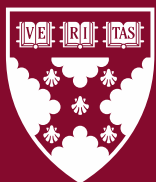


Working Paper 25-023

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Generative AI has the potential to transform productivity and reduce inequality, but only if adopted broadly. In this paper, we show that recently identified gender gaps in generative AI use are nearly universal. Synthesizing data from 18 studies covering more than 140,000 individuals worldwide, combined with estimates of the gender share of the hundreds of millions of users of popular generative AI platforms, we demonstrate that the gender gap in generative AI usage holds across nearly all regions, sectors, and occupations. Using newly collected data, we also document that this gap remains even when access to try this new technology is equalized, highlighting the need for further research into the gap’s underlying causes. If this global disparity persists, it risks creating a self-reinforcing cycle: women’s underrepresentation in generative AI usage would lead to systems trained on data that inadequately sample women’s preferences and needs, ultimately widening existing gender disparities in technology adoption and economic opportunity.

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Generative AI is expected to have profound economic and social impacts. Recent studies demonstrate that tools like ChatGPT have already begun to impact the skills, knowledge, and productivity 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). Moreover, because these tools are often both widely accessible and easy to use, they have the potential to help billions of people from historically underserved groups across the world (Björkegren, 2023; Otis et al., 2023). This is especially true for women, who still face institutional, career, and cultural barriers that prevent them from gaining the valuable skills and knowledge needed to succeed at work (England, Levine, and Mishel, 2020; Goldin, 2021). If generative AI lowers the barriers to gaining the skills and knowledge required to be productive at work, then these tools might especially benefit women in the face of these challenges.

However, work on the sociology and economics of technology adoption suggests that despite this potential, numerous frictions may cause women to use generative AI at lower rates than men. First, because women tend to work in different types of firms, jobs, and occupations than men, they may be less exposed to this new technology. Such differences are often further reinforced by the gendered differences in women’s personal and professional networks, further limiting diffusion and learning (DiMaggio and Garip, 2012). Beyond differences in awareness, stereotypes and status differences can also lead women to be less likely to use new technology even when presented with the opportunity (Correll and Ridgeway, 2003; Ridgeway, 2011). For example, women may face a greater risk of being penalized or perceived as “cheating” when they choose to use generative AI tools (Exley et al., 2024; Carvajal, Franco, and Isaksson, 2024). And even when women do get to use these tools, their efficacy could be hindered by the fact that these generative AI systems are often trained on biased data (Guilbeault et al., 2024), including data from their predominantly male users. This can result in self-reinforcing gender gaps as these systems learn from, adapt to, and so sample from more men (Cao, Koning, and Nanda, 2023).

In this paper, we show that—consistent with these gendered adoption frictions—there is a large, persistent, and nearly universal gender gap in generative AI use. We do so by first assembling data from 18 scholarly and practitioner studies that measure men and women’s use of chat-based generative AI tools like OpenAI’s ChatGPT and Anthropic’s Claude. Our results reveal a remarkably consistent gap: women are about 20% less likely than men to directly engage with this new technology. This gap is not merely the result of gendered survey response bias, as it exists across novel data we collect on the gender shares of generative AI websites and app users. Additionally, included in our analysis are new results from a large-scale study of over 17,000 women and men in Kenya in which we offered participants the chance to use ChatGPT. We find that even when opportunities to access generative AI were equalized, the gender gap in generative AI use persists. Our findings highlight how policymakers, managers, and researchers across the world must urgently

wrestle with and address the gendered adoption and use of generative AI. First, the consistency of the gender gap across 18 surveys, as well as in estimates from web traffic and app download data, highlights that the user data collected by generative AI platforms is heavily skewed by gender. This imbalance—if not addressed—may result in inequities in who is more likely to benefit from these tools. Second, more research exploring how to enable women to use these tools is needed, as our study shows that simply equalizing access will not suffice. More broadly, and in line with work studying the impact of past technological revolutions on gender differences, without intentional efforts to address these usage gaps, generative AI might not just perpetuate existing inequalities but potentially widen them.

Data and Results

To estimate the extent of the gender gap in generative AI use, we first identified every publicly available study that has surveyed people about generative AI use along with their gender (see [Appendix A](#) for details on each study, including the specific questions used to measure generative AI use). These 17 studies include data from individuals ranging from tech employees to science postdocs to working adults from around the world, which we complement with a novel survey that we ran with 17,541 Kenyan adults. Altogether, these data encompass 143,008 individuals. Rows 1-18 in Panel A of [Figure 1](#) illustrate the percentage of women (red triangles) and men (black circles) using AI in each study. This panel shows a remarkably consistent pattern in generative AI use: men are more likely to adopt generative AI tools than women in all but one survey.

The size of these gender gaps is meaningful. In the United States, targeted and nationally representative samples show a roughly 10 to 20 percentage point gap (rows 6,7,10-12,16,17). For example, a representative survey by the New York Federal Reserve ([Aldasoro et al. \(2024\)](#)) finds that half of men used generative AI in the last 12 months compared to only about one-third of women (row 12). To further contextualize the magnitude of these gaps, Panel B of [Figure 1](#) shows the gaps in relative percentages. We find that relative to the share of men who use generative AI, the share of women is often about 10% to 40% smaller. The exception is a Boston Consulting Group (BCG) study showing that women are 3% more likely to use generative AI than men in a convenience sample of 6,558 tech employees ([Barisano et al. \(2024\)](#)). This positive gap is driven primarily by women working in senior technical roles, whereas junior women are significantly less likely to use generative AI than junior men (see [Appendix A](#)). This suggests that experience working in and using technology may play a critical role in eliminating the gender gap. However, across the other 136,576 individuals in our data, we find that women are much less likely to use generative AI than men in occupations ranging from postdocs across the world (21%) to business owners in the US, Australia, the UK, and Canada (11%) to college students in the US and Sweden (25% and 31%). For twelve of the studies in our sample, we were able to manually extract enough data to complete

a formal meta-analysis. These twelve studies suggest that women have about 22% ($p < 0.0001$) lower odds of using generative AI tools than men (see [Appendix C](#)).

That the gender gap holds across people from such diverse backgrounds and regions suggests that the gap is not merely the result of women’s under-representation in particular areas of the economy (e.g., as computer scientists or software developers). The yellow squares in Panel B of [Figure 1](#) show two prior and five new regression estimates of the gap that control for a range of potentially gendered differences ranging from location to field of study to occupation. The adjusted gender gap persists across a variety of different controls and samples. The estimate produced by [Humlum and Vestergaard \(2025\)](#), which includes the most detailed occupational and task variables, suggests that the gendered nature of the division of labor accounts for only 25% of the observed gap in generative AI usage.

