Global Evidence on Gender Gaps and Generative AI

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Generative AI has the potential to transform productivity and reduce inequality, but only if used broadly. In this paper, we show that recently identified gender gaps in AI use are nearly universal. Synthesizing evidence from 16 studies that surveyed 100,000 individuals across 26 countries, along with new data on the gender of AI platform users, we show that the AI gender gap is present in nearly all regions, sectors, and occupations. Using data from two studies that offered participants the chance to use AI tools, we then show that even when the opportunity for men and women to access AI is equalized, women are still less likely to use AI. Our findings underscore the critical need for targeted interventions that go beyond access to address the structural and behavioral barriers that have resulted in a global gender gap in AI use.

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Generative AI is expected to have profound economic and social impacts. Recent studies demonstrate that generative AI has already begun to impact the productivity and performance of professionals across various domains, including college-educated workers, customer support agents, job seekers, students, and entrepreneurs (Brynjolfsson, Li, and Raymond, 2023; Dell'Acqua et al., 2023; Noy and Zhang, 2023; Otis et al., 2023). Moreover, unlike previous waves of automation (Agrawal, Gans, and Goldfarb, 2023), most early evidence suggests that AI might increase productivity while simultaneously decreasing inequality (Noy and Zhang, 2023; Brynjolfsson, Li, and Raymond, 2023; Dell'Acqua et al., 2023; Otis et al., 2023).

If generative AI can reduce inequality, it might especially benefit working women. In the United States, gender gaps remain pervasive: women account for only 15% of inventors (Koning, Samila, and Ferguson, 2021), receive less than 20% of venture capital funding (Pitchbook, 2024), and earn 82 cents for every dollar earned by men (Pew Research Center, 2023). Globally, these gaps are often wider (Perez-Alvarez, Porter, and Ramachandran, 2023). No matter the region, the pervasiveness of these gaps stems from the fact that they are rooted in a multitude of causes: women have access to fewer mentors, unequal household and childcare burdens reduce women's time for work, and social norms and constraints hinder women from gaining the skills required for high-paying STEM careers (Goldin, 2021). While far from a panacea, the general-purpose nature of AI has the potential to address many of these inequities (Eloundou et al., 2024). Generative AI can *advise* when mentors won't, *automate* tasks to help manage work-family time demands, and *augment* learning to enable women to reap the benefits of high-paying STEM skills.

However, for generative AI tools to close these gaps, women must use this new technology. Yet the history of technology adoption shows that a multitude of frictions—from social norms to capital constraints—causes women to adopt innovations at a lower rate than men. That said, AI tools differ from the majority of past innovations in that for both women and men generative AI is cheap and easy to use. Most humans have access to a smartphone, powerful versions of generative AI are free, and usage requires only knowing how to read and write. With much lower barriers to adoption, women might be as likely as men to adopt. Yet recent surveys of AI adoption in the United States and Denmark suggest that women are much less likely to use this new technology (Aldasoro et al., 2024; Humlum and Vestergaard, 2024).

In this paper, we document that this gender gap in adoption is nearly universal. To do so, we first assemble data from every scholarly and practitioner study we could identify which surveyed men and women about their use of Generative AI. We find remarkably consistent gaps, with a meta-analysis suggesting that women are 25% less likely to use this new technology. We confirm the pervasiveness of this gap by also analyzing novel data on the gender breakdown of visitors to top Generative AI websites. We again find gaps for all major Generative AI products and that these gaps hold in nearly all countries. Finally, we use data from two studies in Kenya that offered participants the chance to use real AIs tools to test if equalizing access to AI will close the Generative AI gender gap. We find that women are still less likely to use AI even when presented with the opportunity to do so. Taken together, these findings highlight how policymakers, managers, and researchers across the globe must wrestle with and address the gendered use of this new technology.

Data and Results

To estimate the extent of the gender AI usage gap, we started by identifying every publicly available study that has surveyed people about their self-reported AI use. We conducted a comprehensive search on Google Scholar using in July of 2024 including all studies from any geography either unpublished or published as long as they measured (1) AI use and (2) the respondent's gender. We were able to identify 14 such surveys (Table A1). We then combined these data with two studies we conducted that directly measured AI use by people in Kenya along with their self-reported gender. These 16 studies cover 107,607 individuals who range from U.S. workers to Kenyan entrepreneurs to science postdocs. Figure 1 illustrates the percentage of women (red triangles) and men (black circles) using AI across these samples. Our results document a consistent pattern in generative AI adoption and use: men are more likely to adopt generative AI than women in all but one dataset.

The size of these gender gaps is meaningful. In the US, targeted and nationally representative samples show a roughly 5 to 20 percentage point gap (rows 4,5,7,9-11,14,15). For example, in a representative survey by the New York Federal Reserve we find that half of men used AI in the last 12 months compared to one-third of women (row 10). To further contextualize the magnitude of these gaps, Figure A1 shows the gaps in relative percentages. We find that relative to the share of men who use AI, the share of women is 10 to 35% smaller. The exception is a Boston Consulting Group (BCG) study showing that women are 3% more likely to use AI than men in a convenience sample of 6,558 US tech employees. Across 100,000 other individuals in our data, we find that women are much less likely to use AI than men in occupations ranging from postdocs across the globe (19%) to Kenyan small business entrepreneurs (14%) to college students in the US and Sweden (25% and 31%). For 10 of the 16 studies we were able to manually extract enough data to complete a formal meta-analysis. Our meta-analysis in Figure A3 of these 10 studies suggests that women are 24.6% ($p < 0.0001$) less likely to use Generative AI tools than men.

That the gender gap holds across people with such diverse backgrounds and regions suggests that the gap is not merely the result of women's under-representation in particular areas (e.g., as computer scientists or as workers in Silicon Valley). In Table A2 we present estimates from two prior studies and three new analyses that control for potential gendered differences in terms along dimensions ranging from location to field of study to preferences and beliefs. In all five studies the adjusted gender gap remains and, intriguingly, in three the adjusted gap is larger than the unadjusted difference in means. This finding suggests that the gender gap is not merely reducible to well known differences in where or what women work on.

