the impact of Generative AI on real GDP, productivity and income inequality using tools such as Hulten's theorem, industry shares and estimated cost savings.

Brynjolfsson and Unger (2023) forecast the effects of Generative AI on productivity and income inequality.

In a 2023 Goldman Sachs report, the firm suggested that generative AI could increase global GDP by 7% in the next ten years, and that 300 million jobs globally are susceptible to automation.[5]

At the lower end of projected estimates of the contribution of AI to economic growth, Acemoglu (2024) in an evaluation of claims about large macroeconomic implications of new advances in AI finds a 0.66 % increase in total factor productivity over 10 years. Brynjolfsson and Mitchell (2024) uses Hulten's theorem to forecast such effects on GDP finding larger effects.

[5]Goldman Sachs, "Generative AI could raise global GDP by 7%", April 5, 2023 https://www.goldmansachs.com/intelligence/pages/generative-ai-could-raise-global-gdp-by-7-percent.html

Many of these macro studies could be described as proforma and speculative. Without more detailed survey data, conducting such macroeconomics analyses without further precision will continue to be difficult.

3 Generative AI Survey

3.1 Survey Instrument

This paper conducts a survey of U.S. workers (similar to the Pew and Bick, Blandin, and Deming (2024) Generative AI surveys) with IncQuery specifically asking about the use of LLMs in specific tasks and occupations. One goal is to determine whether AI automatable tasks identified by papers such as Eloundou et al (2023), Brynjolfsson, Mitchell, Rock (2018), Webb (2020), and Felten et al. (2023), are actually being used in the context of LLMs.

The first wave of survey results includes 4,278 respondents in a U.S. sample conducted in early December 2024. The survey used a simple random sampling approach with a probabilistic draw of the sample from Dynata. The unit of analysis are workers in the U.S. The survey was self-administrated using a CAWI script.

This questions used in our survey are similar to the survey conducted by Bick, Blandin, and Deming (2024) (which instead uses Qualtrics), asking several questions about Generative AI use as well as other democratic questions about education level, industry, income and many other metrics.

Many of their questions are repeated verbatim in our survey. Many of their questions are focused on the extensive margin in terms of AI use. With respect to time and frequency of Generative AI use, their central question (which we repeat in our survey) is fairly generic and begins with defining Generative AI and Large Language Models.

"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. A Large Language Model is A type of artificial intelligence (AI) model that uses machine learning to understand and generate human language." followed by questions such as “Have you heard of generative AI before?", “Have you used generative AI tools before?", “Do you use generative AI for your job?".

For the purpose of maximizing our sample size of respondents using Generative AI, we ask demographic questions prior to the Generative AI questions and then screen respondents out who do not use Generative AI at work while maintaining the demographic data of those removed in order to produce estimates of Generative AI use. We also screen out respondents under the age of 18 like Bick, Blandin, and Deming (2024), however we include those above age 65 as one difference between surveys. We also use several attention checks.

We also ask further questions about the intensive margin of Generative AI use. For example, we ask questions such as “How many days each week do you use generative AI tools at work?" and “When did you most recently use generative AI tools at work?"

We also ask questions about what types of tasks are being used to complete with Generative AI: "In what tasks are you using generative AI/Large Language models at work?"

See Appendix B for our complete survey instrument.

3.2 Survey Results

Overall, we find that as of December 2024 close to 30.1% of respondents in our nationally representative survey have used Generative AI at work at some point since Generative AI tools became public (Figure 2).[6]

This headline result is close to the December 2024 Generative AI use at work population estimate of Bick, Blandin, and Deming (2024) of 27.1%. One main difference between the two surveys is that our survey is conducted using

[6]To reweight our results, we took the November 2024 CPS (the closest time to when we ran the survey) and restricted to those who were working or held jobs (so not unemployed or NILF), aggregated into two education groups (< BA or >= BA), four age groups (18-34, 35-44, 45-54, 55+), and four races (white, black, hispanic, and other). We then collapse the data by using “wtfinl” which is the variable which estimates how many total Americans a given respondent should represent how many Americans are in a particular age/sex/education/race cell and then divide by the overall working population to determine the nationally reresentative weights.

IncQuery whereas the survey of Bick, Blandin, and Deming (2024) uses Qualtrics.

With respect to education, we find in our survey (consistent with the surveys of Pew and Bick, Blandin, and Deming (2024)) more educated workers are more likely to use Generative AI (Figure 3). Nearly 50% of those in the sample with a graduate degree use Generative AI. 37% of those with a college degree as their highest level education attained use Generative AI. Roughly 20% of those who are only high school graduates or have some college use Generative AI.

With respect to industries, there is a varied picture (Figure 4). Industries most likely to use Generative AI at work include "Information Services" and "Management of Companies" (using Generative AI tools more than 60% of the time) and "Real Estate, Rental, Leasing", "Construction", and "Education" (using such tools more than 40% of the time). Meanwhile workers in industries such as "Agriculture, Forestry, Fishing", "Mining, Quarrying, Oil & Gas", and "Government & Military" use it far less.

Generative AI use is increasing with incomes (Figure 5). However, the increase begins to happen at income levels around above $50,000 where approximately 20% of individuals below this amount say they have used Generative AI at work. Nearly 50% of workers making above $200,000 annually use Generative AI at work.

With respect to gender (Figure 6), a greater proportion of men claim to use Generative AI at work than women in the survey. 38.0% of men report to use Generative AI at work in the sample while 27.8% of women report to use Generative AI at work. With respect to race (Figure 7), we find that Hispanics are most likely to use Generative AI, followed by Black, Other, and White individuals in the sample.

ChatGPT remains the most popular Generative AI tool, closely followed by Gemini (Figure 8). The next most popular tools are GitHub Copilot and Scribe.

On the extensive margin, we found that 30.1% of survey respondents have used Generative AI at work at some point since Generative AI tools became public.

However, the intensive margin of using Generative AI tools at work also tells a different story. Conditional on using Generative AI at work, about 33% of workers use Generative AI five days per week at work (every weekday). Roughly 12% of Generative AI users use such tools at work only 1 day at work. About 17% and 18% of Generative AI users use Generative AI tools at work two and three days per week respectively (Figure 9). The number of hours at work each week using Generative AI tools tells a somewhat different story (the distribution of hours* using Generative AI tools at work however is perhaps less than the number of days worked would imply). While many workers may use Generative AI tools every weekday (or several weekdays), the total hours at work each week using Generative AI tools is reported to be in most cases less than 15 hours, suggesting there is intermittent use of Generative AI throughout the workday (Figure 10).

We also found several other surprising results. For instance, we ask a question about whether one used Generative AI tools to assist in job search if one was unemployed over the past 2 years (since the public release of ChatGPT). We find that over 50% of those unemployed over that time actually used Generative AI tools.

On the whole, these results combined suggest that Generative AI is in part used by those who are most productive (those with highest incomes and most education) and is used in many cases each day at work, albeit intermittently.

3.3 Estimating Productivity Gains

Focusing the analysis on the users of Generative AI reveals insights in the inclusion of this form of intangible capital in the production process. Technological advances have led to Schumpeterian creative destruction, in which less productive firms are replaced with more productive ones. However, with respect to labor markets, the impact of emergent technologies such as generative AI can have varying effects. On the one hand, the new technologies have complementary effects that make some workers more productive than they already are. On the other hand, some jobs in the long-run, or at the very least some tasks, will be substituted.

Through this survey, we observe the labor productivity effects through the time it takes to complete a task with and without the complementarities of intangible capital in the form of Generative AI. On average, workers that use generative AI to complete their task, they spend about 30 minutes working with a generative AI tool, feeding it the necessary information and then using the output to complete the task. Without the use of generative AI, workers

estimate that it would take them about 90 minutes on average to complete the same task (that is about 1 hour of their time at work saved). Hence, this would be a tripling of the productivity of the workers if all tasks can be completed with the use of generative AI. Figure 11 shows the average time needed to complete various tasks with and without the use of generative AI, while Figure 12 shows the productivity gains associated with each task.

