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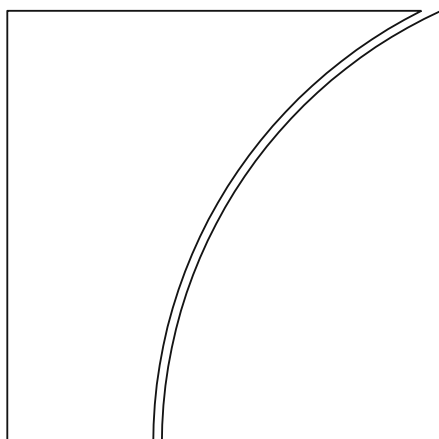
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# The gen AI gender gap\*

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## Abstract

Generative artificial intelligence (gen AI) is expected to increase productivity. But if unequally adopted across demographic groups, its proliferation risks exacerbating disparities in pay and job opportunities, leading to greater inequality. To investigate the use of gen AI and its drivers we draw on a representative survey of U.S. household heads from the Survey of Consumer Expectations. We find a significant “gen AI gender gap”: while 50% of men already use gen AI, only 37% of women do. Demographic characteristics explain only a small share of this gap, while respondents’ self-assessed knowledge about gen AI emerges as the most important factor, explaining three-quarters of the gap. Gender differences in privacy concerns and trust when using gen AI tools, as well as perceived economic risks and benefits, account for the remainder. We conclude by discussing implications for policy to foster equitable gen AI adoption.

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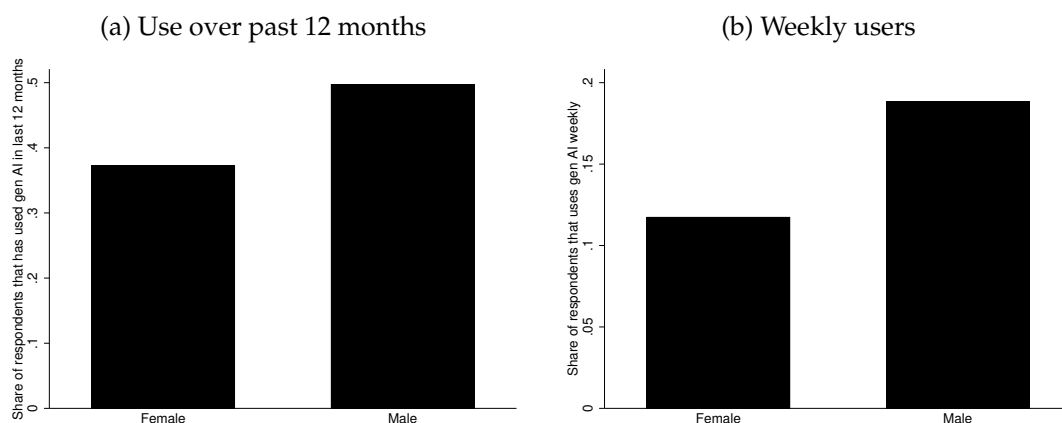
# 1 Introduction

Generative artificial intelligence (gen AI) holds the potential to boost economic activity. Evidence suggests it makes workers more productive, especially in occupations that require cognitive abilities (Brynjolfsson et al., 2023; Noy and Zhang, 2023; Peng et al., 2023), and spurs firm growth and innovation (Babina et al., 2024). Gen AI is thereby poised to have profound effects on aggregate output and wages (Baily et al., 2023; Aldasoro et al., 2024).

A key concern, however, is that increasing AI adoption will lead to greater inequality (Cazzaniga et al., 2024), especially if unequally adopted across demographic groups. For example, previous work has shown stark differences in the use of financial technology (fintech) between men and women – leading to a “fintech gender gap” (Chen et al., 2023). If there are similar disparities in gen AI usage, it could exacerbate existing differences in pay and job opportunities. To assess who will benefit from gen AI and how it will shape inequality, it is thus crucial to understand who uses it and why (not).

This paper investigates gender differences in the use of gen AI and their drivers, based on a representative survey of U.S. consumers. It draws on questions that were added to the Federal Reserve Bank of New York’s Survey of Consumer Expectations (SCE), fielded in February 2024.