Reinforcing these findings is the fact that web traffic data also shows a substantial gap in who visits the websites of the world's most popular generative AI tools. Building on data described and validated in Koning, Hasan, and Chatterji (2022) and Cao, Koning, and Nanda (2023b), Figure 2 shows data pulled from the web traffic analytics platform Similarweb on the gender breakdown of visitors to OpenAI's ChatGPT, Anthropic's Claude, Midjourney, and Perplexity. Globally, between November 2022 and May 2024, women made up only 42% of the roughly 200 million average monthly users who engaged with ChatGPT, 42.4% of Perplexity users, 39.6% of Midjourney users, and just 31.2% of Anthropic users. These gender gaps are present in high-income countries like Canada and Japan and low- and middle-income countries like India and Brazil (Figure A2). That the gap holds in web analytics data also suggests that estimated gendered gaps in use are not merely an artifact of gendered survey response bias.

Finally, we turn to potential solutions. While the potential mechanisms driving differences in men and women's AI usage are myriad—Figure A4 outlines the mechanisms from trust to AI training that prior work has outlined—here we focus on a simple solution: equalizing access. If the gender gap is rooted in women being less likely to stumble upon, hear about, or be invited to use new AI tools, then equalizing the opportunity to engage with an AI tool should close the gap.

To test if equalizing access explains—and so can close—the gender gap in AI use, we turn to two studies that both directly offered and measured participant AI use. First, we use data from a field experiment with 640 small business entrepreneurs in Kenya that randomized access to an AI-powered WhatsApp business mentor (Otis et al., 2023). Treated male and female entrepreneurs received the same training on how to use the WhatsApp AI tool and were similarly encouraged to ask it questions, equalizing access. Second, we use data from the Kenya AI Adoption Study (KAAS) which we launched in August, 2023. The KAAS collected data on the demand for generative AI from over 17,000 Kenyan Facebook users, crucially providing both men and women equal access to try out ChatGPT (Appendix C.2). Despite equalizing access, women still used Generative AI tools less than men. The field experiment with Kenyan small business entrepreneurs finds that women are 14% ($p < 0.01$) less likely to seek AI advice over WhatsApp. Similarly, our KAAS results show that women are approximately 12% ($p < 0.001$) less likely than men to use ChatGPT when presented with the opportunity to learn how to use these tools. Comparing to our meta-analysis estimate showing women are 25% less likely to use these tools than men, the findings from these two studies suggest that equalizing access might help shrink the gender gap, but is unlikely to fully close it.

Discussion

The findings above document that gender gaps in AI are nearly universal. From mothers in Mumbai to managers in Madrid, women use AI less than men when analyzing data from 16 studies covering over 100,000 people along with novel data measuring who visits the top Generative AI websites. Moreover, equalizing access does not appear to fully close the gap, even when presented with the chance to use Generative AI women are less likely to use this new technology than men.

This disparity has the potential to be significant. As generative AI systems are still in their formative stages, the under-representation of women in their early use and testing risks shaping tools that fail to meet the needs of half the population (Koning, Samila, and Ferguson, 2021; Cao, Koning, and Nanda, 2023a). Biases in user data—similar to those that have previously led to racial disparities in AI performance—could result in AI systems that reinforce gendered stereotypes and overlook tasks more often performed by women (Koenecke et al., 2020; Guilbeault et al., 2024). Ensuring that AI tools are designed inclusively will be crucial for unlocking their full potential to enhance productivity and reduce inequality. Given recent estimates that AI has the potential to increase US economic output and worker productivity levels by nearly 20% over the next decade (Baily, Brynjolfsson, and Korinek, 2023), and that women make up just under 50% of the US workforce, a persistent 25% usage gap could result in hundreds-of-billions of dollars of lost productivity and output gains in the US alone.

Given the potential ramifications of this global AI gender gap, these findings also point to the need for policy and managerial efforts aimed at closing it. As our findings show, even when efforts to increase participation by equalizing access are in place, women are still less likely to use AI than men. This suggests that policy must go beyond simply equalizing access to AI, but must wrestle with and address the social and behavioral barriers to AI use. Without such efforts, AI's potential to drive economic growth and improve productivity will disproportionately benefit male users, not only entrenching existing gender gaps, but also opening up the possibility that society will miss out on the work, inventions, and ideas women would have produced with this new technology.

