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Exploring Household Adoption and Usage of Generative AI: New Evidence from Italy

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Abstract

We present findings from a specialized module on generative artificial intelligence (gen AI) included in the Italian Survey of Consumer Expectations (ISCE), conducted in 2024 with a representative sample of Italian individuals. This analysis offers novel insights into current and anticipated interactions with gen AI tools and the potential benefits from adoption. As of April 2024, 75.6% of the Italian population aged 18–75 was aware of gen AI, 36.7% had used it in the previous 12 months, and 20.1% reported monthly usage. Socio-economic factors significantly influence adoption rates, with higher usage observed among men, individuals with college degrees, and younger individuals, particularly students. Looking ahead, gen AI is expected to be used more frequently for education and leisure activities in the coming months. Finally, using a Mincer earnings regression, we highlight that the income return associated with gen AI usage is around 2%.

JEL classification: D10; O33.

Keywords: Generative AI; households' survey.

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1. Introduction

The widespread availability of modern generative artificial intelligence (gen AI, hereafter) is predicted to have a profound socio-economic impact on our societies. Since late 2022, tools such as ChatGPT and Google Gemini have been freely accessible, influencing daily activities such as shopping, personalized financial and medical advice, information acquisition, and education.[1] Furthermore, the adoption of gen AI tools can change the landscape of job conditions, on both the labor market's supply and demand sides. Compared with earlier groundbreaking technologies, such personal computers and the internet, the adoption of gen AI has been faster (Bick et al., 2024). For these reasons, there is growing interest in investigating the extent to which individuals use of gen AI. Who uses gen AI, how much do they use it, and what do they use it for? What are the potential returns from AI use? This paper tackles these issues.

This paper contributes to the literature by presenting results from a comprehensive nationally representative Italian survey of gen AI adoption. Our data come from a nationwide survey, the Italian Survey of Consumer Expectations (ISCE). The survey is benchmarked to national estimates of employment and earnings, ensuring representativeness (Guiso and Jappelli, 2024). In prior research, similarly structured surveys of Italian households have been employed to study the reactions of Italian households to the Covid-19 pandemic (Immordino et al., 2022, 2024).

To study the users of gen AI, the third wave of ISCE included an additional ad-hoc module. This module asked detailed questions on respondents' knowledge and use of gen AI, as well as prospective use in various socio-economic contexts. In what follows, we use this information to investigate whether these aspects vary across households based on their age, gender, education, and income, among other factors. We also analyze how gen AI use impacts income returns. [2]

The data show that in April 2024, 75.6% of the Italian population aged 18-75 was aware of gen AI tools, and about 37% had used them at least once during the preceding 12 months. The use of gen AI tools is more common outside of work, but less intensive. One in three

[1] For a broader discussion on the implications of AI on households' activities, see West and Allen (2018) and McKinsey & Company (2021).

[2] Our study complements Loschiavo et al. (2025), who compare gen AI adoption in the U.S. and Italy using the US Survey of Consumer Expectations and the Conjunctural Survey on Italian Households. They find higher adoption in the U.S., driven by demographics and sectoral composition, while Italians show greater trust in institutions and gen AI's potential to enhance well-being.

respondents (32.7 percent) said that they used gen AI outside of work, but only 6.4 percent used it outside of work every day. We find that men are about 8 percentage points more likely to be aware of gen AI than women; conditioning on awareness, men are about 7 percentage points more likely than women to have used gen AI tools at least once in the year preceding the survey. This significant gender gap in the adoption of gen AI tools confirms the results of a related study that exploited similar survey questions inserted in the FED Survey of Consumer Expectations in early 2024 (Aldasoro et al., 2024b). We find that the gender gap in awareness and use of gen AI tools also persists when accounting for socio-demographic and individual characteristics, a result in line with Otis et al. (2024) who find that men are significantly more likely to use gen AI than women, even when opportunities for access are equalized among them.