Figure 1: The gen AI gender gap



This figure shows the share of male and female respondents that has used gen AI at least once (panel a) or weekly (panel b) over the past 12 month.

Our key finding is the presence of an economically and statistically significant “gen AI gender gap”. Figure 1 shows that women are significantly less

likely than men to use gen AI. On average, 50% of men report having used gen AI over the previous twelve months. The respective number for women is 37% (panel (a)). A significant gender gap is also present among frequent users of gen AI, i.e., those that have used gen AI weekly over the previous twelve months (panel (b)).

What explains the gender gap in the use of gen AI technology? We find that it is not driven by demographic characteristics such as income, education, age, or race. Instead, respondents' knowledge about gen AI emerges as the most important driver of the gap, explaining almost three-quarters. This result echoes findings of a gender gap in the use of technology more broadly (Scheerder et al., 2017; Lythreatis et al., 2022). The remainder of the gap is explained by gender differences in attitudes towards privacy and trust in counterparties, consistent with previous findings that women are generally more concerned about the negative consequences of sharing data (Armantier et al., 2021, 2024; Aldasoro et al., 2024; Prince and Wallsten, 2022; Tang, 2024); as well as perceived opportunities and risks from gen AI for employment.

These findings suggest that gen AI could amplify the gender pay gap. To address this issue, privacy regulations as well as policies that promote AI-related knowledge and skills could be put in place. These could help to ensure equal opportunity for everyone to benefit from the capabilities of gen AI.

## 2 Data, Empirical Strategy and Results

**The Survey of Consumer Expectations.** We investigate the use of gen AI with data from the Survey of Consumer Expectations. The SCE is a high-quality monthly, internet-based survey designed by the Federal Reserve Bank of New York and fielded by the private firm NielsenIQ. Launched in 2013, the SCE has been used extensively to help researchers and policymakers understand how expectations are formed and how they affect consumer behavior.

The SCE uses a 12-month rotating panel of roughly 1,300 nationally representative U.S. household heads. New respondents are drawn each month to match demographic targets from the American Community Survey with respect to education, income, age and region. They stay on the panel for up to 12 months before rotating out. The survey collects expectations for a wide range of economic outcomes and includes detailed demographic information.

The February 2024 survey included an *ad hoc* module on patterns in gen AI adoption which was completed by 890 respondents.<sup>1</sup> This module includes detailed questions about the opportunities and risks respondents see in gen AI, their concerns regarding trust and privacy, as well as their understanding of the technology.<sup>2</sup> To assess the use of gen AI, we asked the following question: “How often have you used artificial intelligence tools (such as ChatGPT, Google Bard, DALL-E, ...) in the past 12 months?” Respondents could answer “Never”, “Less than once a month”, “Once a month”, “Once a week”, and “More than once a week”.

To understand what determines use of gen AI, the survey asks users about their concerns regarding privacy and trust when using gen AI tools. On a Likert scale from 1 to 7, respondents could indicate their concerns about data breaches or data abuse when using gen AI tools, how much they trust gen AI relative to humans in different areas (banking, public policy, medical, information provision and education), and how much they trust different counterparties (traditional financial institutions, the government, fintechs and big techs) to safely store their personal data when offering gen AI tools. The survey also asks about the perceived benefits (higher salary, better job opportunities) and risks (lower salary, job loss) of gen AI on a scale from 0 to 100, as well as about the perceived knowledge of gen AI (on a scale from 1 to 7). We report the detailed questions and summary statistics in the Appendix (see [Table A1](#)).

**Summary statistics.** We identify several significant gender differences in our sample. Half of all male respondents report having used gen AI over the past 12 months, and 19% have done so weekly (see [Table 1](#)). For women, the respective numbers are 37% and 12%. Men also indicate significantly higher levels of trust and lower levels of privacy concerns than women. They see greater benefits for their job opportunities and lower risks from the use of gen AI. Finally, men report significantly higher knowledge about gen AI than women.

The demographic composition of our sample is summarized in [Table 2](#). The average age of respondents is 48. About 82% of respondents are White, 10.7% are Black, 8.8% are Hispanic, and 5.4% are Asian. Regarding other characteristics, 59% of respondents have a bachelor’s degree or higher, 43% have

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<sup>1</sup>The module was fielded to a subset of the core SCE respondents – 1,024 household heads. Hence the response rate was 87%.