The gender gap also holds when we analyze novel internet traffic data that measures who uses some of the world’s most popular generative AI tools, ruling out the possibility that the findings in [Figure 1](#) are merely the result of a gendered survey response bias. Building on data described and validated in [Koning, Hasan, and Chatterji \(2022\)](#) and [Cao, Koning, and Nanda \(2023\)](#), Panel A of [Figure 2](#) shows data pulled from the internet analytics platform SimilarWeb on the gender breakdown of website and smartphone app users of OpenAI’s ChatGPT, Anthropic’s Claude, 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 the ChatGPT website, 42.4% of Perplexity users, and just 31.2% of Anthropic users (see [Section A](#) for details). Panel B of [Figure 2](#) shows that these gaps grow when we focus on smartphone app usage: only about 27.2% of total ChatGPT application downloads are estimated to come from women (25.2% in the U.S.), with similarly low shares for Anthropic’s Claude and Perplexity.

Finally, we turn to mechanisms and solutions. As we document in [Appendix D](#), prior work suggests multiple mechanisms could explain the generative AI gender gap with the strongest evidence emerging for (1) differences in knowledge of and familiarity with generative AI, (2) differences in confidence and persistence when using this new technology, and (3) differences in beliefs about whether using these tools is unethical or perceived as cheating. Building on the first set of knowledge and familiarity mechanisms, if the gender gap is rooted in women being less likely to be informed of and so know about new generative AI tools, then equalizing the opportunity to engage with a generative AI tool should close the gap.

To test if equalizing access explains—and so can close—the gender gap in generative AI use, we use data from the Kenya Generative AI Adoption Study (KGAAS), which we launched in August 2023. The KGAAS collected data on the demand for generative AI from 17,541 Kenyan Facebook users,

reducing the barriers for both men and women to try out ChatGPT (Section A). The KGAAS results show that women are still approximately 13.1% ($p < 0.01$) less likely to want to adopt ChatGPT when presented with the opportunity to learn how to use these tools. Compared to our meta-analysis estimate showing that women have about 20% lower odds of using these tools than men, the findings from this study suggest that, while equalizing access might help shrink the gender gap, it is unlikely to fully close it.

Discussion

The findings above document that gender gaps in generative AI are nearly universal. We find women use generative AI less than men in data from 18 studies covering 143,008 people from across the world as well as data on who uses top generative AI websites and apps. 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. Akin to efforts to equalize female labor market participation and pay (England, Levine, and Mishel, 2020), it appears that social, cultural, and institutional frictions have led to a gendered gap in generative AI adoption.

This disparity has the potential to be significant. As generative AI systems are still in their formative stages, the under-representation of women may result in early biases in the user data these tools learn from, resulting in self-reinforcing gender disparities (Cao, Koning, and Nanda, 2023). Such biases in user data—similar to those that have previously led to racial disparities in generative AI performance—could result in generative AI systems that reinforce gendered stereotypes and in tools that are less effective at the tasks more often performed by women (Koenecke et al., 2020; Guilbeault et al., 2024). Ensuring that generative AI tools are both designed inclusively and do not inadvertently substitute for broader efforts to reduce gendered inequalities in everything from pay to childcare responsibilities to emotional labor, will be crucial for unlocking their full potential to enhance productivity and to reduce inequality (Pugh, 2024). Given recent estimates that generative 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 growth in the US alone.

Given the potential ramifications of this global generative AI gender gap, these findings also point to the need for further research, policy, and managerial efforts aimed at closing this gap. As our findings show, even when efforts to increase participation by equalizing access are in place, women are still less likely to use generative AI than men. Combined with the ubiquity of the gap, these findings suggest researchers and policymakers must build on recent work that has identified potential mechanisms for this gap (see Appendix D) in order to better understand why women—

even when exposure is equalized and tasks are similar—are less engaged with generative AI tools. Without such efforts, generative AI’s potential to drive economic growth and improve productivity will almost surely disproportionately benefit male users, not only entrenching existing gender gaps, but also opening the possibility that society will miss out on the work, inventions, and ideas women would have produced with this new technology (Koning, Samila, and Ferguson, 2021).