However, not all tasks can be completed with the use of generative AI at this state, whether that is due to the nature of work (think of the waiting staff at a restaurant) or firm-intrinsic restrictions their use (example data privacy considerations). On average, workers use generative AI for about one-third of their work week, which is equivalent to an average of 7 tasks per week.

For the majority of tasks, Generative AI has been used to assist workers in doing the task more quickly (Figure 13). Only with about 16 percent of respondents, Generative AI was used to complete a full task (instances where the respondent said "Generative AI completed the task" for them. Nevertheless, the large efficiency gains of this technology in the form of intangible capital will likely affect labor markets, whereby the demand for labor for some jobs would decrease as a result of substitution, while in others demand will increase resulting from the complementarities of generative AI. Future iterations of this survey aims to study this more closely.

As a general hypothesis for further research, we postulate that lower-skilled jobs, those jobs that where workers can be easily replaced with other workers, would be displaced. High-skilled workers, however, will have their productivity multiplied as they can complete more tasks for the same time constraint. Medium-skilled workers with jobs that require physical interaction are likely to be the ones to be less affected by this technological shock.

Standard economic models whereby labor markets are perfectly competitive result in wages reflecting the labor productivity of the workers. Although evidence has shown that wages deviate from labor productivity, nevertheless labor productivity directly affects the compensation of workers. Figure 14 shows the efficiency gains from the use of generative AI by various income groups. While additional data is required to make a causal claim, an introspection of the descriptive data does seem to point out that our hypothesis has some validity. As shown in Figure 14, the relationship between income and the efficiency gains of Generative AI follow a U-shape form, where the gains tend to be higher on the lower and higher ends of the income distribution. Further study is required to fully understand the outcomes of the joint production of labor and generative AI.

4 Conclusion

To summarize, in this paper we develop a new survey analyzing Generative AI use in the labor market to assist in measuring the economic effects of Generative AI. We find, consistent with other surveys (Bick, Blandin, and Deming (2024) and Pew) that Generative AI tools like large language models (LLMs) are most commonly used in the labor force by younger individuals, more highly educated individuals, higher income individuals, and those in particular industries such as customer service, marketing and information technology. Overall, we find that 30.1% of survey respondents have used Generative AI at work at some point since Generative AI tools became public (consistent with the other survey evidence). Among those who report to use Generative AI at work, about 33% claim to use it every workday, while selectively using it for a limited number of hours per week. Generative AI seems to decrease the time spent on a task by an average of one hour, resulting in tripling the productivity in tasks where this technology is used. We also seek to examine the effects of LLMs on productivity and the labor market using a number of additional datasets.

The findings of this study highlight the uncertain and multifaceted nature of the impacts induced by LLM adoption. As evidenced in previous research on automation and technological progress (Acemoglu & Restrepo (2019), Brynjolfsson & McAfee (2014)), our analysis reinforces the notion that the introduction of LLMs can be a substitute for some forms of labor as well as a productivity-enhancing complement for other forms of labor.

There are several avenues for public policy as it relates to Generative AI. One is the government subsidization for the development of AI models to researchers outside of firms that have developed LLMs (OpenAI, Anthropic, and

Google) along with further support for broad public R&D investments.[7] There is also the question on the part of firms of whether to further open source large language models (publicly providing associated weights with actual models like what Facebook's Llama or DeepSeek). There is also the broader policy question about regulating Generative AI in economic contexts ranging in areas from labor market regulation to areas such as copyright licensing in data used to train large language models. Some like Acemoglu and Johnson (2023) have even proposed a new governmental department with the sole purpose of regulating AI.

Policymakers, businesses, and educational institutions may want to consider such results to foster a resilient labor market in the face of ongoing technological disruptions.

We intend to continue running future waves of the survey and expand the metrics with which we track Generative AI and its potential effects on the labor market in real-time.

[7] A recent report from Stanford University researchers estimated that Google DeepMind's large language model, Chinchilla, cost $2.1 million to develop. https://www.washingtonpost.com/technology/2024/03/10/big-tech-companies-ai-research/

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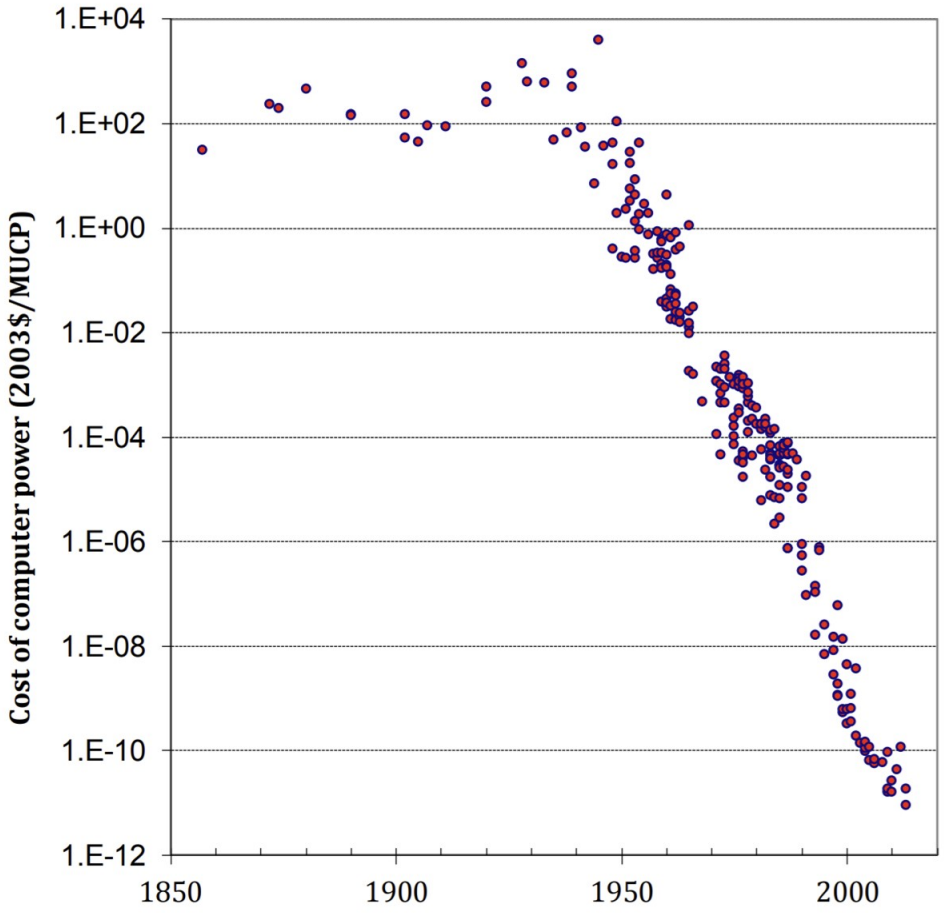
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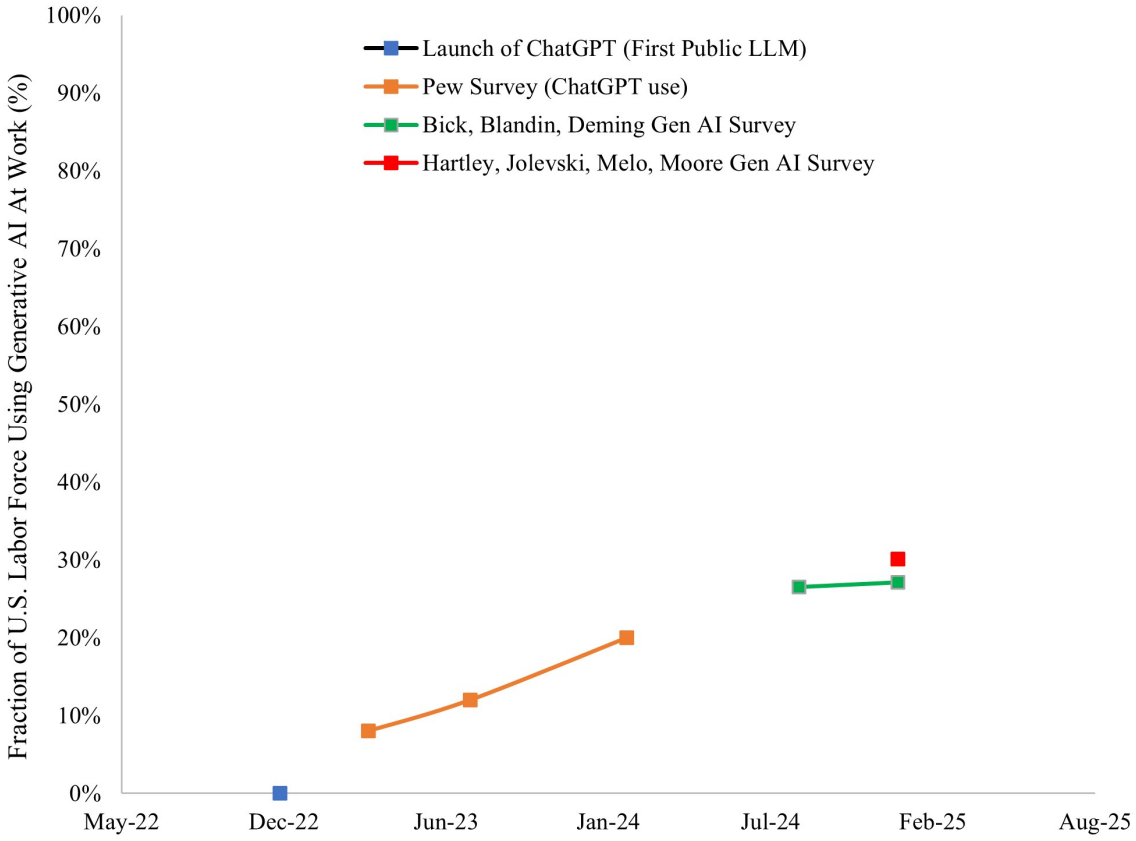
Figures