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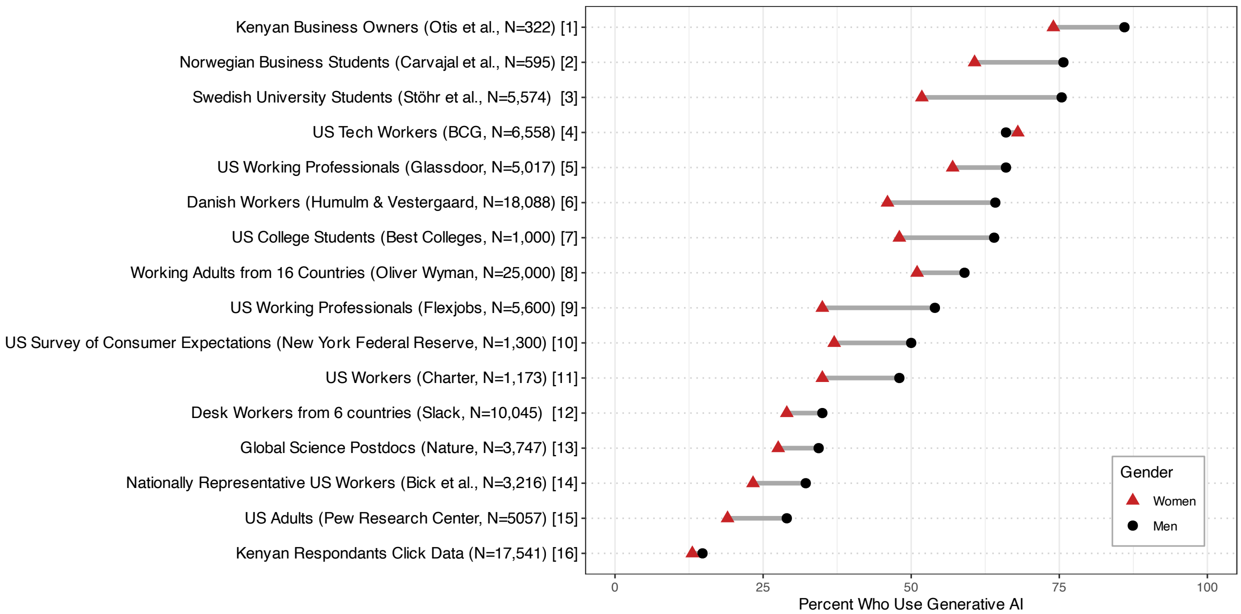
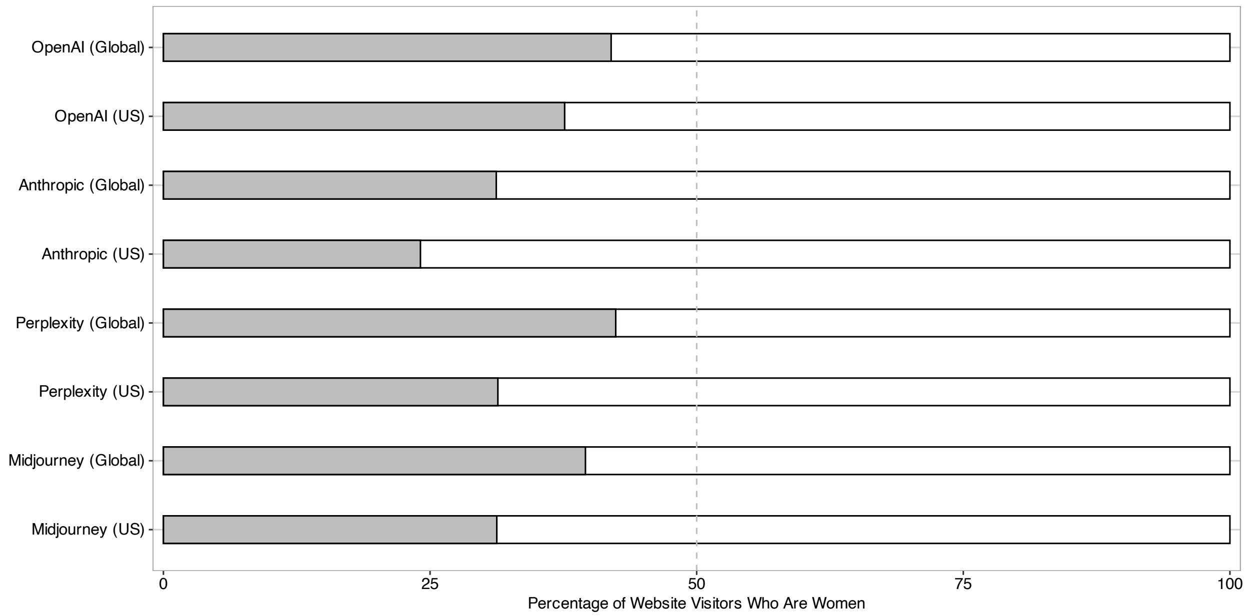
Figure 1: Generative AI Usage by Gender Across Studies



This figure presents generative AI use and adoption by gender across 16 data sets. Red triangles represent the percentage of women who use AI, and black circles represent the percentage of men using AI. The gray bar between each point represents the gender gap in AI use. Estimates are ordered by overall AI usage in each study. N refers to the total number of respondents for which we have data from each respective source. All sources are from surveys and represent self-reported AI use besides two studies. “Kenyan Respondents Click Data” and “Kenyan Business Owners” datasets capture actual AI usage and demand.

Figure 2: Percentage of Generative AI Website Visitors Who Are Women



This figure presents the estimated percentage of total unique users that are predicted by Similarweb to be women for three widely used AI platforms measured using website traffic data collected by Similarweb. The data is the average from November 2022 through May 2024, the lifetime of ChatGPT, the most popular and first widely-used generative AI tool. The predicted monthly average number of unique website visitors from each platform is as follows: OpenAI (Global): 172.9 million users, OpenAI (US): 18.01 million users, Perplexity (Global): 7.13 million users, Perplexity (US): 0.773 million users, Anthropic (Global): 1.888 million users, Anthropic (US): 0.281 million users, Midjourney (Global): 10.04 million users, Midjourney (US): 1.304 million users. See Table A3 and Appendix subsection C.1 for additional information.