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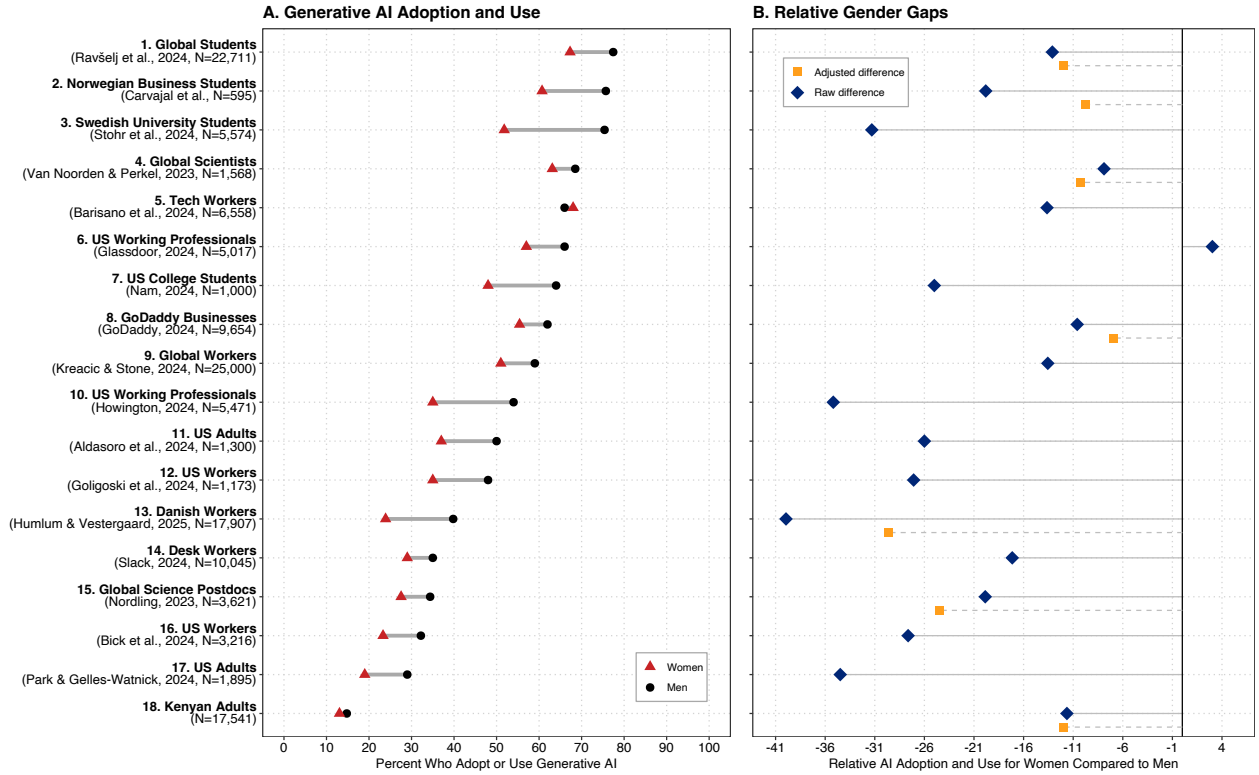
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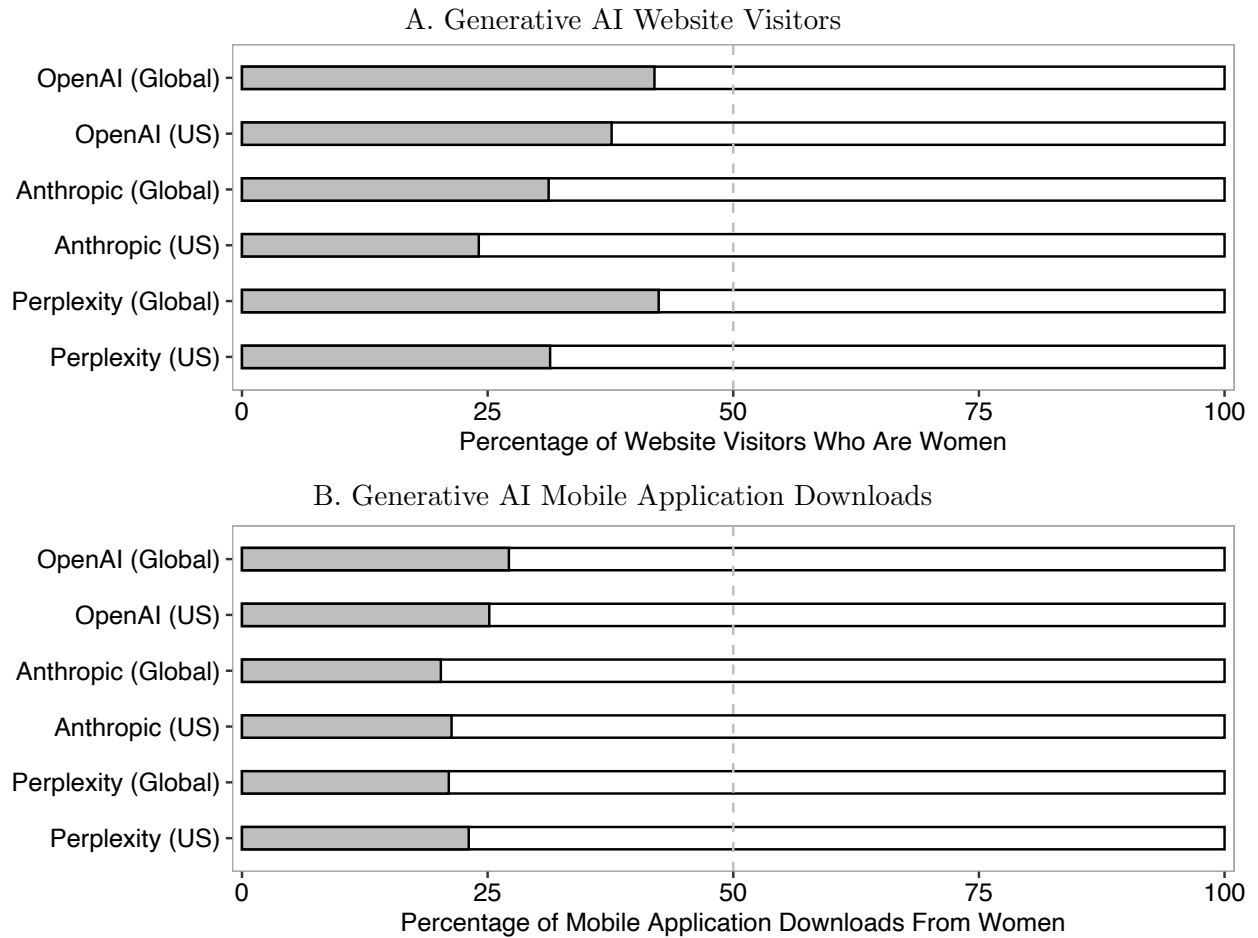
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Figure 1: Generative AI Adoption and Use by Gender Across Studies



Panel A shows the adoption and use of generative AI by gender in 18 datasets (see [Appendix A](#) for additional details on data sources and variable definitions). Red triangles indicate the percentage of women using Generative AI, while black circles indicate the percentage of men. The gray bars between each point represent the gender gap in AI adoption and use. Estimates are ordered by the overall generative AI use rates reported in each study. N denotes the total number of respondents with available data from each respective source. Panel B illustrates the relative percentage difference in generative AI adoption and use, calculated as $(p(\text{women}) - p(\text{men}))/p(\text{men})$. Blue diamonds indicate the unadjusted relative difference, while yellow squares represent the covariate-adjusted relative difference (when available). The covariate-adjusted relative difference is calculated by estimating the gender difference in adoption rates after controlling for covariates and then dividing this difference by $p(\text{men})$ (see [Appendix B](#)).

Figure 2: Percentage of Women Among Generative AI Website Visitors and Mobile Application Downloads



Panel A presents the estimated percentage of total unique users predicted to be women for three widely used generative AI platforms, based on website traffic data collected by SimilarWeb. The data represent averages from November 2022 through May 2024, covering the entire lifetime of ChatGPT, the first widely used generative AI tool and the most popular to date. Panel B provides estimates for the percentage of total application downloads predicted by SimilarWeb to be women for the same platforms. These data, collected from May 2023 through November 2024, also span the lifetime of the ChatGPT mobile application. See [Appendix A](#) for additional details.

Online Appendix

Global Evidence on Gender Gaps and Generative AI

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A Overview of Data

To identify relevant datasets, we conducted a comprehensive search on Google Scholar in July and December 2024. This search included studies from all geographies, whether published or unpublished, as long as they measured both (1) generative AI use and (2) the respondent’s gender. Through this process, we identified 17 such studies. One key advantage of studying a new technology like generative AI is that to use it requires directly engaging with branded tools that almost always highlight that the user is engaging with a generative AI system. In contrast, more developed technologies ranging from electricity to traditional machine learning can easily be overlooked as a critical input that enables a product or service people use. The fact that using generative AI still requires deliberate use suggests that surveys asking about use of this technology should yield relatively precise measures. Below, we provide an overview of the pre-existing survey data we analyze, our new Kenya Generative AI Adoption Study (KGAAS), and the SimilarWeb internet analytics data.