<sup>2</sup>The Appendix reports the full questionnaire.

Table 1: Summary statistics by gender – gen AI questions

	Male		Female		Mean diff. t-stat
	Mean	Std.Dev	Mean	Std.Dev	
Have you used AI tools in the past 12 months? (0/1)	0.50	(0.50)	0.37	(0.48)	3.77
Have you used AI tools weekly in the past 12 months? (0/1)	0.19	(0.39)	0.12	(0.32)	2.95
Sharing personal info with AI tools will increase risk of data breaches (1-7)	5.71	(1.34)	5.71	(1.56)	-0.08
Sharing personal info with AI tools could lead to data abuse (1-7)	5.77	(1.42)	5.79	(1.51)	-0.26
Relative trust in AI vs humans in banking (1-7)	3.02	(1.62)	2.60	(1.57)	3.92
Relative trust in AI vs humans in public policy (1-7)	2.70	(1.57)	2.40	(1.46)	2.92
Relative trust in AI vs humans in medical (1-7)	3.09	(1.75)	2.45	(1.53)	5.74
Relative trust in AI vs humans in information provision (1-7)	3.73	(1.85)	3.29	(1.90)	3.51
Relative trust in AI vs humans in education and training (1-7)	3.93	(1.77)	3.43	(1.84)	4.11
Trust in government to safely store your data when they use AI tools? (1-7)	2.95	(1.69)	2.90	(1.72)	0.37
Trust in banks to safely store your data when they use AI tools? (1-7)	3.20	(1.61)	3.01	(1.66)	1.76
Trust in big techs to safely store your data when they use AI tools? (1-7)	2.37	(1.50)	2.26	(1.42)	1.10
Trust in fintechs to safely store your data when they use AI tools? (1-7)	2.82	(1.52)	2.65	(1.52)	1.65
Chances that AI will increase your productivity at work (0-100)	26.40	(29.01)	18.96	(25.91)	4.03
Chances that AI will help you find new job opportunities (0-100)	22.55	(25.18)	18.75	(25.01)	2.26
Chances that you will lose your current job because of AI (0-100)	11.05	(18.59)	8.43	(15.39)	2.28
Chances that your salary in your current job will decrease because of AI (0-100)	10.58	(17.93)	7.93	(14.53)	2.42
Knowledge about gen AI tools (1-7)	3.40	(1.77)	2.71	(1.62)	6.13
Observations	456		434		890

This table shows summary statistics for the main variables by gender.

an income above \$100,000, and 63% are working full-time, with a further 11% working part-time. Finally, 70% own their primary residence.

Table 2: Summary statistics – demographics

Variable	Obs.	Mean	Std. Dev.	Min	Max	P25	P50	P75
Female (0/1)	890	.488	.5	0	1	0	0	1
Married (0/1)	890	.633	.482	0	1	0	1	1
Bachelor (0/1)	890	.588	.493	0	1	0	1	1
High numeracy (0/1)	890	.694	.461	0	1	0	1	1
Working full-time (0/1)	890	.629	.483	0	1	0	1	1
Working part-time (0/1)	890	.111	.315	0	1	0	0	0
Income > 100k (0/1)	890	.431	.496	0	1	0	0	1
Age (years)	890	47.855	13.952	19	91	37	46	58
White (0/1)	890	.824	.381	0	1	1	1	1
Black (0/1)	890	.107	.309	0	1	0	0	0
Asian (0/1)	890	.054	.226	0	1	0	0	0
Hispanic (0/1)	890	.088	.283	0	1	0	0	0
Owner of primary residence (0/1)	890	.701	.458	0	1	0	1	1

This table shows summary statistics for respondents' demographic characteristics.

**Empirical specification.** To investigate the use of gen AI by men and women and its drivers, we estimate the following regression at the respondent level:

$$uses\ gen\ AI_i = \beta\ female_i + demographic_i + factors_i + \varepsilon_i, \quad (1)$$

where the dependent variable is a dummy that takes a value of one if a respondent has used gen AI tools over the last twelve months, and zero if he/she has not. We control for demographic characteristics with dummies for whether the respondent owns their primary residence, whether they are married, whether they belong to a racial or ethnic minority, whether they are working (with separate dummies for full-time and part-time work), dummies for their educational attainment, income group and numeracy, as well as their age. To explain potential gender differences we subsequently add factors discussed in more detail below. The coefficient  $\beta$  reflects the extent to which male and female respondents differ in their use of gen AI, conditional on covariates. We estimate logistic regressions with robust standard errors that are robust.