Figure 1: Cost of Computing per Second Deflated by the Price Index for GDP in 2006 Prices



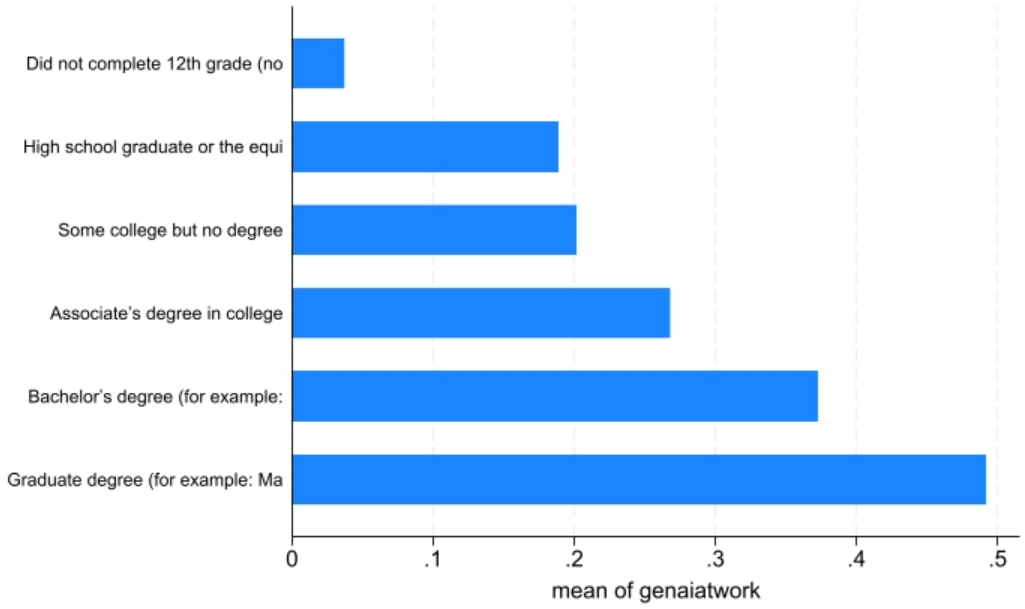
Notes: Obtained from Nordhaus (2021).

Figure 2: Fraction of U.S. Labor Force Using Generative AI Use At Work



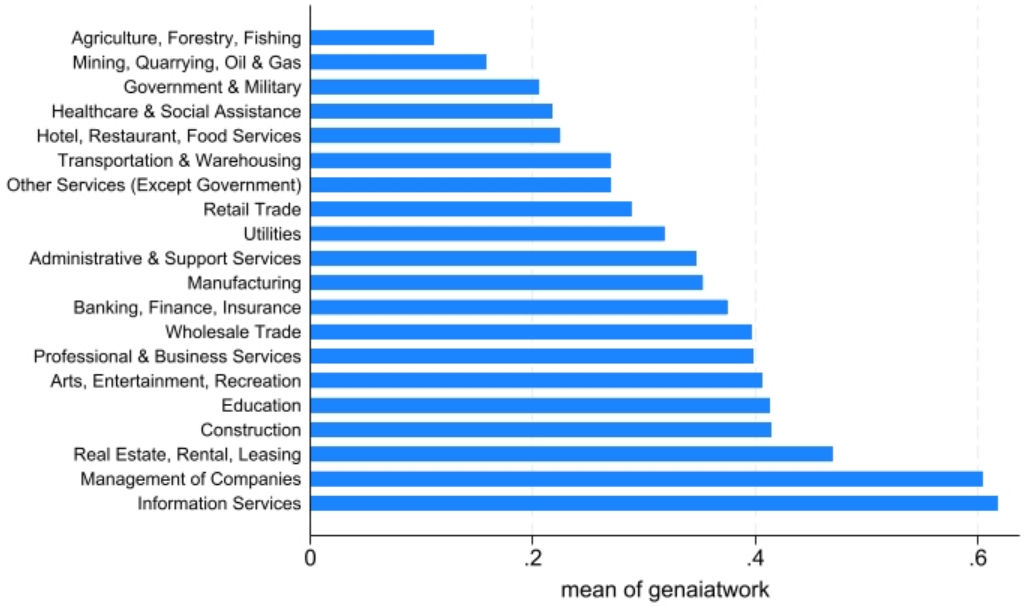
Notes: Survey from Pew Charitable Trusts.

Figure 3: Generative AI Use By Level of Education



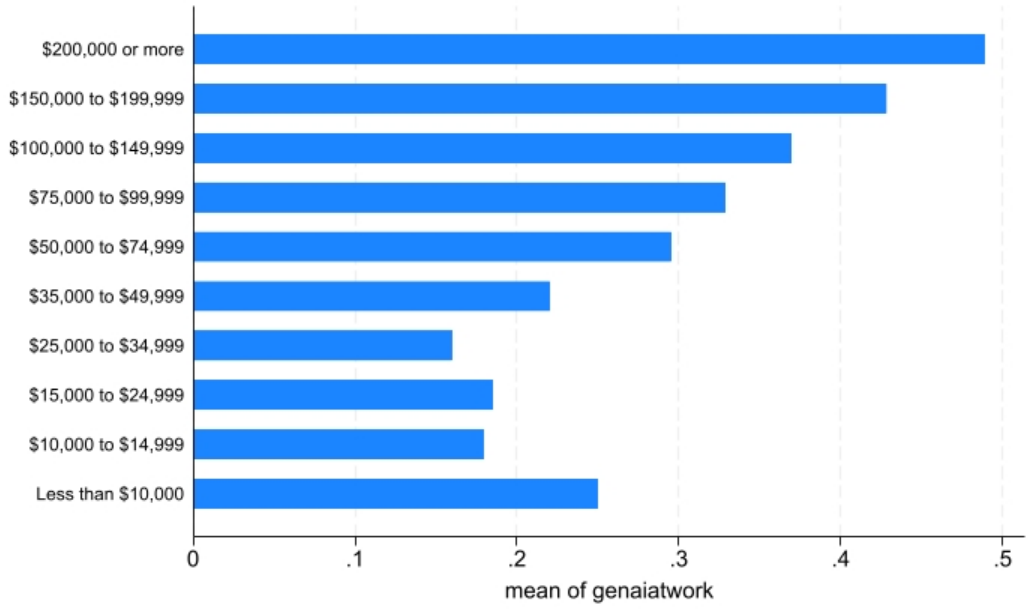
Notes: Data obtained from survey.