Besides gender, differences in education and age can explain differences in knowledge and adoption (Aldasoro et al., 2024a). Younger and college-educated are more likely to perceive gen AI as an opportunity to enhance job prospects (Aldasoro et al., 2024b). The role of age and education is also evident in academic contexts, where students and younger demographics exhibit higher rates of AI adoption (Yusuf et al., 2024). Our results show that knowledge and use of AI vary considerably between different age and education groups. Younger individuals (especially those aged 18-34), and those with higher education levels are also more likely to be aware of and use AI. The pronounced difference between younger and older respondents mirrors the "digital divide" found in other contexts, a divide that could stem from the elderly's limited perceived benefits of new technology (Doerr et al., 2022; Armantier et al., 2024). Conditional on other socio-demographic characteristics, higher income is also associated with greater awareness and usage of AI, though the effect is relatively modest.

Gen AI applications are increasingly used across both educational and professional settings, with the potential to enhance both productivity and efficiency. In education, students report positive experiences with AI-powered tools for grammar checks, plagiarism detection, language translation, and essay outlining (Malik et al. 2023). These tools can enhance students' writing abilities and understanding of academic integrity. However, concerns remain about their effects on creativity, critical thinking, and ethical writing practices. Acknowledging the importance of assessing the knowledge and use of gen AI tools in education, our findings show that students exhibit high levels of awareness and use. In contrast, teachers demonstrate lower awareness but — conditional on awareness — a substantial rate of adoption and use.

We also find that residing in larger cities has only a small and statistically weak effect on AI awareness and use. As with any emerging open technology, the adoption of gen AI tools depends, to some extent, on societal trust (Brockman et al., 2018). Unlike many previous technologies, however, gen AI has the distinctive potential to influence individual behavior in broader social contexts (Klockmann et al., 2022; 2025). In our analysis, both openness to innovation and active engagement in social activities are positively associated with the likelihood of adopting gen AI tools.

Overall, these findings underscore the importance of demographic and socio-economic factors in shaping AI awareness and usage, highlighting areas where targeted interventions might encourage broader adoption, especially among older age groups, and less-educated individuals.

A highly debated aspect of the development of gen AI tools regards their impact on employment and working conditions. The literature suggests that labor productivity increases following the adoption of gen AI tools for job-related reasons (Brynjolfsson et al. 2023; Peng et al., 2024) but with significant heterogeneous effects across workers. For instance, a recent experiment by Noy and Zhang (2023) documents that ChatGPT raises the average productivity of mid-level professional writing tasks, decreasing the time taken and raising the output quality of writing tasks. Similarly, the use of AI tools such as GitHub Copilot improves productivity by up to 26% in software development tasks (Cui et al., 2024),[3] and other gen AI applications tailored for strategy consulting yield productivity gains of about 25% (Dell'Acqua et al., 2023); the adoption and use of AI by firms has also been shown to enhance productivity across a range of sectors (Czarnitzki et al., 2023). These findings illustrate the broad applicability of gen AI in enhancing efficiency across diverse professions.

Using our data, we estimate the returns to AI by analyzing the impact of AI use on earnings. Specifically, we apply a Mincer-type earnings regression to a subsample of 2,700 employed respondents. Our results indicate that AI use is associated with a 1.8-2.2% earnings increase, comparable to half a year of additional education and one-tenth the return to computer use in the early 90s (Di Nardo and Pischke, 1997). This estimated impact remains robust across specifications that include sector and occupation fixed effects and is slightly higher for males,

[3] Using a quasi-experiment in the coding industry, Gambacorta et al. (2024) find that while large language models can significantly boost productivity among programmers, the effects are more pronounced for junior staff. This difference appears to stem from lower engagement with the large language models by senior programmers, rather than the tool being less useful to them.

suggesting that AI adoption may contribute to a widening of the gender wage gap. Despite this significant individual gain from gen AI adoption, the relationship between AI exposure and broader economic metrics, such as aggregate wage growth and employment, remains inconclusive, with some studies reporting limited aggregate impacts (Acemoglu, 2025), and others more significant impacts (Baily et al., 2023; Briggs et al., 2024; Filippucci et al., 2024).