Summary of Datasets in Figure 1

For each dataset, we provide a brief overview of the analytic sample used in this study, along with the survey measure included in our analysis. Note that some surveys include multiple measures of generative AI adoption and use. In papers with multiple measures, we use the most general measure or the first measure for which the authors provide an aggregate gender gap. We encourage readers to consult the cited papers for a comprehensive description of the data collection procedures and measures.

1. [Ravšelj et al. \(2024\)](#) surveyed 22,711 respondents (after excluding 507 respondents who do not report their gender as male or female) through a global survey that targeted higher education students. The ten most common countries of origin were: Turkey, Ghana, Chile, Tanzania, Egypt, Romania, Spain, Italy, Mexico, and Ecuador.

Measurement: Respondents were asked “Have you ever used ChatGPT?” with response options “No” (coded as 0) and “Yes” (coded as 1).

2. [Carvajal, Franco, and Isaksson \(2024\)](#) surveyed 595 bachelor’s and master’s students at a Norwegian business school between November 2023 and early 2024.

Measurement: We follow the authors’ definition of AI adoption: “To generate our adoption measure we focus on students’ answers to the question ‘How familiar are you with generative AI?’ In the analysis we use a binary variable equal to zero for low use if the student indicated ‘not heard about it,’ ‘heard about it but not using it myself’ or ‘used it a few times,’ which indicates none or limited use, and equal to one for high use if the participant indicated ‘use it occasionally’ or ‘use it all the time,’ which indicates a more regular use” ([Carvajal, Franco, and Isaksson, 2024](#), p. 104).

3. **Stohr, Ou, and Malmström (2024)** surveyed students from 28 Swedish universities in April 2023. Row 1 of Table 4 of their paper reports a sample size of 5,574.

Measurement: Respondents were asked: “Rate your familiarity and frequency of use with a selection of AI chatbots: ChatGPT”, with response options {Unfamiliar, Familiar but never use it, Familiar but rarely use it, Familiar and regularly use it}. Following correspondence with the authors, “Familiar but rarely use it” and “Familiar and regularly use it” are classified as using AI (coded as 1) and “Unfamiliar” and “Familiar but never use it” are classified as not using AI (coded as 0).

4. **Van Noorden and Perkel (2023)** report results from a survey of 1,568 researchers surveyed by *Nature* (after excluding 91 respondents whose gender was listed as “other” or who did not answer the survey question on generative AI use). Respondents had either “published papers in the last 4 months of 2022” or were “readers of the *Nature* Briefing” (Van Noorden and Perkel, 2023, p. 673).

Measurement: Participants were asked: “How often do you use generative AI tools (such as ChatGPT) at work?” with response options {I use them every day, I use them more than once a week, I use them occasionally, I’ve used them only a few times, Never}. Responses of “Never” were coded as 0, and all other values were coded as 1.

5. **Barisano et al. (2024)** conducted a survey through Boston Consulting Group in January 2024 with 6,558 workers in both senior and junior roles in the technology industry from India, the United States, Japan, the United Kingdom, and Germany. The authors collect data from workers in both technical and non-technical functions. The authors define senior roles as roles where the worker has more than five years of experience in the tech industry. They classify technical functions as engineering, IT, customer support, sales or marketing, and non-technical functions as HR, legal, or finance.

Measurement: Respondents were asked: “How frequently do you use any GenAI tool at work?” We follow the authors’ classification of respondents as having “adopted GenAI if they use it more than once a week” (coded as 1), and all other options were coded as 0. The full set of response options are not provided in the paper.

Note: In their sample, the authors find that women are 3% more likely to use AI than men. However, this outlier result is driven primarily by women in senior roles with technical functions. Women in junior roles significantly lag men in generative AI use in both technical (-7pp) and non technical functions (-21pp). Senior women in non-technical functions are also less likely to use generative AI, with gaps from -2pp to -12pp depending on the level.

6. **Glassdoor Economic Research (2024)** conducted a survey with 5,017 U.S. professionals in November 2023.

Measurement: Respondents were asked about whether they had “ “Have you used ChatGPT, or other AI Tools, to help you with tasks at work?” with response options “No” (coded as 0) and “Yes” (coded as 1).

7. **Nam (2024)** surveyed 1,000 U.S. undergraduate and graduate students enrolled in various programs during September and October 2023.

Measurement: The authors do not provide the survey questions. Instead they state “A higher percentage of men than women report having used AI tools such as ChatGPT to help complete assignments or exams (64% vs. 48%).”

8. **GoDaddy (2024a)** surveyed users of the GoDaddy domain and web hosting company. They state: “Eligibility is determined by several factors including evidence that the respondent has an active microbusiness, the respondent has granted GoDaddy permission to send them emails, and residency in the target geographic area” (GoDaddy, 2024a). For this study, we pool together four different survey waves measuring generative AI use, which took place in the U.S. in February 2024, in Australia and Canada in July 2024, and in the UK in May 2024. Across these surveys, 9,654 individuals responded after excluding 1,421 who did not list their gender as male or female, or who did not respond to the survey question which elicited gender information.

Measurement: Respondents were asked “In the past few months, have you tried using a Generative AI tool (like Airo, ChatGPT, DALL-E, Stable Diffusion, Jasper or Bard)?” with response options {Yes, for fun / out of curiosity, Yes, for personal use, Yes, for my business, No (Exclusive)}. “No (Exclusive)” was coded as 0, and all other options were coded as 1 (GoDaddy, 2024b).

9. **Kreacic and Stone (2024)** surveyed 25,000 adults aged 18-65 across 16 countries—including the U.S., Canada, Mexico, Brazil, the U.K., France, Italy, Germany, Spain, China, India, Indonesia, Singapore, the UAE, and Australia—between June and November 2023.

Measurement: The authors do not include the exact survey questions. Instead they state: “59% of male workers aged 18-65 around the world say they use generative AI tools at least once a week, while only 51% of women say the same.”

10. **Howington (2024)** conducted a survey in May 2023 with 5,641 U.S. professionals across various careers and education levels. We emailed the authors who reported to us that women are 69% of the sample, men are 28% and 3% “prefer not to identify or self-describe”. We define the analytic sample as the sum of the rounded gender-based sample sizes ($5,641 * 0.69 \approx X$) + ($5,641 * 0.28 \approx$) = $3,892 + 1,579 = 5,471$.

Measurement: The authors do not provide the survey questions. Instead, they state “men (54%) are using AI in either or both their personal and professional life, while women (35%) are adopting AI at a much slower pace.”