Figure 4: Generative AI Use By Industry



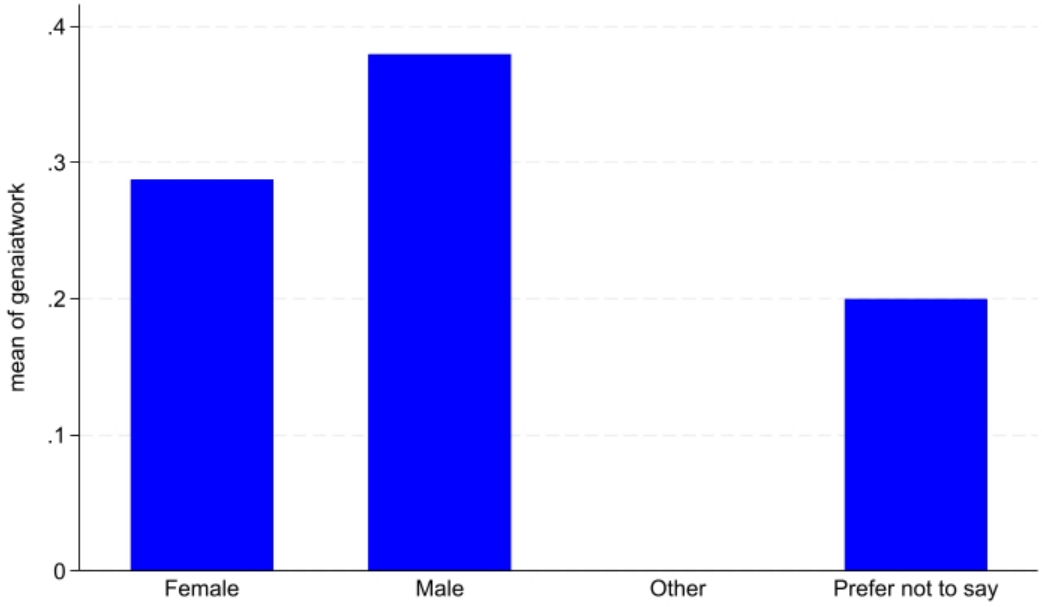
Notes: Data obtained from survey.

Figure 5: Generative AI Use By Income



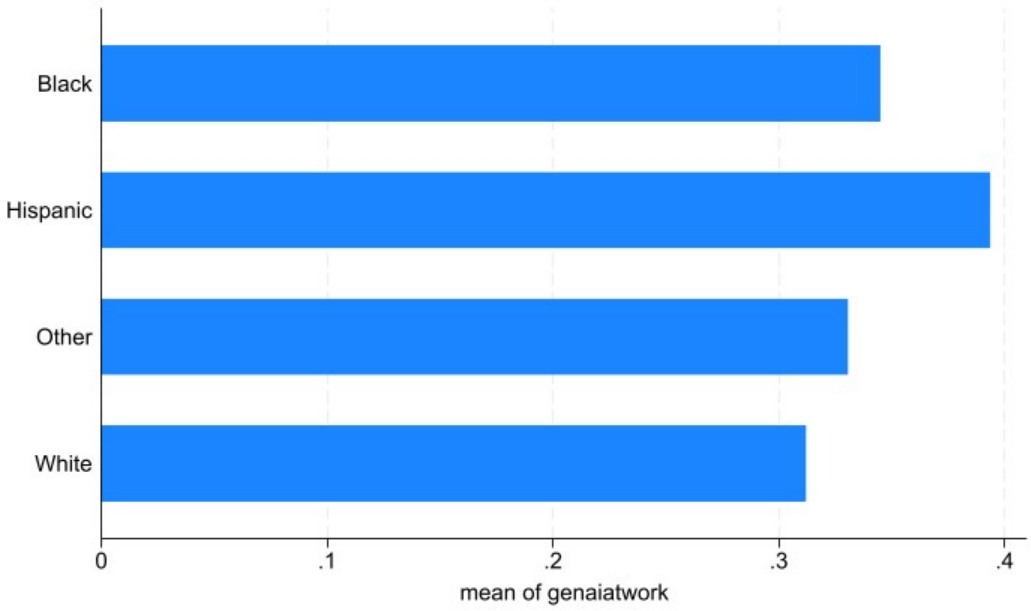
Notes: Data obtained from survey.

Figure 6: Generative AI Use By Gender



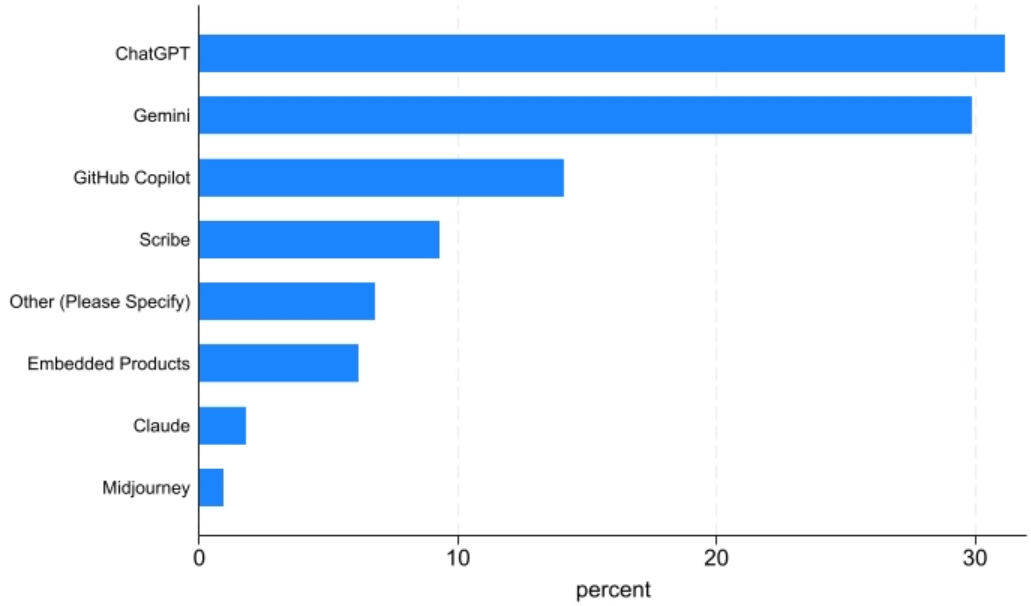
Notes: Data obtained from survey.

Figure 7: Generative AI Use By Race



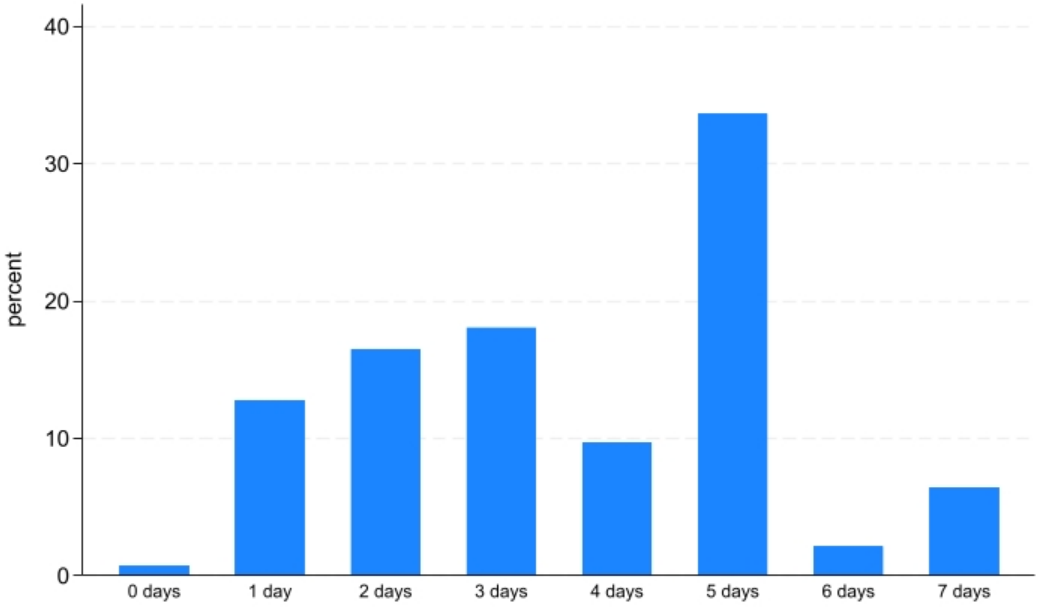
Notes: Data obtained from survey.