Online Appendix

Global Evidence on Gender Gaps and Generative AI

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A Appendix Tables

Table A1: Overview of Assembled Data on AI Adoption and Use

Source (n) (1)	Figure Label (2)	Sample Description (3)	Country (4)	Date (5)	Outcome (6)
Nature Research (2023) n=3,747	Global Science Postdocs	Survey of postdocs across various disciplines and regions.	Global	Sep 2023	Whether participants report using AI chatbots in work.
Slack (2024) n=10,045	Desk Workers from 6 countries	Survey of workers defined as 'desk workers' which they defined as employed full-time who either"work with data, analyze information or think creatively" or who were executive management, senior management, middle management, junior management, senior staff, skilled office worker.	U.S., Australia, France, Germany, Japan, U.K.	Mar 2024	Whether respondents have ever tried using AI tools for work.
Goligoski and Clemente (2024) n=1,173	US Workers	Survey of US workers across three sectors: manufacturing, service, and knowledge work.	U.S.	Aug 2023	Whether workers are using generative AI tools in their jobs currently.
Barisano et al. (2024) n=6,558*	US Tech Workers	Survey across seniority levels and functions in the tech industry.	India, U.S., Japan, U.K., Germany	Jan 2024	Whether respondents use GenAI tools at work more than once a week.
Howington (2024) n=5,600	US Working Professionals (Flexjobs)	Survey of working professionals across a range of career and education levels.	U.S.	May 2023	Whether workers use AI in personal or professional life.
Kreacic and Stone (2024) n=25,000	Working Adults from 16 Countries	Survey of workers aged 18-65 across 16 countries.	U.S., Canada, Mexico, Brazil, UK, France, Italy, Germany, Spain, China, India, Indonesia, Singapore, UAE, Australia	Jun-Nov 2023	Whether respondents "use generative AI tools at least once a week."
Park and Gelles-Watnick (2023) n=5,057†	US Adults	Representative sample of U.S. adults from the PEW Research Center's American Trends Panel.	U.S.	Jul 2023	Among those who have heard of ChatGPT, whether they have ever used it.
Glassdoor Economic Research (2024) n=5,017	US Working Professionals (Glassdoor)	Survey of working professionals in the U.S.	U.S.	Nov 2023	Whether respondents use AI tools to help with work tasks.
Bick, Blandin, and Deming (2024) n=990	Nationally Representative US Workers	Survey targeting a representative sample of U.S. adults.	U.S.	Jun, Aug 2024	Whether respondents used generative AI in the last week.

Table is continued on the next page.

(Continued) Overview of Data on AI Adoption and Use

Source (n) (1)	Figure Label (2)	Sample Description (3)	Country (4)	Date (5)	Outcome (6)
Nam (2024) n=1,000	US College Students	Survey of current undergraduate and graduate students enrolled in on-campus, online, or hybrid programs.	U.S.	Sep-Oct 2023	Whether respondents have "used AI."
Humlum and Vestergaard (2024) n=18,088†	Danish Workers	Survey of Danish workers from 11 exposed occupations, representative of the population.	Denmark	Nov 2023-Jan 2024	Whether respondents answered "Yes" to using ChatGPT.
Stohr, Ou, and Malmström (2024) n=5,574	Swedish University Students	Survey of students from 28 Swedish universities through online campaigns and partner media.	Sweden	Apr 2023	Whether respondents have "ever used" ChatGPT.
Aldasoro et al. (2024) n=1,300†	Survey of Consumer Expectations	U.S. nationally representative panel of household heads collected by the New York Federal Reserve.	U.S.	Feb 2024	Whether respondents have "used GenAI in the past 12 months."
Carvajal, Franco, and Isaksson (2024) n=595	Norwegian Business Students	Survey of bachelor's and master's students at a Norwegian business school.	Norway	Nov 2023-Early 2024	Frequency of generative AI use categorized as low or high usage.
Otis et al. (2023) n=638	Kenyan Business Owners	Field experiment with Kenyan SME owners recruited via Meta ads, capturing interactions with a generative AI chatbot.	Kenya	Jun-Nov 2023	Whether participants used the GPT4-powered AI tool during the 2-month period.
Kenya AI Adoption Study (KAAS) n=17,541	Kenyan Respondents Click Data	Survey of Kenyan participants recruited via Meta ads for this study.	Kenya	Aug-Oct 2023	Clicks on a link to download or access ChatGPT. We report whether participants clicked one of these links. See subsection C.2 for details.

This table reports a summary of each of the 16 datasets we discuss in our paper (besides the website demographic data from Similarweb). Column 1 reports the citation for each assembled data source reported in Figures Figure 1 and Figure A1. n refers to the number of participants that we have data from for each respective study. Column 2 has the figure labels from Figure 1 and Figure A1. Column 3 has a description of the sample from each source, including when the data was collected. Column 4 has the specific outcome that is measured in each study, including the time frame under which the question was asked. Details of the descriptions between samples may vary based on the information available about the data. † denotes surveys that were nationally representative. *The one exception in our combined survey data to the gender gap is a study of US tech workers conducted by Boston Consulting Group (BCG) that finds that 3% more women than men use generative AI (Barisano et al., 2024). This positive gap is driven by senior women in technical functions. At junior levels, they find that women adopt AI at rates 7 percentage points lower (in technical functions) and 21 percentage points lower than men (in non-technical functions).

Table A2: Covariate-adjusted Gender Gaps

Study (1)	Type (2)	Unadjusted Gap (3)	Adjusted Gap (4)	Control Variables (5)
Nature Research (2023)	New analysis	7.4% (p<0.001)	8.5% (p<0.001)	Age, field of study, location
Kenya AI Adoption Study (KAAS)	New data and analysis	1.7% (p<0.01)	2.1% (p<0.001)	Age, education, location
Otis et al. (2023)	New data and analysis	10.4% (p<0.01)	11.1% (p<0.01)	Age, Education, Location (Nairobi)
Carvajal, Franco, and Isaksson (2024)	Reported elsewhere	15.0% (p<0.001)	7.5% (p<0.05)	Year in college, admission year, risk preferences, and time preferences
Humlum and Vestergaard (2024)	Reported elsewhere	21.9% (p<0.001)	15.0% (p<0.001)	Occupation, task importance, workplace, beliefs, uncertainty*

This table reports covariate-adjusted gender gaps for studies where we have the study data, or for which adjusted and unadjusted gaps are reported in the paper. The “Type“ column reflects whether the results in this table come from new data (and analysis), from new analysis of existing data, or from results reported in other published or working papers. The “Unadjusted Gap“ reflects the percentage point difference in AI adoption between male and female users, and the “Adjusted Gap“ reports the magnitude of the gap after adjusting for covariates as described in the final column. *The “unadjusted” differences reported in this paper already controls for Age, Experience, log(Earnings), (Net Wealth/Earnings).