11. **Aldasoro et al. (2024)** conducted a survey with a “nationally representative panel of approximately 1,300 US household heads” in February 2024 through the New York Federal Reserve’s Survey of Consumer Expectations (Aldasoro et al., 2024, p. 1).

Measurement: The paper reports that generative AI use is elicited by asking: “How often have you used artificial intelligence tools (such as ChatGPT, Google Bard, DALL-E, ...) in the past 12 months?”; a dummy variable has been constructed taking a value of zero if the response is ‘Never’ and a value of one if the response is ‘Less than once a month’, ‘Once a month’, ‘Once a week’ or ‘More than once a week’” (Aldasoro et al., 2024, p. 2).

12. **Goligoski et al. (2024)** surveyed 1,173 U.S. workers across manufacturing, service, and knowledge sectors in August 2023.

Measurement: The authors report that “Women respondents (35%) are less likely than male respondents (48%) to be using generative AI tools in their jobs currently.” Details on the construction of this variable are not provided.

13. **Humlum and Vestergaard (2025)** report results from a large survey conducted in Denmark between November 2023 and January 2024. Results reflect “a representative sample of 18,000 workers from 11 exposed occupations between November 2023 and January 2024” out of a larger sample of survey respondents targeted through a collaboration with Statistics Denmark (Humlum and Vestergaard, 2025, p. 1). The gender proportions of respondents are based on estimates from Table S5, which reports 49% of respondents as female out of a total of 18,088 observations (Humlum and Vestergaard, 2025, Appendix p. 7). We approximate the number of men and women in the analytic sample who “could be linked to our register variables in Table 1 in the main text” (Humlum and Vestergaard, 2025, Appendix p. 4) by multiplying 17,907 by 0.49 and 0.51 respectively and then rounding to the nearest whole number.

Measurement: Results are based on Table 1, which reports whether respondents “have used ChatGPT for work” (Humlum and Vestergaard, 2025, p. 3). Further details about the survey questions are available on page 34 of the paper’s “Supporting Information.”

14. **Slack (2024)** conducted a survey in March 2024 with 10,045 desk workers across six countries: the U.S., Australia, France, Germany, Japan, and the U.K.

Measurement: The survey questions are not provided by the authors. Instead they write: “There remains a small but stubborn gender gap in AI uptake, with more men trying AI for work (35% of respondents) compared with women (29% of respondents).”

15. **Nordling (2023)** reports on a *Nature* survey of postdoctoral researchers across various disciplines and regions around the world in September 2023. This survey had 3,621 responses after excluding 217 respondents who either did not list their gender as Male or Female, who

did not respond to the survey question on generative AI, or who responded that they were “unsure” whether they had used generative AI.

Measurement: Respondents were asked “Do you use artificial intelligence-based ‘chatbots’, such as ChatGPT, in your work?” Response options were coded as 0 for “No” and 1 for “Yes.”

16. **Bick, Blandin, and Deming (2024)** surveyed a representative sample of U.S. adults. Gender differences are reported for 3,216 employed individuals (Bick, Blandin, and Deming, 2024, p. 13). However, the authors report the gender breakdown of employed individuals as 46.7% women for 3,506 employed individuals (Bick, Blandin, and Deming, 2024, p. 6). We approximate the number of men and women in the analytic sample by multiplying the number of employed individuals from Figure 3 (reported sample size of 3,216) (Bick, Blandin, and Deming, 2024, p. 13) by the proportion of women (0.467) and men (calculated as 1-0.467), and then rounding.

Measurement: Respondents were told “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.” Respondents were then asked “whether they had heard of the concept prior to the survey. Respondents who answer ‘No’ skip the remainder of the module, while those who answer ‘Yes’ [were then asked] ‘Do you use Generative AI for your job?’”, with response options “No” (coded as 0) and “Yes” (coded as 1) (Bick, Blandin, and Deming, 2024, p. 9).

17. **Park and Gelles-Watnick (2023)** surveyed 5,057 U.S. adults through the PEW Research Center’s American Trends Panel in July 2023. Of these, 1,895 reported having heard of ChatGPT. Details on the precise exclusion criteria rely on survey questions that are not available from PEW and are “being held for future release” (Research, 2023). Gender data is only provided for these 1,895 participants.

Measurement: Participants were first asked whether they had heard of ChatGPT. Participants who said they had heard of ChatGPT were asked “Have you ever used ChatGPT?” with response options “No, I have not done this” (coded as 0) or “Yes, I have done this” (coded as 1).

18. The **Kenya Generative AI Adoption Study (KGAAS)** surveyed 17,541 Kenyan participants between August and October 2023. Participants were recruited via Meta ads, and the study tracked their engagement with ChatGPT by recording whether they clicked on a link to download or access the tool. For more details, see [Section A](#).

Measurement: Respondents were first asked: “Would you like to download ChatGPT or learn how to access GPT on your browser?” with response options “No (I do NOT want to learn how to download ChatGPT or access it on my browser)” and “Yes (I DO want to learn

how to download ChatGPT or access it on my browser)”. If they answered “Yes,” they were shown the following two statements: “Click here to view a guide to download ChatGPT.” and “Click here to learn how to use ChatGPT in a browser.” This survey allowed us to track whether or not a participant clicked these links. The outcome was coded as 1 if the user clicked a link, and was coded as 0 otherwise.

SimilarWeb Data

SimilarWeb is a data aggregation and market analysis platform that offers detailed estimates of website traffic, user demographics, and mobile application download metrics. Leading firms such as Airbnb, Walmart, Adidas, and J.P. Morgan rely on SimilarWeb for performance benchmarks, competitor analysis, and lead generation. For further discussion and validation of SimilarWeb’s data, see [Koning, Hasan, and Chatterji \(2022\)](#) and [Cao, Koning, and Nanda \(2023\)](#).

SimilarWeb - Website Visits

We use SimilarWeb to determine the number of unique website visitors to three popular generative AI websites. We also use their predicted gender estimate of unique visitors to understand the proportion 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\(age%20and%20gender\)](https://support.SimilarWeb.com/hc/en-us/articles/115005835169-Website-Demographics#:~:text=How%20does%20SimilarWeb%20collect%20website,information%20(age%20and%20gender))).

SimilarWeb - Mobile Application Downloads

Application download data were sourced from SimilarWeb. Demographic breakdowns of these downloads are available exclusively for Android applications. It is important to note that the application download data represent “...multiple downloads from the same device. These include multiple downloads of a specific app by the same user on separate devices, as well as re-downloads on the same device. Data may include both app store and non-app store-installed apps.” (see <https://support.SimilarWeb.com/hc/en-us/articles/7507365132829-Installs-Downloads#UUID-38d2f8cd-058f-489a-4d01-5306ef2f7292> for more information). Additional information on application demographics can be found at <https://support.SimilarWeb.com/hc/en-us/articles/214573665-App-Demographics>.