Figure 8: Generative AI Use By Tool



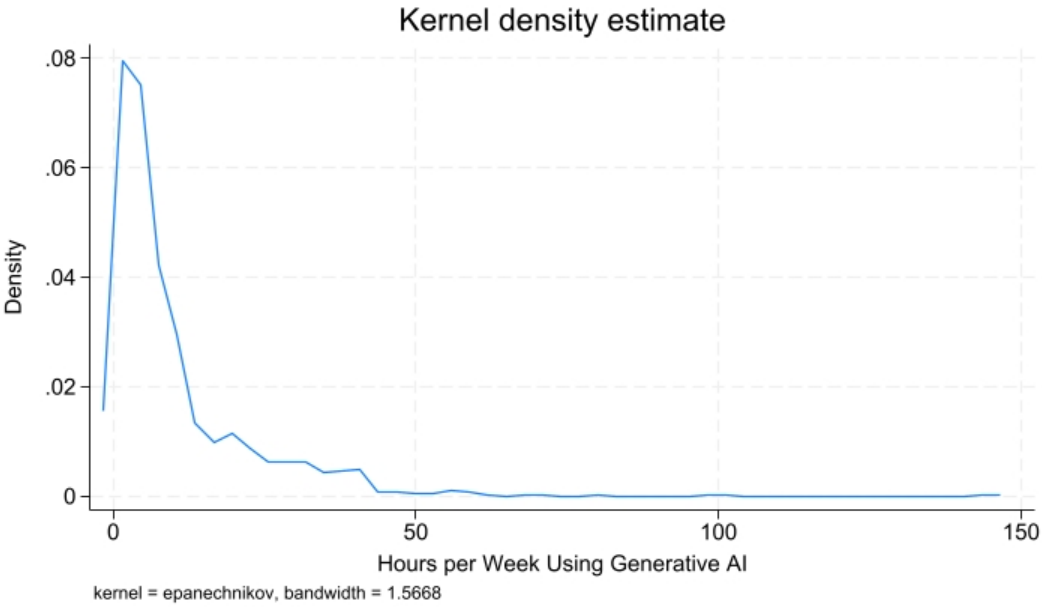
Notes: Data obtained from survey.

Figure 9: Number of Days At Work Each Week Using Generative AI Tools



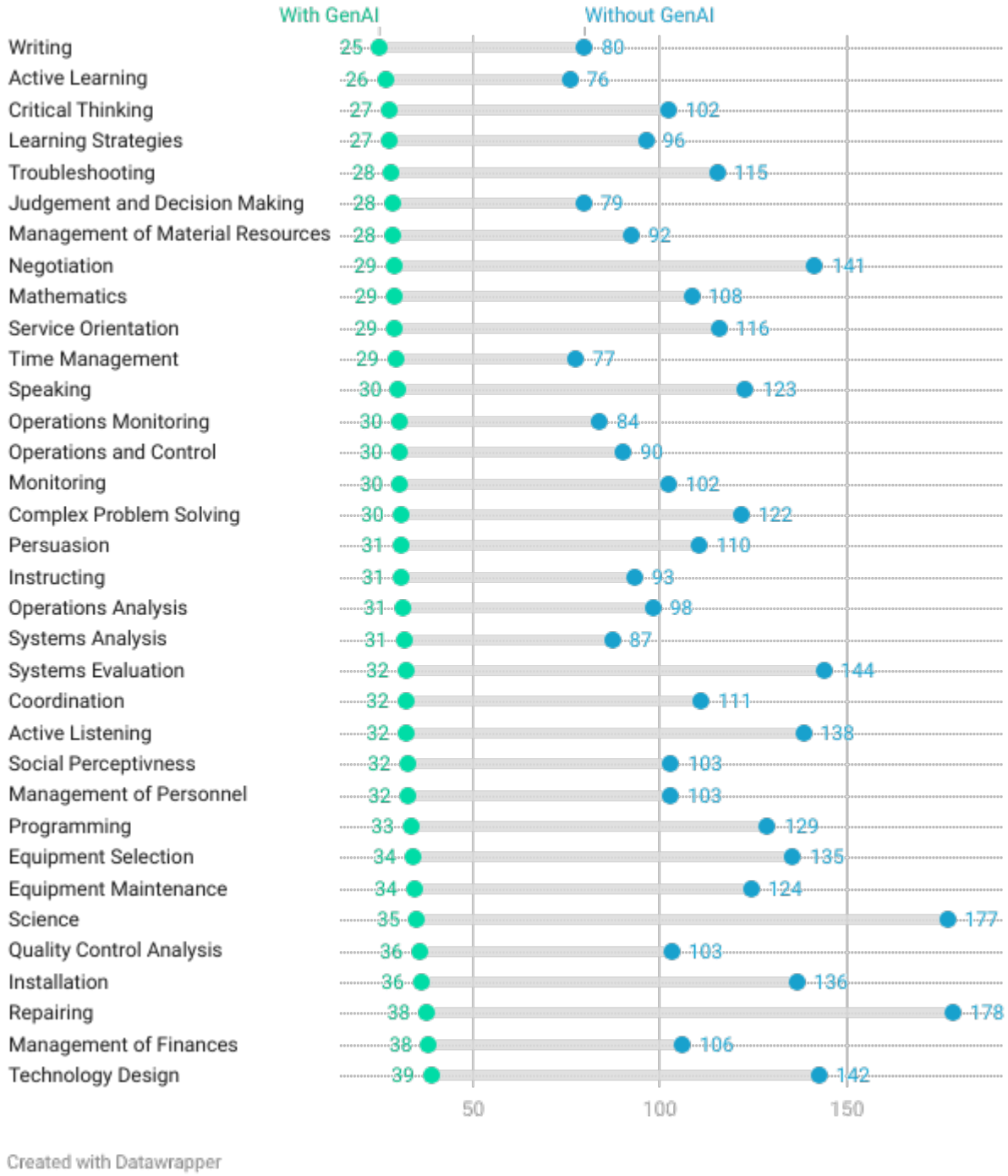
Notes: Data obtained from survey. Survey Question: "How many days each week do you use generative AI tools at work?"

Figure 10: Number of Hours At Work Each Week Using Generative AI Tools



Notes: Data obtained from survey. Survey Question: "How many hours per week do you use generative AI tools at work?"

Figure 11: Average number of minutes to complete a task with and without Generative AI



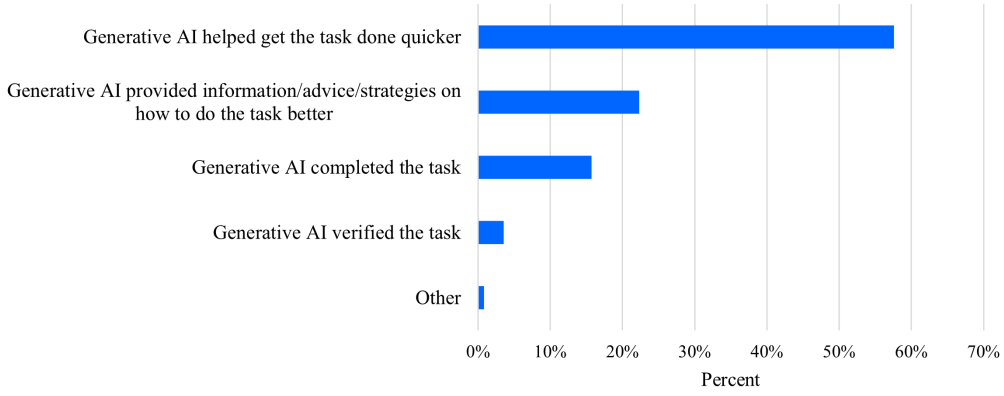
Notes: Author's calculation using data obtained from survey.