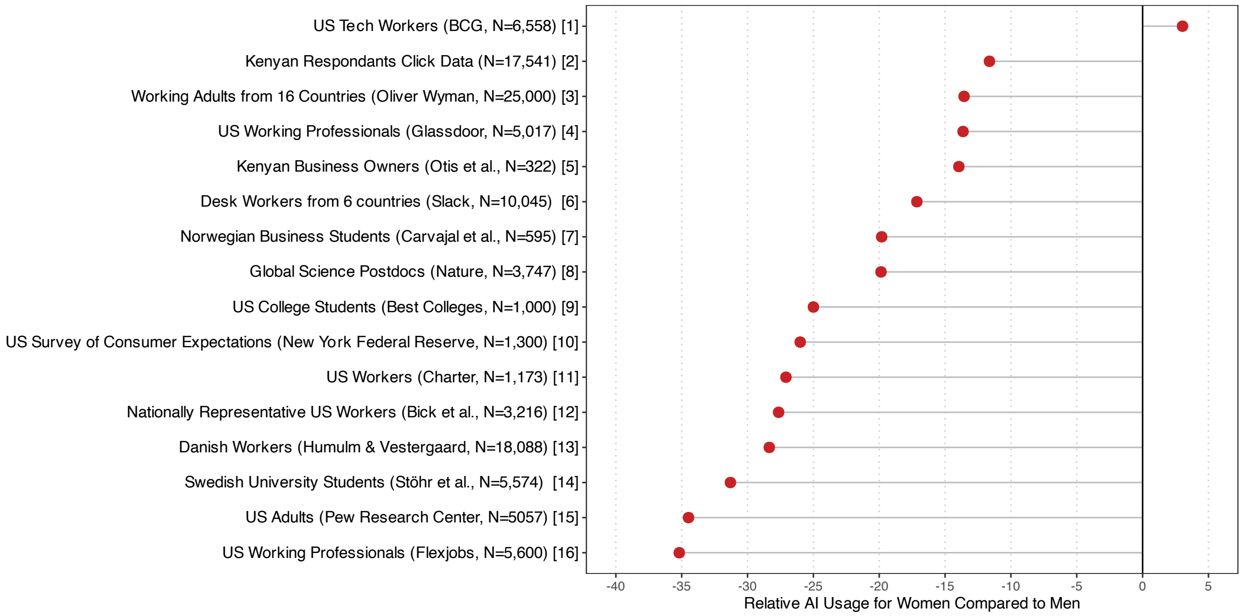
Table A3: Similarweb Website Visitor Data

Website (n) (1)	Description (2)
OpenAI n=172.9M Average Monthly Unique Visitors	Website link used on Similarweb was "chat.openai.com"
Midjourney n=10M Average Monthly Unique Visitors	Website link used on Similarweb was "midjourney.com"
Anthropic n=1.9M Average Monthly Unique Visitors	Website link used on Similarweb was "anthropic.com"
Perplexity n=7.1M Average Monthly Unique Visitors	Website link used on Similarweb was "perplexity.ai"

This table reports additional information about the Similarweb data we use for demographic estimates of popular GenAI website visitors. Column 1 reports Similarweb's estimate of the average unique visitors per month to each respective website between November 2022 and May 2024. Column 2 has the website link that was used to look up Similarweb data. For more information about Similarweb, see C.1.