**Results.** The results are reported in [Table 3](#). Column (1) shows that women are significantly less likely to use gen AI than men, by 12.5%. When we add the rich set of demographic controls in column (2), the estimated coefficient remains statistically significant at the 1% level. The magnitude of the effect decreases only slightly to 10.4%. This suggests that differences in income, education, age, race or ethnicity explain only a small share of the observed gender gap.

The specification in column (3) includes variables that control for respondents' privacy and trust concerns when using gen AI.<sup>3</sup> The gender coefficient declines by almost 30% in magnitude and becomes significant only at the 10% level. When we control for economic benefits and risks in column (4), we find a decline in the gender coefficient by around 20%, compared to column (2). These results suggest that a substantial part of the relationship between the use of gen AI and gender is explained by differences in privacy/trust concerns and perceived benefits and risks of gen AI. This is also reflected in the substantial increase in the R-squared. Finally, column (5) controls for respondents' self-assessed knowledge about gen AI. The "gender gap" now becomes economically and statistically insignificant, suggesting that gender differences in knowledge about the technology are a key driver of differences in use. Of course, knowledge and use go hand in hand, meaning that our findings are not necessarily causal, a caveat that needs to be kept in mind.

One drawback of sequentially adding controls to explain the gender gap

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<sup>3</sup>For expositional clarity, we do not report individual coefficients on the control variables added in columns (3) to (5). [Table A2](#) in the Appendix provides the full set of estimates.



Table 3: The drivers of the gen AI gender gap

VARIABLES	(1) Uses AI	(2) Uses AI	(3) Uses AI	(4) Uses AI	(5) Uses AI
Female (0/1)	-0.509*** (0.137)	-0.425*** (0.158)	-0.306* (0.175)	-0.342** (0.170)	-0.022 (0.187)
Observations	890	890	889	890	890
Demographic Controls	-	✓	✓	✓	✓
Privacy & Trust	-	-	✓	-	-
Risks & Benefits	-	-	-	✓	-
Knowledge	-	-	-	-	✓
Marginal Effect	-0.125	-0.104	-0.075	-0.084	-0.005
Pseudo R2	0.0115	0.115	0.194	0.219	0.326

This table shows results from logit regressions for Equation (1) at the respondent level. The dependent variable is a dummy that takes on a value of one if a respondent has used gen AI over the last 12 months. *Female* is a dummy with a value of one if the respondent is female. Demographic controls include dummies for whether the respondent owns their primary residence, whether they are married, whether they belong to a racial or ethnic minority, whether they are working (with separate dummies for full-time and part-time work), their educational attainment, income category, age and numeracy. The row *Marginal Effects* reports marginal effects evaluated at the mean. All regressions use robust standard errors. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

is that the sequencing might affect the results. We thus perform a mediation analysis and decomposition exercise following Gelbach (2016) to assess the impact of each factor. The decomposition provides an accounting that is invariant to the order in which the individual controls are included. Decomposing the overall decline in the coefficient as we add controls from column (3) to column (5) into its mediators shows that gen-AI knowledge accounts for around 74% of the decline in the gender gap, while privacy/trust and opportunities/risk account for the remainder in roughly equal parts.

**Extensions and robustness.** Table 4 shows that the use of gen AI is significantly lower for older respondents – echoing findings that older people are less likely to use technology (Doerr et al., 2022; Babina et al., 2024) – but higher for those with a bachelor’s degree or higher income. We find no significant differences in use by race or ethnicity. Our main analysis focuses on whether someone has or has not used gen AI. In the Appendix, we also show that women are less likely to use gen AI on a weekly basis compared to men (see Table A3). Gen AI knowledge remains the most important factor explaining

the gap.