Figure 12: Productivity increase in completing various tasks using Generative AI



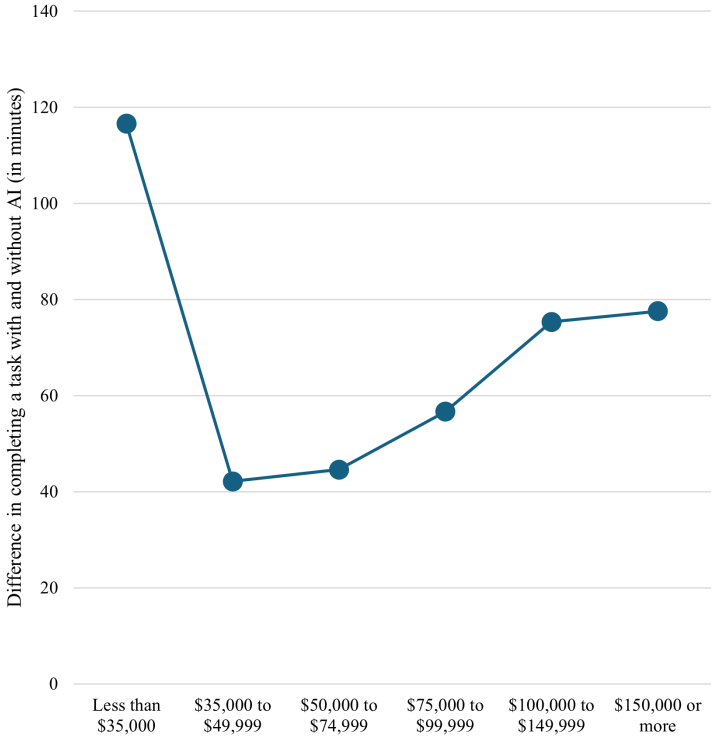
Notes: Author's calculation using data obtained from survey.

Figure 13: Uses of Generative AI to complete tasks



Notes: Author's calculation using data obtained from survey.

Figure 14: Time saved (in minutes) when completing tasks using Generative AI by income groups



Notes: Author's calculation using data obtained from survey.

Table 1: Usage of Generative AI Tools for Job Search Conditional On Using Generative AI At Work

	Percent of Generative AI Users Who Have Searched for Work Last 2 Years	Percent Used Generative AI to Find Work Among Job Seekers
Overall Sample	51.0%	57.6%
A. Gender		
Men	49.6%	56.0%
Women	52.4%	59.0%
B. Age		
18-34	58.7%	56.3%
35-44	53.5%	63.2%
45-54	47.2%	52.8%
55+	37.5%	52.2%
C. Race		
White	50.0%	55.1%
Black	48.3%	63.7%
Hispanic	58.4%	55.4%
D. Educational Attainment		
High school graduate or equivalent	45.9%	60.0%
Some college but no degree	52.3%	56.8%
Associate's degree in college	43.7%	45.2%
Bachelor's degree	53.1%	53.3%
Graduate degree	51.5%	65.8%

Notes: The first column of this table presents the percent of our sample that uses generative AI that also reports having searched for a job in the past two years. The second column reports, conditional on job searching and using generative AI more broadly, the percent that used generative AI tools to search for a job (i.e. write cover letters, refine resumés, direct search, etc.). Table presents these statistics for the overall sample and by demographic group.

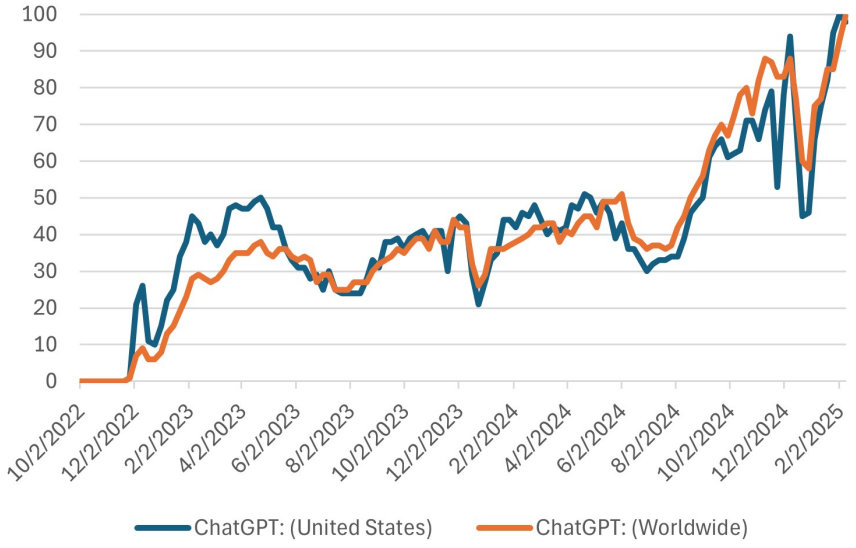
Table 2: Sample Representativeness: CPS vs Survey Population Shares

	CPS %	Survey %
A. Age		
18-34	33.5	24.3
35-44	22.6	30.8
45-54	20.0	26.8
55+	23.9	18.1
B. Education		
BA or more	42.3	55.5
Less than BA	57.7	44.5
C. Race/Ethnicity		
White	58.9	69.5
Black	12.7	12.3
Hispanic	19.5	12.4
Other	9.0	5.7

Notes: CPS data from November 2024 wave, which was conducted most closely to our survey in December 2024.