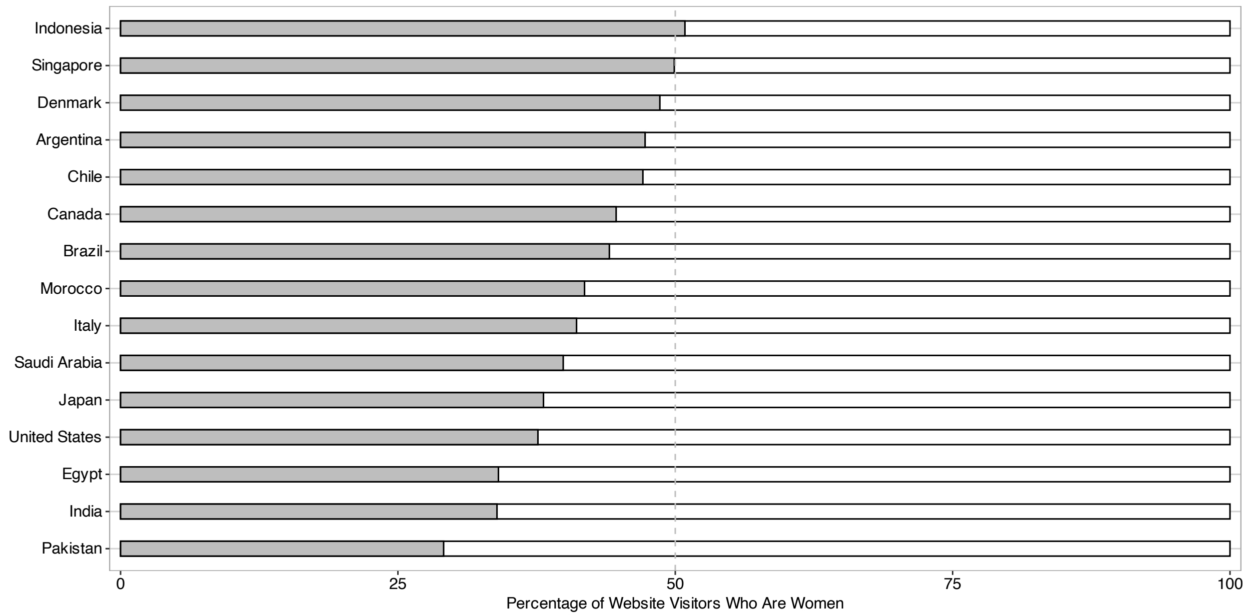
B Appendix Figures

Figure A1: Relative Gender Ratio of Generative AI Users Across Studies, 107,607



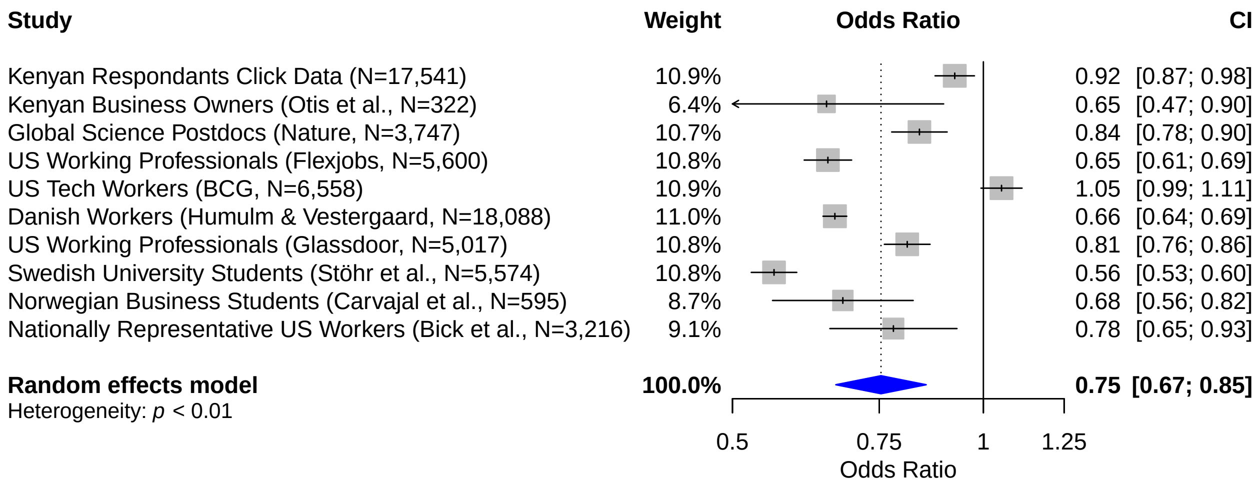
This figure represents the relative percent difference in AI use, calculated as $\big(p(\text{women}) - p(\text{men})\big)/(p(\text{men})$. Estimates are ordered by effect size. Details on the data sets are presented in Table A1. N refers to the total number of respondents for which we have data from each respective source. All sources are from surveys and represent self-reported AI use besides two studies. "Kenyan Respondents Click Data" and "Kenyan Business Owners" datasets capture actual AI usage and demand.

Figure A2: Percentage Visitors Who Are Women to ChatGPT - OpenAI



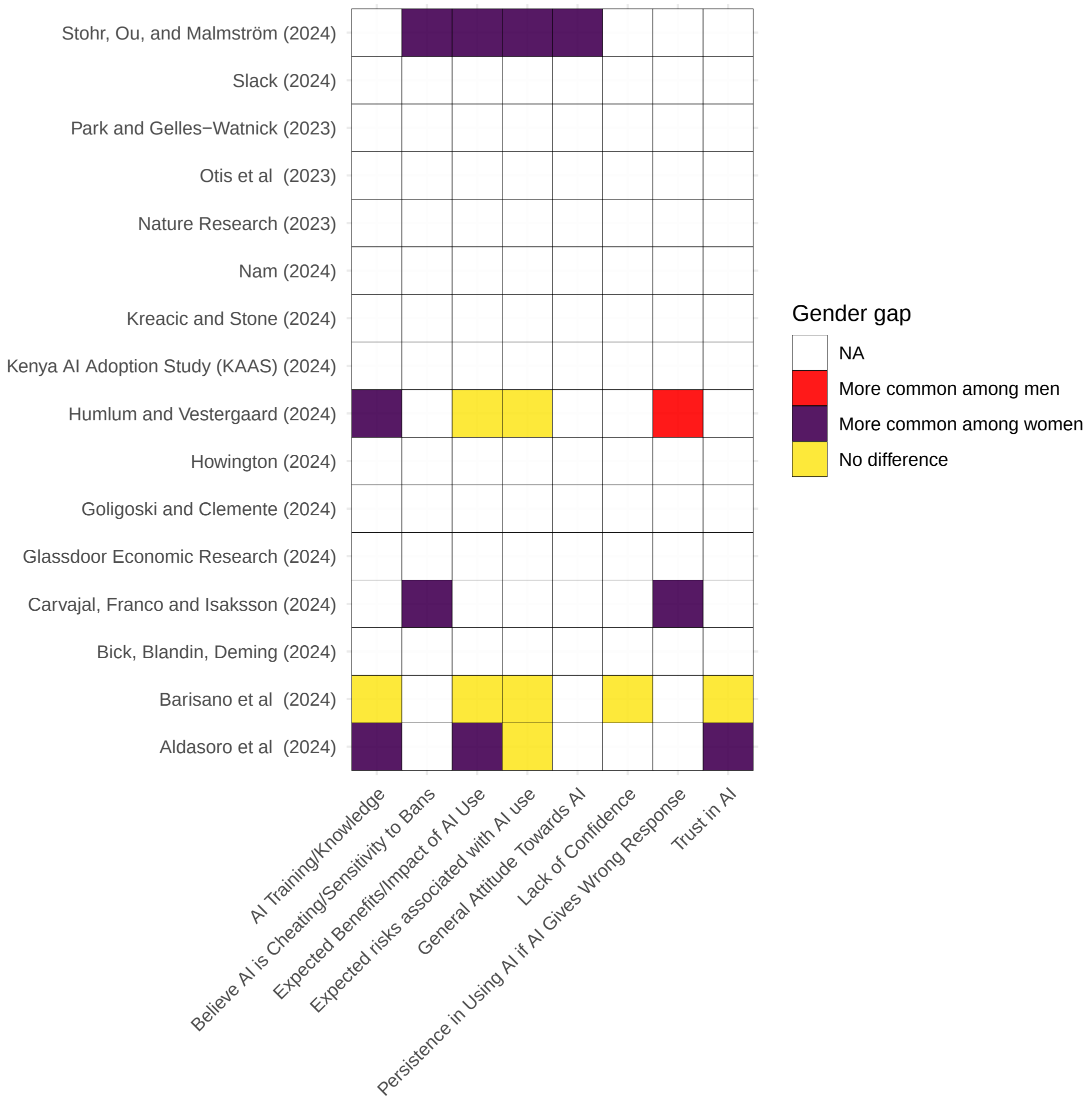
This figure presents the estimated percentage of total unique website visitors that are predicted to be women for OpenAI's ChatGPT (chat.openai.com). We selected 14 countries with a sufficient number of ChatGPT users to have aggregate data available from Similarweb for that country. We include data from 7 low and lower-middle-income countries (Argentina, Brazil, Egypt, India, Indonesia, Morocco, and Pakistan) and 7 upper-middle- and high-income countries (Canada, Chile, Denmark, Japan, Italy, Saudi Arabia, and Singapore). We also include the United States as a reference point. In all but one country (Indonesia), there is a greater percentage of male visitors than female visitors. "Users" refers to the predicted average number of unique website visitors (not deduplicated across devices) from November 2022 - May 2024 (the lifetime of ChatGPT, the first widely popular GenAI tool). See Table A3 for additional information about Similarweb data. Argentina: 1.905 million users, Brazil: 6.422 million users, Egypt: 1.08 million users, India: 14.36 million users, Indonesia: 7.619 million users, Morocco: 1.211 million users, Pakistan: 0.895 million users, Canada: 4.606 million users, Chile: 1.919 million users, Denmark: 0.51 million users, Japan: 11.61 million users, Italy: 2.234 million users, Saudi Arabia: 0.296 million users, Singapore: 1.062 million users, United States: 18.01 million users.