Kenya Generative AI Adoption Study (KGAAS)

This section provides an overview of the data collection procedures for the Kenya Generative AI Adoption Study (KGAAS). Kenyan survey respondents were recruited through an online advertisement placed on the Meta ad platform, after approval from the UC Berkeley Office for the Protection of Human Subjects. The ad targeted individuals in Kenya aged 18 and older, with no additional geographical restrictions. Participants received a payment of 30 Kenyan Shillings as compensation for completing the survey.

The survey began with the collection of basic demographic information. Respondents had a median age of 23, with the majority having at least some post-secondary education. On average, 73.9% of participants were male. This gender disparity in survey responses likely reflects the Meta platform’s ad auction system, which determines ad visibility. Due to higher demand for female “eyeballs,” ads are disproportionately shown to men unless they explicitly target a specific group—a factor not employed in this study (Lambrecht and Tucker, 2019).

B Methodology: Adjusted Gender Gaps

Here we describe the method used to calculate the relative covariate-adjusted gender gaps shown in Panel B of Figure 1. The relative (unadjusted) gender gap is defined as the percentage point difference in generative AI adoption rates between male and female users, expressed relative to the male adoption rate. It is calculated as: $(p(\text{women}) - p(\text{men}))/p(\text{men})$. The relative *adjusted* gender gap is calculated as: $\Delta/p(\text{men})$, where Δ represents the estimated gender difference in AI adoption after controlling for covariates. Below, we report the specific calculations for Δ , as well as the unadjusted differences in AI adoption, for studies with sufficient data.

Analysis of a *Nature* survey of postdoctoral researchers Nordling (2023), the unadjusted gender gap in generative AI adoption was -7.4pp ($p < 0.001$). This gap increased to -8.4pp ($p < 0.001$) after adjusting for age, field of study, and location. Similarly, Van Noorden and Perkel (2023) analyzed data from a *Nature* survey of scientists. Their data indicate an unadjusted gender gap of -5.4pp ($p = 0.052$), which increased to -7.0pp ($p < 0.05$) after controlling for career stage, field, and location.

In the Kenya Generative AI Adoption Study (KGAAS), the unadjusted gender gap was -1.7pp ($p < 0.01$), increasing slightly to -1.8pp ($p < 0.01$) after controlling for age and education. Additionally, analysis of data from a survey of higher education students (Ravšelj et al., 2024) reveals an unadjusted gender gap of -10.1pp ($p < 0.001$), which narrowed slightly to -9.3pp ($p < 0.001$) after accounting for level of study and field of study.

Findings from Carvajal, Franco, and Isaksson (2024) reported a -15.0pp unadjusted gap ($p < 0.001$),

but the adjusted gap fell to -7.5pp ($p < 0.05$) when accounting for variables such as year in college, admission year, risk preferences, and time preferences. Analysis of data on the use of generative AI among microbusinesses from [GoDaddy \(2024a\)](#) finds a gender gap of -6.6pp ($p < 0.001$), which falls to -4.3pp ($p < 0.001$) after controlling for country, business type, and number of businesses owned.

Lastly, [Humlum and Vestergaard \(2025\)](#) reported the largest unadjusted gap at -15.9pp ($p < 0.001$), which decreased to -11.8pp ($p < 0.001$) after adjusting for age, experience, earnings, and workplace, occupation, and task fixed effects. Notably, the unadjusted gap in this study already controls for occupation fixed effects.

These studies show that even after controlling for key demographic, professional, and contextual factors, a considerable gender gap still remains.

C Methodology: Meta-analysis

We conducted a meta-analysis using twelve studies with sufficient available data: [Van Noorden and Perkel \(2023\)](#); [GoDaddy \(2024a\)](#); [Ravšelj et al. \(2024\)](#); [Nordling \(2023\)](#); [Howington \(2024\)](#); [Barisano et al. \(2024\)](#); [Humlum and Vestergaard \(2025\)](#); [Glassdoor Economic Research \(2024\)](#); [Stohr, Ou, and Malmström \(2024\)](#); [Carvajal, Franco, and Isaksson \(2024\)](#); [Bick, Blandin, and Deming \(2024\)](#) and the Kenya Generative AI Adoption Study (KGAAS). A random-effects meta-analysis model was employed to assess gender differences in generative AI usage. This model accounts for variability between studies, such as differing sample populations, by allowing the true effect size to vary, providing a weighted average of effect sizes, and giving more weight to larger studies while incorporating variability from smaller ones. The random-effects odds ratio model shows a gender gap in generative AI usage, with a combined odds ratio of 0.78 (95% CI = [0.70, 0.86], $p < 0.0001$), indicating that women have 22% lower odds of using generative AI than men across the analyzed studies. Unlike many standard meta-analyses that report effect sizes such as Cohen’s d for continuous outcomes, we report odds ratios because our treatment effect is binary, focusing on whether women use generative AI or not.

D Mechanisms

This section provides an overview of the mechanisms that are likely driving the observed gender gap in generative AI adoption. To systematically document the potential mechanisms, we first searched for mechanism questions that directly tested the gender gap in generative AI use in each of the surveys included in our analysis. For example, we did not look at gender differences in risk preferences unless they were explicitly related to generative AI adoption. We report the mechanism survey questions when available; otherwise, we provide a summary of the information supplied by

the authors. In each case, we classify a gender gap as occurring for a given mechanism if the authors report a significant gender gap for that mechanism ($p < 0.05$), or, in some instances, if they report a gap but do not specify the level of significance (e.g., see [Barisano et al. \(2024\)](#)). When papers report multiple mechanisms, we present them in order from the largest (gendered) differences to the smallest. After each reported mechanism and survey question, we clarify the interpretation of that result in italicized parenthesis. We first summarize key trends across the papers in the Discussion of Mechanisms, then report mechanism information by paper.

Discussion of Mechanisms

The mechanism that emerges most often across studies is that women consistently report lower familiarity and knowledge about generative AI tools ([Aldasoro et al., 2024](#); [Stohr, Ou, and Malmström, 2024](#)). Women are also more likely to report not knowing how to use AI tools ([Humlum and Vestergaard \(2025\)](#)). This implies that improving knowledge about and familiarity with AI could significantly reduce observed gender gaps.