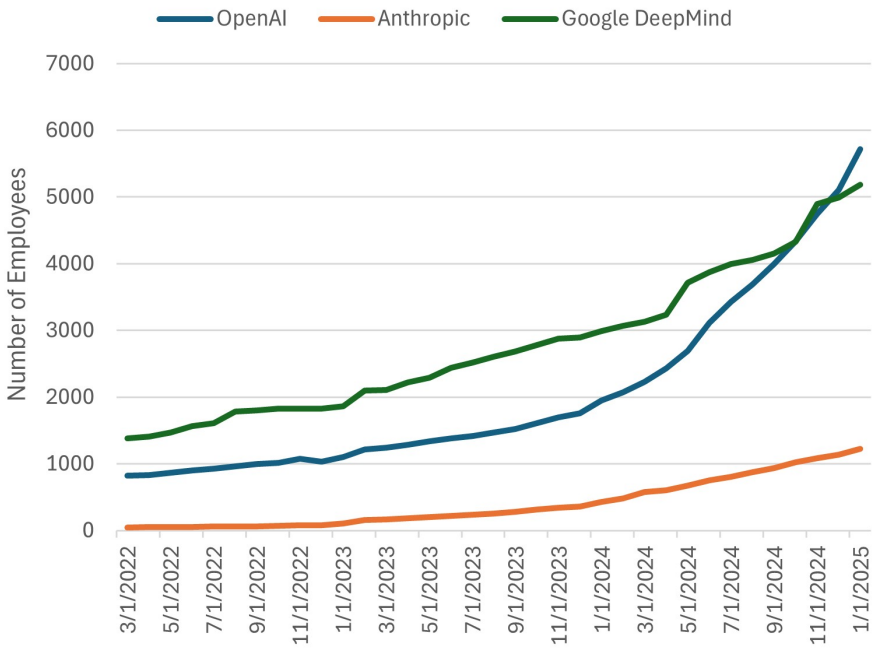
Appendix A

Figure 15: ChatGPT Google Search Volume Worldwide and in the United States



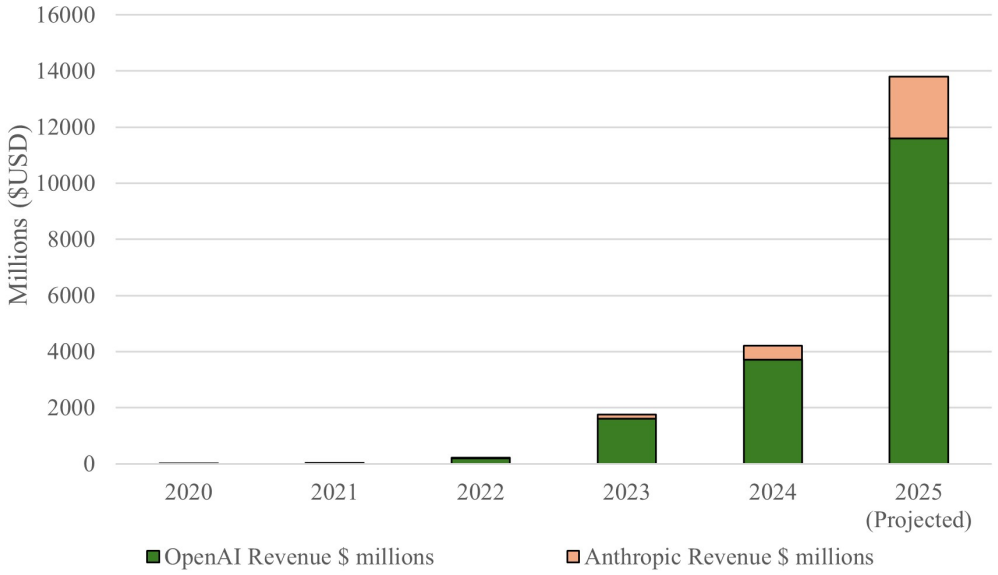
Notes: Data obtained from Google Trends.

Figure 16: Generative AI Company Number of Employees



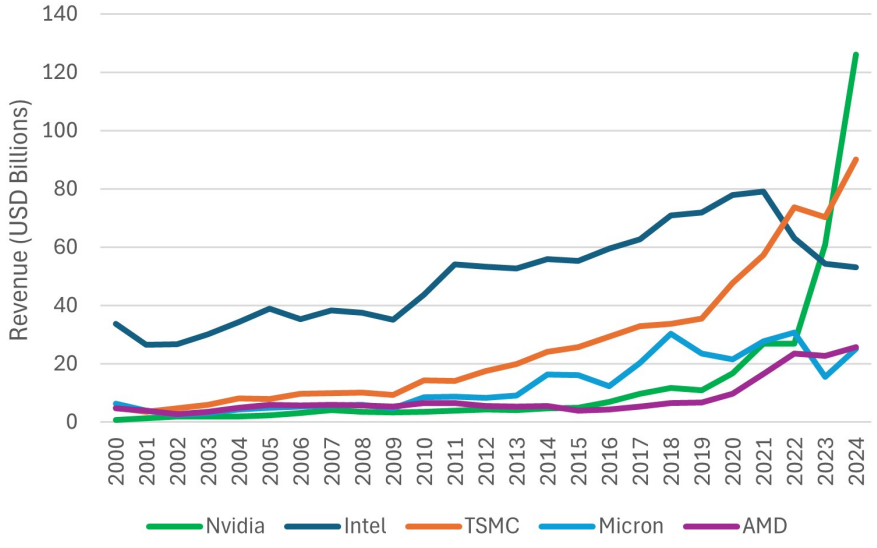
Notes: Data obtained from LinkedIn.

Figure 17: Generative AI Company Revenue



Notes: Data obtained from public company financials.

Figure 18: Chip Company Revenue



Notes: Data obtained from Pitchbook.

Appendix A: Generative AI Research Survey Instrument

Legend

Blue = coding instructions

Green = reader notes

Red = termination logic

Introduction

Screening questions

1. Thank you for agreeing to participate. Honest responses and your full attention are very important for research such as this. Are you able to give your undivided attention to answer to the best of your ability to give the most accurate answers to this survey?

   Multiple choice | Required | Vertical | Single-select

   a) Yes

   b) No **[TERMINATE]**

2. What is your age?

   Number | Required | Min: 0 | Max: 130

[If Q2 answer < 18, TERMINATE]

Demographics.

3. What is your gender?

   Multiple choice | Required | Vertical | Single-select

   a) Male

   b) Female

   c) Other

   d) Prefer not to say

54. What year were you born?

   Number | Required | Min: 1900 | Max: 2010

Flag `qc_age` if True if Q2 is more than a year off from age in Q54

4. What is the highest level of school you have completed or the highest degree you have received?

Multiple choice | Required | Vertical | Single-select

a) Did not complete 12th grade (no high school degree)

b) High school graduate or the equivalent (for example: GED)

c) Some college but no degree

d) Associate's degree in college

e) Bachelor's degree (for example: BA, AB, BS)

f) Graduate degree (for example: Master's, Professional, or Doctorate degree)

5. What is your zip code?

`Q_zip` | Text input | Required | Single line

Min length: 5

Max length: 5

Set `state` to state for zip code

Set `region` to US census region

6. Do you consider yourself to be of Hispanic origin?

Multiple choice | Required | Vertical | Single-select

a) Yes

b) No

7. Here is a list of categories of race and origin. Please select all that apply to you. You may choose more than one.

Multiple choice | Required | Vertical | Multi-select

a) White

b) Black or African American

c) American Indian or Alaska Native

d) Asian

e) Native Hawaiian or Other Pacific Islander

f) Hispanic Origin

g) Other

8. What was the total income of your household in the last year (2023) before any taxes or deductions? Please include all sources of income from everyone who currently lives with you

Multiple choice | Required | Vertical | Single-select

a) Less than $10,000
b) $10,000 to $14,999
c) $15,000 to $24,999
d) $25,000 to $34,999
e) $35,000 to $49,999
f) $50,000 to $74,999
g) $75,000 to $99,999
h) $100,000 to $149,999
i) $150,000 to $199,999
j) $200,000 or more

Industry Occupation

9. Which of the following best describes your employment status?

Multiple choice | Required | Vertical | Single-select

a) Employed full-time (30 hours or more a week)
b) Employed part-time (less than 30 hours a week)
c) Contractor / Freelancer / Temporary Employee
d) Self-employed
e) Retired
f) Unemployed
g) Temporarily laid off
h) None of the above

[Q10 logic: Show if Q9 selected choice is any of "Employed full-time (30 hours or more a week)", "Employed part-time (less than 30 hours a week)", "Contractor / Freelancer / Temporary Employee", "Self-employed"]

10. In this job, what type of employer do you work for?

Multiple choice | Required | Vertical | Single-select

a) Government (including state or local governments, a public school, university or hospital)

b) Private-sector, for-profit company

c) Non-profit organization (including charitable organizations)

d) Self-employed

e) Work in a business owned by someone else in this household

[Q11 logic: Show if Q9 selected choice is any of "Employed full-time (30 hours or more a week)", "Contractor / Freelancer / Temporary Employee", "Employed part-time (less than 30 hours a week)", "Self-employed"]

11. What kind of business or industry is this job?

Multiple choice | Required | Vertical | Multi-select

a) Agriculture, Forestry, Fishing and Hunting

b) Mining, Quarrying, and Oil and Gas Extraction

c) Utilities

d) Construction

e) Manufacturing

f) Wholesale Trade

g) Retail Trade

h) Transportation and Warehousing

i) Information Services (including Publishing or Media)

j) Banking, Finance, or Insurance

k) Real Estate, or Rental and Leasing

l) Professional, Technical, or Business Services

m) Education

n) Health Care and Social Assistance

o) Arts, Entertainment, and Recreation

p) Hotel, Accommodation, Restaurant, or Food Services

q) Other Services (except Government)

r) Government, including Military

s) Management of Companies and Enterprises

t) Administrative and Support and Waste Management and Remediation Services

Set `hover_defs` to:

a) **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.

b) A **large language model** is a type of artificial intelligence (AI) model that uses machine learning to understand and generate human language.

AI Usage

"**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."

Large language model A type of artificial intelligence (AI) model that uses machine learning to understand and generate human language.