Figure A3: Metaanalysis of Gender Gaps in AI Adoption



The analysis employs a random-effects meta-analysis model to examine gender differences in AI usage across multiple studies. This model is designed to account for variability between studies, such as differences in sample populations, by allowing the true effect size to vary across studies. The random-effects model provides a weighted average of the effect sizes from each study, giving more weight to larger studies while still incorporating the variability observed in smaller ones. We include 10 of the 16 studies in our meta-analysis, as these are the studies for which we have data on the gender breakdown of participants. The analysis is limited to these studies due to the availability of gender-specific proportions, which allows us to accurately assess gender differences in AI usage and conduct these tests. The random-effects odds ratio model indicates a gender gap in AI usage, with a combined odds ratio of 0.754 (95% confidence interval = [0.67, 0.85]), with a p-value < 0.0001. This suggests that women are 24.6% less likely to use AI compared to men across the analyzed studies.

Figure A4: Survey Evidence on Mechanisms Underlying Gender Gap



This figure provides an overview of the survey mechanisms identified as underlying the gender gap presented in each paper. Empty cells indicate that a particular survey mechanism is not measured in the given dataset. Yellow cells represent cases where data was collected, but where no significant gender gap was found for a specific mechanism. Purple cells indicate that a given friction was more prevalent in women, and red cells a given friction was more prevalent in men. Note that Barisano et al. (2024) provides mixed evidence on mechanisms across levels of employee seniority. See Figure 2 of Barisano et al. (2024) for details. We include all mechanisms that are reported in the body of each manuscript. We classify a gender gap as occurring for a given mechanism if the authors report a significant gap for that mechanism ($p < 0.05$), or in some cases, if they report a gap but do not note the level of significance (e.g., see Barisano et al. (2024)). Details on the classification procedure are outlined in subsection C.3.

C Overview of Data

Our assembled data includes samples from 26 countries: Argentina, Australia, Brazil, Canada, Chile, China (Hong Kong), Denmark, Egypt, France, Germany, India, Indonesia, Italy, Japan, Kenya, Mexico, Morocco, Norway, Pakistan, Saudi Arabia, Singapore, Spain, Sweden, the U.K., the United Arab Emirates, and United States.

C.1 Similarweb

Similarweb is a data aggregation market analysis platform that provides estimates for website traffic and user demographics, as well as other website performance metrics such as total page visits, new vs returning users, and time spent on site. Similarweb's data is updated monthly. Other firms such as Airbnb, Walmart, Adidas, and J.P. Morgan use Similarweb to benchmark performance and for lead generation. See Koning, Hasan, and Chatterji (2022) and Cao, Koning, and Nanda (2023) for additional discussion and validation of the Similarweb data.

We use Similarweb to determine the number of unique website visitors to four popular GenAI websites. We also use their predicted gender estimate of unique visitors to understand the ratio of women vs men that use these tools.

How does Similarweb predict the gender of website visitors? According to their website, "Similarweb has access to hundreds of thousands of internal analytics accounts that provide us with their demographic information (age and gender). Similarweb also has the largest and most diverse contributor network in the industry. Combining these data sources enables us to build audience profiles and map out the web by seeing the digital journey of hundreds of millions of users" (see `https://support.similarweb.com/hc/en-us/articles/115005835169-Website-Demographics#:~:text=How%20does%20Similarweb%20collect%20website,information%20(age%20and%20gender)`).

C.2 Kenya AI Adoption Study (KAAS)

This section provides an overview of the data collection procedures for the Kenya AI Adoption Study (KAAS). In this study, Kenyan survey respondents were recruited through an online advertisement run on the Meta ad platform. This project was approved by the UC Berkeley Office for the Protection of Human Services and has not been reported on elsewhere. The ad targeting was restricted to individuals from Kenya, and no additional geographical targeting was applied. In total, 17,541 Kenyan participants clicked on the link and completed the survey. As compensation for participating in the survey individuals were sent a small payment of 30 Kenyan shillings.