A second potential mechanism identified in multiple prior studies is confidence in AI tool usage. Multiple studies have found that women have lower confidence in their ability to use AI tools effectively, such as crafting queries or applying AI tools for tasks ([Carvajal, Franco, and Isaksson, 2024](#); [Barisano et al., 2024](#)), and this is especially true for women with less workforce experience. An intriguing result in [Humlum and Vestergaard \(2025\)](#) is that women say they need training before they can benefit from ChatGPT whereas men do not. In one survey, women were worse at effectively prompting generative AI ([Carvajal, Franco, and Isaksson \(2024\)](#)). [Carvajal, Franco, and Isaksson \(2024\)](#) also found that men were more persistent in using GenAI and more likely to attempt prompting two or more times when ChatGPT gave undesired results.

The third class of mechanisms that prior work has consistently identified is that women are more likely than men to perceive AI usage on coursework or assignments as unethical or equivalent to cheating ([Carvajal, Franco, and Isaksson, 2024](#); [Stohr, Ou, and Malmström, 2024](#)). They are also more likely to have a negative attitude towards AI [Stohr, Ou, and Malmström \(2024\)](#). Results on whether women and men equally perceive the benefits and usefulness of generative AI is mixed. [Aldasoro et al. \(2024\)](#) finds that women perceive lower productivity benefits of using generative AI at work than men and are less likely to agree that generative AI could be useful in job search. Female students are less likely to agree that generative AI is useful in educational settings ([Carvajal, Franco, and Isaksson, 2024](#); [Stohr, Ou, and Malmström, 2024](#)). However, there are no gender differences in the expected time savings that come from using generative AI ([Carvajal, Franco, and Isaksson, 2024](#); [Humlum and Vestergaard, 2025](#)).

Notably, several other hypothesized mechanisms show no gender differences. There are no statis-

tically significant differences in men and women trusting the accuracy of generative AI (Carvajal, Franco, and Isaksson, 2024; Humlum and Vestergaard, 2025; Barisano et al., 2024). Women are not more likely to express concerns about risks of using generative AI like data breaches, data abuse, and compromised data storage Aldasoro et al. (2024). Women are also not more likely to express hesitancy to use AI in fear of becoming dependent on generative AI or generative AI making their job redundant Humlum and Vestergaard (2025). In fact, in Aldasoro et al. (2024), they find that men are more likely to be worried about the implications of generative AI on their future job and salary. Overall, these findings indicate that gender differences in generative AI adoption and use are likely driven by disparities in knowledge, familiarity, and confidence, rather than differences in trust or risk perceptions.

Mechanisms by Paper

Paper: Aldasoro et al. (2024)

Mechanisms that are more common among women:

- **Knowledge about Generative AI:** “How much do you know about artificial intelligence tools (such as ChatGPT, Google Bard, DALL-E, . . .)?” (*i.e., women more likely to report they know less about artificial intelligence tools than men. This is by far the largest gender gap driver these authors find.*)
- **Awareness of Benefits of Generative AI—Productivity:** “What do you think are the chances that artificial intelligence will increase your productivity at work?” (*i.e., women are less likely to believe that that generative AI will increase their productivity at work.*)
- **Trust in Generative AI:** “In the following areas, would you trust artificial intelligence (AI) tools less or more than traditional human-operated services? Areas: education and training, information, banking, health, public policy.” (*i.e., on average, women trust generative AI less than men in the aforementioned areas.*)
- **Awareness of Benefits of Generative AI—Job Search:** “What do you think are the chances that artificial intelligence will help you find new job opportunities?” (*i.e., women are less likely to think that AI can help them find new job opportunities.*)

Mechanisms that are more common among men:

- **Risks of Generative AI—Salary Implications:** “What do you think are the chances that your salary in your current job will decrease because of artificial intelligence tools?” (*i.e., men are more likely to think their salary will decrease because of generative AI tools*)
- **Risks of Generative AI—Job Implications:** “What do you think are the chances that you will lose your current job because of artificial intelligence tools?” (*i.e., men are more likely to think there are higher chances that they will lose their job because of generative AI*)

Mechanisms that have no gender differences:

- **Risks of Generative AI—Data Breaches and Data Abuse:** “Sharing personal info with

AI tools will increase risk of data breaches” and “Sharing personal info with AI tools could lead to data abuse” (*i.e., there are no statistically significant differences between genders in the perceived risks of using generative AI.*)

- **Risks of Generative AI—Data Storage:** “How much do you trust the following entities to safely store your personal data when they use artificial intelligence tools? Entities: Government agency, financial institution, big tech.” (*i.e., there are no statistically significant differences between men and women in trusting the previous entities to store their data when using generative AI tools. If anything, the results indicate that women have slightly less trust than men, but the gap is relatively small and economically insignificant.*)

Paper: [Carvajal, Franco, and Isaksson \(2024\)](#)

Mechanisms that are more common among women

- **Actual Ability to Use Generative AI (Prompt Success Rate):** Students were given a task to come up with a prompt they could give AI to learn the name of a visual phenomenon they were provided. They were told “Please write down the question that you would ask to ChatGPT to learn about the official name of this visual phenomenon.” The authors found that male students had success rates 34% higher than female students. The authors did clarify that gap could be explained by whether the student recognized the Ebbinghaus illusion, not on the quality of prompts (see Appendix C.1 of their paper for details) and they report that “women with top admission grades perform just as well in the prompting exercise as their male counterparts.”
- **Confidence in Generative AI Ability:** “How confident do you feel that the query you just provided will make ChatGPT get the information you need?” (*i.e., men are much more confident than women in their ability to effectively query ChatGPT to get accurate information.*)
- **Perceived Benefits of Generative AI—Usefulness in Courses:** “What do you believe are the main advantages of using ChatGPT in coursework?”
 - “Improves my grade in the course”
 - “Increases accuracy or quality”
 - “Improves learning of course methods”
 - (*i.e., women are less likely than men to agree that ChatGPT can be beneficial for coursework in improving their grades, increasing accuracy or quality of coursework, and improving learning*)
- **Morality of Generative AI**
 - “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.”
 - (*i.e., women are more likely than men to agree that using AI in a course is cheating*)
- **Preferences about Generative AI:** “I think ChatGPT is enjoyable to use” (*i.e., men are*

more likely to think that ChatGPT is enjoyable to use)

- **Correctness of Generative AI:** “Have you ever received inaccurate or misleading information from ChatGPT?” (*i.e., more men report having received inaccurate or misleading information from ChatGPT than women*).
- **Persistency with Generative AI:** “Attempts two or more times when ChatGPT gives undesired result.” (*i.e., men are more persistent in attempting additional generative AI queries than women*)

Mechanisms that have no gender differences

- **Difficulty of Use:** “I think ChatGPT is difficult to use” (*i.e., there are no statistically significant differences between genders in the perceived difficulty of using ChatGPT*).
- **Awareness of Benefits of Generative AI—Time-Saving:** “What do you believe are the main advantages of using ChatGPT in coursework?” – “Saves time” (*i.e., there are no gender gaps in student’s perceptions that ChatGPT will save them time in their coursework*)
- **Trust Generative AI Accuracy** “Trust accuracy of info provided by ChatGPT” (*i.e., there are no statistically significant differences between men and women trusting the accuracy of ChatGPT*)