Table 4: The drivers of the gender gap – other demographic characteristics

VARIABLES	(1) Uses AI	(2) Uses AI	(3) Uses AI	(4) Uses AI
Female (0/1)	-0.458*** (0.155)	-0.360** (0.171)	-0.372** (0.169)	-0.059 (0.184)
Age (years)	-0.030*** (0.006)	-0.029*** (0.007)	-0.022*** (0.007)	-0.019*** (0.007)
White (0/1)	-0.337 (0.291)	-0.343 (0.307)	-0.234 (0.321)	-0.202 (0.327)
Black (0/1)	0.285 (0.329)	0.358 (0.356)	0.329 (0.370)	0.579 (0.397)
Asian (0/1)	0.264 (0.380)	0.094 (0.403)	0.128 (0.412)	0.321 (0.420)
Hispanic (0/1)	0.311 (0.260)	0.414 (0.268)	0.285 (0.274)	0.402 (0.315)
Bachelor (0/1)	0.614*** (0.160)	0.670*** (0.174)	0.377** (0.177)	0.347* (0.195)
Income > 100k (0/1)	0.414** (0.175)	0.434** (0.192)	0.364* (0.197)	0.575*** (0.209)
Working full-time (0/1)	0.194 (0.190)	0.123 (0.203)	-0.502** (0.224)	0.044 (0.231)
Working part-time (0/1)	0.326 (0.249)	0.417 (0.262)	-0.146 (0.279)	0.296 (0.296)
Owner of primary residence (0/1)	-0.142 (0.180)	-0.105 (0.194)	0.060 (0.207)	0.040 (0.224)
Observations	890	889	890	890
Demographic Controls	✓	✓	✓	✓
Privacy & Trust	-	✓	-	-
Risks & Benefits	-	-	✓	-
Knowledge	-	-	-	✓
Pseudo R2	0.0969	0.176	0.210	0.317

This table shows regression results from Equation (1) at the respondent level. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

### 3 Conclusion

Using representative survey data for U.S. consumers, we find a large and statistically significant gender gap in the use of gen AI. Privacy concerns, as well

as perceived economic benefits and risks explain around one-quarter of the gap. Respondents' knowledge about gen AI emerges as the most important explanatory factor, explaining three-quarters of the difference in gen AI use between men and women. Since our survey does not allow us to establish the casual effect of these drivers, further research on the topic is necessary.

These findings hold important policy lessons. First, to the extent that gen AI will boost productivity and wages, greater adoption of AI tools by men could exacerbate the gender pay gap. Second, privacy regulation, by giving individuals control over their data and assuaging concerns about their use (Armantier et al., 2024; Doerr et al., 2023), could spur the adoption of gen AI among women and contribute to reducing, or at least avoid aggravating, the gender gap. Third, policies may need to be put in place to promote the teaching of AI-related knowledge and skills, and provide equal opportunity for everyone to benefit from the capabilities of generative AI.

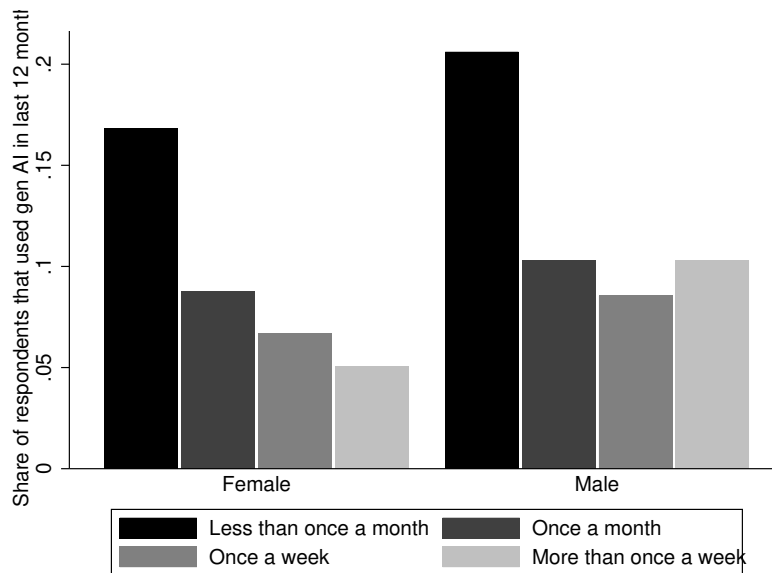
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# A Appendix

Figure A1: Use of gen AI over past 12 months by gender



This figure shows the share of male and female respondents that has answered “Less than once a month”, “Once a month”, “Once a week”, or “More than once a week” used to the following question: “How often have you used artificial intelligence tools (such as ChatGPT, Google Bard, DALL-E, ...) in the past 12 months?”.