The survey began by collecting basic demographic information on respondents. Individuals who completed the survey were on average 23 years old, had at least some college education, and were 73.9% male. This gender difference in survey response rates likely stems from the fact that the Meta platform runs an auction determining who to show advertisements to. Because there is greater demand for female "eyeballs," ads are shown disproportionately to men unless the ads explicitly target a particular group, which this ad did not. (Lambrecht and Tucker, 2019)

After completing the basic demographic survey, the following strategy was used to elicit use of and interest in AI tools in a way that is not susceptible to the social desirability bias that may be present in surveys. Specifically, we first asked participants: *Would you like to download ChatGPT or learn how to access GPT on your browser?*

If they answered "Yes," they were provided with web links to either download the ChatGPT app or use ChatGPT in their browser. We built a custom feature into our survey which allowed us to track whether or not a participant clicked on one of these two buttons. This allows us to passively collect information on participants demand for generative AI absent susceptibility to social desirability related biases.
We find that 13.052% of women clicked on one of the links, while 14.77% of men clicked on one of the links. This results in a male click rate that is 13% higher for men than for women. Table A2 prudence evidence that this gap is stable and even increases in size when adjusting for covariates.

C.3 Mechanism Questions

This section provides an overview of the methodology used to analyze the mechanisms underlying gender gaps in AI adoption (Figure A4). We identified mechanism results using the following procedure. First, we only searched for mechanism questions that directly asked about artificial intelligence. For example, we did not look at gender differences in risk preferences, but we included gender differences in risk preferences if they were explicitly related to AI adoption. This was to ensure that the mechanisms were closely tied to the focus of this paper, which is gender differences in AI adoption. We then had a research assistant classify each mechanism into a topic or theme that summarized its focus. We reviewed this larger set of topics and consolidated them down into the number of topics highlighted in the figure. For example, we grouped together questions on training related to AI and knowledge about how to use AI. Below, we report the survey question. When reported by the authors, the actual question text is provided. Otherwise, we report a summary of whatever information on these mechanisms was provided by the authors.

Paper: Aldasoro et al. (2024) **AI Training/Knowledge** • How much do you know about artificial intelligence tools (such as ChatGPT, Google Bard, DALL-E, . . .)? **Expected Benefits/Impact of AI Use** • What do you think are the chances that artificial intelligence will help you find new job opportunities? • What do you think are the chances that artificial intelligence will increase your productivity at work? **Trust in AI** • In the following areas, would you trust artificial intelligence (AI) tools less or more than traditional human-operated services? • How much do you trust the following entities to safely store your personal data when they use artificial intelligence tools? **Expected Risks Associated with AI Use** • What do you think are the chances that you will lose your current job because of artificial intelligence tools? • What do you think are the chances that your salary in your current job will decrease because of artificial intelligence tools?
Paper: Carvajal, Franco, and Isaksson (2024) **Believe AI is Cheating/Sensitivity to Bans** • Using ChatGPT as an aid to solve assignments in a course is equivalent to cheating. • Using ChatGPT as a learning aid in a course is equivalent to cheating. **Persistence in Using AI if it Gives the Wrong Response** • If ChatGPT does not provide the desired answer on your first attempt, how many additional attempts do you typically make?
Paper: Stohr, Ou, and Malmström (2024) **Expected Benefits/Impact of AI Use** • Do you agree or disagree with the following statements about AI chatbots in general? • The chatbots I use make me more effective as a learner. • The chatbots I use improve my study grades. • Chatbots generate better results than I can produce on my own. • The chatbots I use improve my general language ability. **Expected Risks Associated with AI Use** • I am concerned about how AI chatbots will impact students' learning in the future. **General Attitude Towards AI** • Overall, I have a positive attitude towards the use of chatbots in education. **Believe AI is Cheating/Sensitivity to Bans** • Using chatbots to complete assignments and exams is cheating. • Using chatbots should be prohibited in educational settings. • Using chatbots goes against the purpose of education.
Paper: Humlum and Vestergaard (2024) **AI Training/Knowledge** • It would require training before I can benefit from ChatGPT. **Expected Benefits/Impact of AI Use** • We will next ask for your assessment of whether ChatGPT can save time on various job tasks. Note: Your answers are important regardless of your knowledge of ChatGPT. If you are not familiar with ChatGPT, we ask you to give your best guess. You will later get the opportunity to indicate how certain you are in your evaluations. • Productivity of ChatGPT [all tasks]: Think of a [journalist] with an average level of experience and expertise trying to complete a given task. The worker has access to ChatGPT, the internet, a computer with existing software, and other tools typically used to complete the task. Specify the following tasks according to the description below: • Small or no time savings from ChatGPT • Large time savings from ChatGPT • We now ask you to assess how the potential time savings from ChatGPT relate to [journalists'] expertise in given job tasks. Expertise Complementarity of ChatGPT [all tasks]: Imagine two [journalists] with average levels of experience and expertise but who differ in their expertise in a given task. Specify whether access to ChatGPT in the task yields smaller, similar, or larger time savings for the worker with greater expertise compared to the worker with less expertise in the task. **Expected Risks Associated with AI Use** • I fear that ChatGPT will eventually make me redundant in my job. • ChatGPT will reduce my joy of performing the task. • I am concerned about how ChatGPT will handle my data confidentially. • I am concerned about becoming dependent on ChatGPT in the task. **Believe AI is Cheating/Sensitivity to Bans** • I am subject to restrictions on using ChatGPT in my job.
Paper: Barisano et al. (2024) *Note: The actual survey measures were not reported in this study.* **AI Training/Knowledge** • "Feelings of competence in using GenAI tools" **Expected Benefits/Impact of AI Use** • Awareness of GenAI's criticality to future job success **Trust in AI** • "Trust that GenAI tools would accomplish their objectives" **Expected Risks Associated with AI Use** • Risk tolerance for using GenAI prior to having a company policy **Lack of Confidence** • Confidence in GenAI skills

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