12. Have you heard of `generative AI` before?

Multiple choice | Required | Vertical | Single-select

a) Yes

b) No **[TERMINATE]**

13. Have you used `generative AI` tools before?

Multiple choice | Required | Vertical | Single-select

a) Yes

b) No **[TERMINATE]**

14. Do you use `generative AI` for your job?

Multiple choice | Required | Vertical | Single-select

a) Yes

b) No **[TERMINATE]**

Gen AI usage

15. Check off which `generative AI` tools you use

Multiple choice | Required | Vertical | Multi-select

a) ChatGPT
b) Midjourney
c) Claude
d) Gemini
e) Github Copilot
f) Scribe
g) Embedded products
h) Other (please specify) [text input]

16. How many days each week do you use generative AI tools at work?

Number | Required | Min: 0 | Max: 7 | Decimals: 0

17. How many hours per week do you use generative AI tools at work?

Number | Required | Min: 0 | Max: 168 | Decimals: 1

18. When did you most recently use generative AI tools at work?

Multiple choice | Required | Vertical | Single-select

a) During the most recent day at work
b) During the most recent week at work
c) During the most recent month at work
d) During the most recent year at work

19. In what tasks are you using generative AI/Large Language models at work?

Multiple choice | Required | Vertical | Multi-select | Randomize

a) Active Listening
b) Writing
c) Speaking
d) Mathematics
e) Science
f) Critical Thinking
g) Active Learning
h) Learning Strategies

i) Monitoring

j) Social Perceptiveness

k) Coordination

l) Persuasion

m) Negotiation

n) Instructing

o) Service Orientation

p) Complex Problem Solving

q) Operations Analysis

r) Technology Design

s) Equipment Selection

t) Installation

u) Programming

v) Operations Monitoring

w) Operation and Control

x) Equipment Maintenance

y) Troubleshooting

z) Repairing

aa) Quality Control Analysis

bb) Judgment and Decision Making

cc) Systems Analysis

dd) Systems Evaluation

ee) Time Management

ff) Management of Financial Resources

gg) Management of Material Resources

hh) Management of Personnel Resources

ii) Other (please specify) [text input]

20. In reference to your most recent task in which you used `generative AI` at work, how long did it take you to complete the task using `generative AI`? (in number of minutes)?

Number | Required | Min: 0

_____ minutes

21. How did you use `generative AI` for this task**?**

Multiple choice | Required | Vertical | Single-select

a) GenAI did the task for me.

b) GenAI helped me to do the task quicker.

c) GenAI provided information/advice/strategies on how to do the task better.

d) GenAI verified checked the task for me.

e) Other

22. In reference to your most recent task in which you used generative AI at work, how long did it take you to complete the task using Gen AI?"

Combination | Required

Ensure minutes row < 60

Hours Minutes	**Number input** Min: 0

23. How many days do you usually work from home in a given week?

Number | Required | Min: 0 | Max: 7 | Decimals: 2

Employed Block

show block if Q9 selected choice is any of "Employed full-time (30 hours or more a week)", "Employed part-time (less than 30 hours a week)"

24. How many hours per week do you usually work for your job? (0-168)

Number | Required | Min: 0 | Max: 168

_____ hours

25. How many days do you usually work for your job? (0-7)

Number | Required | Min: 0 | Max: 7 | Decimals: 1

_____ days

26. How many days do you usually commute to your job?

Number | Required | Min: 0 | Max: 7 | Decimals: 1

_____ days

[Q27 logic: Show if Q26 answer > 0]

27. Which of the following best explains why you commuted to work last week?

Multiple choice | Required | Vertical | Single-select

a) Some aspects of my job could not be done from home

b) Some or all of my job could have been done from home, but my employer required me to commute

c) Some or all of my job could have been done from home, but I preferred to commute

28. For how long have you been working for this employer?

Multiple choice | Required | Vertical | Single-select

a) 0-2 years

b) 3-5 years

c) 6-9 years

d) 10 or more years

Unemployed block

show block if Q9 selected choice is "Unemployed"

29. When was the last time you worked for pay or profit?

Multiple choice | Required | Vertical | Single-select

a) 1 to 2 months ago

b) 2 to 6 months ago

c) 6 to 12 months ago

d) One to two years ago

e) More than two years ago

30. Have you searched for a job in the past 2 years, since November 2022?

Multiple choice | Required | Vertical | Single-select

a) Yes

b) No

[Q31 logic: Show if Q30 selected choice is "Yes"]

31. Did you use generative AI to search for a job? For example, to help write cover letters or resumés, prepare for interviews, or conduct research about job opening

Multiple choice | Required | Vertical | Single-select

a) Yes

b) No

32. Do you directly use computer at home?

Multiple choice | Required | Vertical | Single-select

a) Yes

b) No

33. Do you use computer for your job?

Multiple choice | Required | Vertical | Single-select

a) Yes

b) No

34. Do you use internet at any location?

Multiple choice | Required | Vertical | Single-select

a) Yes

b) No

Final Demographics

35. How would you describe your marital status?

Multiple choice | Required | Vertical | Single-select

a) Married, spouse currently lives in this household

b) Married, spouse currently lives outside this household

c) Widowed

d) Divorced

e) Separated

f) Never Married

[Q36 logic: Show if Q35 selected choice is any of " Widowed ", " Divorced ", " Separated ", " Never Married "]

36. Do you have a partner/boyfriend/girlfriend who currently lives in this household?

Multiple choice | Required | Vertical | Single-select

a) Yes

b) No

37. Number of children under age 18 in the household

Multiple choice | Required | Vertical | Single-select

a) No children

b) 1 child

c) 2 children

d) 3 or more children

[Q38 logic: Show if Q37 selected choice is any of "1 child ", "2 children ", "3 or more children "]

38. What is the age of the youngest child under age 18 that currently lives with you?

Number | Required | Min: 0 | Max: 18

39. Attention Check: The color of grass is green. This actually is an attention check question. Make sure that you select purple as an answer so we know you are paying attention.

Multiple choice | Required | Vertical | Single-select

a) Green

b) Purple

c) Blue

d) Black

e) White

f) Brown

Flag `qc_attention_check1` if Q39 selected choice is not " Purple "

Extra QCs

Qsponse\QC module
Skips for testing
Quality Control Basics **1) Monitor survey performance:** While the survey is in the field for data collection, use the Results > Quality Control tab to track the performance of flags and panels. **2) Analyze data post-Soft Launch:** After completing the Soft Launch, download the survey data from Results > Downloads and open it in Excel, Wide file. Scroll through the columns from left to right to locate those with headers beginning with “qc_”. **3) Sum and sort QC flags:** Sum all the QC flags in a new column labeled “qc_count”. Sort the responses by qc_count, from smallest to largest. **4) Evaluate open-ended responses:** Scroll to the right to find an open-ended (OE) data point. As you move from the smallest to the largest qc_count, observe how the quality of the OE answers declines. **5) Determine and apply a quality cutoff:** Identify the point at which OE answers consistently become low quality. Set this qc_count as your cutoff for quality. Remove all responses with a qc_count higher than your determined cutoff. Flag `qc_time` if The respondent takes the survey between 12am and 6am in their local timezone. Flag `qc_speeder` if The respondent completed the survey in <1/3 of the median LOI calculated at Soft Launch: Set `straightline_count` to: > # of straightlined matrices / # of answered matrices Exceptions: 1. Matrices in loops (we use separate QC Flags for these) 2. Matrices by column (not currently checked) 3. Multi-select Matrices (not currently checked) Flag `qc_SingleS_50perc_str8liner` if The respondent answered more than 50% of the Single Select matrices they "saw" in a straight line (selected 1 column only).

Flag `qc_used_vpn` if The respondent took the survey through a Virtual Private Network. Although it is normal for some respondents (especially B2B experts) to use VPN for normal computer operations such as taking a survey, this information can be used together with other flags to assess the level of data quality for each response.

Flag `qc_masked_IP` if The respondent's IP address is found to be associated with any IP masking methods (Tor, Proxy, etc). This information can be used together with other flags to assess the level of data quality for each response.