**Table A1: Summary statistics – gen AI questions**

Variable	Obs.	Mean	Std. Dev.	Min	Max	P25	P50	P75
Have you used AI tools in the past 12 months? (0/1)	890	.437	.496	0	1	0	0	1
Have you used AI tools weekly in the past 12 months? (0/1)	890	.154	.361	0	1	0	0	0
Sharing personal info with AI tools will increase risk of data breaches (1-7)	890	5.71	1.45	1	7	5	6	7
Sharing personal info with AI tools could lead to data abuse (1-7)	890	5.782	1.466	1	7	5	6	7
Relative trust in AI vs humans in banking (1-7)	889	2.818	1.607	1	7	1	3	4
Relative trust in AI vs humans in public policy (1-7)	889	2.55	1.526	1	7	1	2	4
Relative trust in AI vs humans in medical (1-7)	889	2.781	1.678	1	7	1	2	4
Relative trust in AI vs humans in information provision (1-7)	889	3.517	1.885	1	7	2	4	5
Relative trust in AI vs humans in education and training (1-7)	889	3.683	1.824	1	7	2	4	5
Trust in government to safely store your data when they use AI tools? (1-7)	890	2.925	1.706	1	7	1	3	4
Trust in banks to safely store your data when they use AI tools? (1-7)	890	3.11	1.635	1	7	2	3	4
Trust in big techs to safely store your data when they use AI tools? (1-7)	890	2.318	1.464	1	7	1	2	3
Trust in fintechs to safely store your data when they use AI tools? (1-7)	890	2.734	1.522	1	7	1	3	4
Chances that AI will increase your productivity at work (0-100)	890	22.772	27.775	0	100	0	10	40
Chances that AI will help you find new job opportunities (0-100)	890	20.698	25.155	0	100	0	10	36
Chances that you will lose your current job because of AI (0-100)	890	9.774	17.148	0	100	0	1	10
Chances that your salary in your current job will decrease because of AI (0-100)	890	9.289	16.406	0	100	0	.5	10
Knowledge about gen AI tools (1-7)	890	3.063	1.734	1	7	2	3	4

This table shows summary statistics for the survey questions on gen AI.

Table A2: The drivers of the gender gap – full table

VARIABLES	(1) Uses AI	(2) Uses AI	(3) Uses AI	(4) Uses AI	(5) Uses AI
Female (0/1)	-0.509*** (0.137)	-0.425*** (0.158)	-0.306* (0.175)	-0.342** (0.170)	-0.022 (0.187)
Data breach (1-7)			-0.044 (0.077)		
Data abuse (1-7)			-0.017 (0.081)		
Relative trust in AI in banking (1-7)			0.202** (0.083)		
Relative trust in AI in public policy (1-7)			-0.105 (0.086)		
Relative trust in AI in medical (1-7)			-0.138* (0.073)		
Relative trust in AI in information provision (1-7)			0.094 (0.073)		
Relative trust in AI in education and training (1-7)			0.307*** (0.070)		
Trust to safely store data - Government (1-7)			0.024 (0.071)		
Trust to safely store data - Financial Inst. (1-7)			0.047 (0.088)		
Trust to safely store data - BigTech (1-7)			-0.137* (0.082)		
Trust to safely store data - FinTech (1-7)			0.123 (0.088)		
Productivity gains (0-100)				0.035*** (0.005)	
Job opportunities (0-100)				0.001 (0.005)	
Job loss (0-100)				0.014 (0.009)	
Salary loss (0-100)				-0.007 (0.008)	
Gen AI knowledge (1-7)					0.872*** (0.066)
Observations	890	890	889	890	890
Demographic Controls	-	✓	✓	✓	✓
Privacy & Trust	-	-	✓	-	-
Risks & Benefits	-	-	-	✓	-
Knowledge	-	-	-	-	✓
Pseudo R2	0.0115	0.115	0.194	0.219	0.326