Paper: Stohr, Ou, and Malmström (2024)

Mechanisms that are more common among women

- **Familiarity with Generative AI** “Rate your familiarity with AI Chatbots” – *Women were much more likely to say there were “unfamiliar” with each AI chatbot than men for the following tools (listed in order of biggest gender gaps in familiarity): Bing AI, Bard AI, Copilot, OpenAI Playground, ChatGPT*
- **General Attitude Towards Generative AI:** “Overall, I have a positive attitude towards the use of chatbots in education” (*i.e., women are less likely to have a positive attitude towards using chatbots in education*)
- **Morality and Purpose of Generative AI:**
 - “Using chatbots should be prohibited in educational settings.”
 - “Using chatbots goes against the purpose of education.”
 - (*i.e., women are more likely to agree that chatbots should be prohibited in educational settings and that using chatbots goes against the purpose of education*).
- **Expected Benefits of Generative AI—Education:**
 - “The chatbots I use make me more effective as a learner” (*i.e., women are less likely to agree that chatbots can make them more effective learners*)
 - “The chatbots I use improve my study grades” (*i.e., women are less likely to agree that chatbots can improve their study grades*)
- **Morality of Generative AI—Cheating:** “Using chatbots to complete assignments and

exams is cheating” (*i.e., women are more likely to agree that using chatbots on assignments and exams is cheating*)

- **Expected Implications of Generative AI:** “I am concerned about how AI chatbots will impact students’ learning in the future” (*i.e., women are more likely to be concerned about how generative AI will impact learning in the future*).
- **Usefulness of Generative AI:** “Chatbots generate better results than I can produce on my own” (*i.e., women are less likely to agree that Chatbots can generate better results than they can on their own*).
- **Perceived Benefits of Generative AI—Language Help:** “The chatbots I use improve my general language ability” (*i.e., women are less likely to agree that chatbots can improve their language ability*).

Mechanisms that have no gender differences

- None (All mechanisms they tested had statistically significant gender gaps)

Paper: Humlum and Vestergaard (2025)

Mechanisms that are more common among women

- **Require Training for Generative AI:** “It would require training before I can benefit from ChatGPT” (*i.e., women are more likely to say that they need training before they can benefit from ChatGPT*) Note: Despite finding this results, the authors also find that men are more likely than women to sign up for information sheets about how to use ChatGPT (see Figure A.1 of their paper)
- **Don’t know how to use Generative AI:** “I don’t know how to use ChatGPT” (*i.e., women are more likely to say that they don’t know how to use ChatGPT*).
- **Concern about Language Capabilities of Generative AI:** “I am concerned about ChatGPT’s lack of capabilities in Danish” (*i.e., women are more likely to be concerned about ChatGPT’s Danish language capabilities—their native tongue*).

Mechanisms that are more common among men

- **Concerns about Helpfulness of Generative AI given Personal Expertise:** “The time savings for an average [worker] are not relevant given my expertise” (*i.e., men are more likely to think the time savings from using ChatGPT for an average worker in their progression is not relevant given their personal expertise in their job. Similarly, the authors also find that the tasks in which workers state ChatGPT can halve working times for an average worker but not for themselves is higher for men than for women, although the gap is not large.*).
- **Risks of Generative AI—Confidentiality:** “I am concerned about how ChatGPT will handle my data confidentially” (*i.e., men are more likely to be worried about data confidentiality with ChatGPT*).
- **Restrictions on Generative AI use:** “I am subject to restrictions on using ChatGPT

in my job” (*i.e.*, men are more likely to report that they are subject to restrictions on using ChatGPT in their job).

Mechanisms that have no gender differences

- **Concern Generative AI will Reduce Joy:** “ChatGPT will reduce my joy of performing the task” (*i.e.*, men and women are approximately equally likely to say that ChatGPT will reduce their joy of doing a task).
- **Risks of Generative AI—Becoming Dependent:** “I am concerned about becoming dependent on ChatGPT in the task” (*i.e.*, there are no statistically significant gender differences in the concern about becoming dependent on AI to do a task).
- **Risks of Generative AI—Becoming Redundant** “I fear that ChatGPT will eventually make me redundant in my job” (*i.e.*, there are no statistically significant gender differences in the concern about AI making someone redundant in their job).
- **Concern about Correctness of Generative AI:** “I am concerned about the correctness of ChatGPT’s responses” (*i.e.*, there are no statistically significant gender differences in the perceived correctness of generative AI).
- **Awareness of Benefits of generative AI—Time Saving:** “Access to ChatGPT can halve the time it takes for you to complete the task with equivalent quality” (*i.e.*, the share of personal job tasks in which workers state ChatGPT can halve their working times is approximately the same for women and men).

Paper: [Barisano et al. \(2024\)](#)

Barisano et al. (2024) provides mixed evidence on mechanisms across levels of employee seniority. See Figure 2 of [Barisano et al. \(2024\)](#) for details. Also note that the the actual survey measures were not reported in this study.

Note: the frictions reported below do not exist for senior women in technical and non-technical functions. In fact, they report that senior women lead senior men for all the mechanisms below, particularly in awareness of generative AI’s criticality to future job success and risk tolerance for using generative AI prior to having a company policy.

Mechanisms that are more common among junior women across functions:

- **Expected Impacts of Generative AI:** “Awareness of generative AI’s criticality to future job success” (*i.e.*, junior women are less likely than junior men to be aware of the importance of GenAI for future job success).
- **Confidence in Generative AI Ability:** “Confidence in generative AI Skills” (*i.e.*, junior women are more likely to be less confident in their generative AI skills than junior men)*
- **Expected Risks Associated with Generative AI:** “Risk tolerance for using generative AI prior to having a company policy” (*i.e.*, junior women are more likely to have a lower risk

tolerance with using generative AI prior to having a company policy than junior men).

**Note: The authors also document that virtually all men across seniority and job types are at "a similar level of awareness about generative AI's criticality for future job success" but this is not the case among women, with junior women being much less aware than senior women.*

Mechanisms that have no gender differences:

- **User Competence:** "Feelings of competence in using generative AI tools" (*i.e., men and women across seniority and job types report similar levels of competence in using generative AI tools. The authors do not explain how this mechanism differs from the "confidence in generative AI skills" reported above*)
- **Effectiveness of Generative AI** "Trust that generative AI tools would accomplish their objectives" (*i.e., men and women across seniority and job types report similar levels of trust that generative AI tools would accomplish their objectives.*)

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