This table shows regression results from Equation (1) at the respondent level. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table A3: The drivers of the gender gap – weekly use**

VARIABLES	(1) Uses AI weekly	(2) Uses AI weekly	(3) Uses AI weekly	(4) Uses AI weekly	(5) Uses AI weekly
Female (0/1)	-0.557*** (0.191)	-0.563*** (0.204)	-0.482** (0.233)	-0.552** (0.247)	-0.259 (0.233)
Observations	890	879	878	879	879
Demographic Controls	-	✓	✓	✓	✓
Privacy & Trust	-	-	✓	-	-
Risks & Benefits	-	-	-	✓	-
Knowledge	-	-	-	-	✓
Pseudo R2	0.0114	0.0735	0.186	0.266	0.256

This table shows regression results from Equation (1) at the respondent level. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1



## SECTION 1 – General question on experience and knowledge

The next few questions are about your perception and usage of artificial intelligence. Artificial intelligence enables computers to learn, process information, and perform tasks similar to humans. You may have already answered similar questions, but in this survey, we are particularly interested in your general views and attitudes toward artificial intelligence

**Q0:** How much do you know about artificial intelligence tools (such as ChatGPT, Google Bard, DALL-E, ...)? Please report your answer on a scale from 1 (I know nothing at all about artificial intelligence tools) to 7 (I know a lot).

Nothing at all  
1                      2                      3                      4                      5                      6                      A lot  
7

**Q1.** How often have you used artificial intelligence tools (such as ChatGPT, Google Bard, DALL-E, ...) in the past 12 months?

Please pick one

- Did not use in the past 12 months
- Less than once a month
- Once a month
- Once a week
- More than once a week

## SECTION 2 – Opportunities and benefits

**Q2.1 (If currently working)** What do you think are the chances that artificial intelligence will increase your productivity at work? \_\_\_% (plus scale)

**Q2.2 (If currently working or looking for work)** What do you think are the chances that artificial intelligence will help you find new job opportunities? \_\_\_% (plus scale)

## SECTION 3 – Risks and concerns

**Q3.1 (If currently working)** What do you think are the chances that you will lose your current job because of artificial intelligence tools? \_\_\_% (plus scale)

**Q3.2 (If currently working)** And what do you think are the chances that your salary in your current job will decrease because of artificial intelligence tools? \_\_\_% (plus scale)

**Q4.1:** Do you think that sharing your personal information with artificial intelligence tools will decrease or increase the risk of data breaches (that is, your data becoming publicly available)? Please report your answer on a scale from 1 (the risk will decrease a lot) to 7 (the risk will increase a lot).

Decrease a lot

Increase a lot

1                      2                      3                      4                      5                      6                      7

**Q4.2:** Are you concerned that sharing your personal information with artificial intelligence tools could lead to the abuse of your data for unintended purposes (such as for targeted ads)? Please indicate your level of concern on a scale from 1 (not concerned at all) to 7 (very concerned).

Not concerned at all

Very concerned

1                      2                      3                      4                      5                      6                      7

**SECTION 4 – Perception and Trust**

**Q5.** In the following areas, would you trust artificial intelligence tools less or more than traditional human-operated services? For each item, please indicate your level of trust on a scale from 1 (much less trust than in a human) to 7 (much more trust).

Much less

Much more

	1	2	3	4	5	6	7
Banking, such as customer support or financial advice							
Public policy interventions, such as government or Central Bank operations							
Medical, such as diagnosis or drug prescriptions							
Information provision, for example summarizing news or scientific articles							
Education and training, such as on-line courses							

**Q6.** How much do you trust the following entities to safely store your personal data when they use artificial intelligence tools? For each of them, please indicate your level of trust on a scale from 1 (no trust at all in the ability to safely store personal data) to 7 (complete trust).

	Not trust at all				Complete trust		
	1	2	3	4	5	6	7
A government agency (such as the IRS, Department of Labor, ... )							
Traditional financial institutions (such as banks, insurers, ...)							
Large technology companies (such as Facebook/Meta, Google, Apple, ....)							
Technology firms that specialize in financial services (such as PayPal, Venmo, Quicken Loans, ...)							

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