The structure of the paper is as follows. Section 2 introduces the ISCE. Section 3 presents empirical analyses of the factors influencing awareness and use of gen AI. Section 4 provides estimates of the income returns associated with gen AI use. The final section summarizes the key findings and discusses their policy implications.

2. The Survey

Our data on AI are derived from responses to the Italian Survey of Consumer Expectations (ISCE), a rotating panel survey representative of the Italian resident population aged 18 to 75 years. The survey was conducted in October 2023 and January, April, July, and October 2024. Administered quarterly, it collects data on demographic variables, income, wealth, consumption, and expectations regarding both microeconomic and macroeconomic variables. Each wave comprises approximately 5,000 individual observations, providing a robust dataset for analysis.

The ISCE builds on two prominent international online, high-frequency surveys that gather information on both realized outcomes and expectations, preferences, and perceptions. The New York Fed Survey of Consumer Expectations collects data on consumers' views and expectations about inflation, employment, income, and household finances. Similarly, the European Central Bank Consumer Expectation Survey collects monthly data on household expectations from about 20,000 individuals across 11 euro-area economies. The ISCE aligns with the structure of these surveys, ensuring high-quality data collection and comparability of results.

The ISCE sampling scheme is modeled on the methodology used in the Bank of Italy Survey of Household Income and Wealth (SHIW). The sample is stratified by area of residence (North-East, North-West, Central, South), age group (18–34, 35–44, 45–54, 55–64, over 65), gender, education (college degree, high school diploma, less than high school), and occupation (employed, unemployed). Data are collected using Computer-Assisted Web Interviewing

(CAWI). The average response rate across waves is 33%, which is comparable to similar high-frequency surveys. Sample weights are applied to ensure population-representative descriptive statistics. Detailed information on the survey design, sample structure, and comparisons with SHIW is provided in the ISCE Statistical Bulletin (see Guiso and Jappelli, 2024).

The questionnaire includes a consistent core section administered every quarter, alongside rotating special sections. For our study, we focus on demographic and economic background variables and the April 2024 (Wave 3) special section, which investigates AI-related topics. In detail, the April 2024 ISCE includes questions on AI knowledge, usage, and purposes of use. One question asks respondents to rate their familiarity with AI tools (e.g., ChatGPT or Gemini) on a 1–7 scale. A second question asks about AI usage frequency in the past 12 months, ranging from "never" to "more than once a week." These data are converted into an annual usage measure (e.g., days of use per year). The final question evaluates respondents' likelihood of using AI across different domains — work, financial advice, medical advice, education or training, and leisure — using a 1–7 scale. To minimize framing effects, these questions are presented in random order, ensuring unbiased responses. The survey questions are reported in Appendix A.

Table 1 provides an overview of key descriptive statistics for the dataset. The sample includes 5,005 respondents, with a breakdown of various demographic, educational, and regional characteristics. The data show that 75.6% of respondents are aware of AI, with 35.7% reporting any AI usage. On average, individuals who use AI engage with it for approximately 10 days, though the standard deviation of 24.9 suggests considerable variation in usage frequency. The table also reports respondents' future use plans for AI across different domains (e.g., jobs, financial advice, medical advice), with leisure and education/training being areas of the highest anticipated future use (mean scores of around 2.92 and 2.99, respectively).

Additionally, the table includes demographic variables such as gender, education, age groups, occupation, income, and city size, offering a comprehensive snapshot of the dataset's characteristics. These variables are crucial for understanding the diverse factors influencing AI awareness and usage among different population segments.

Figure 1 visually demonstrates the relationship between age and AI knowledge and use. It reveals that AI awareness is larger among the younger age groups, with more than 80% of respondents declaring themselves aware; however, awareness is also high among older groups. Despite this widespread awareness, there is a clear pattern of higher AI use among younger age groups, with a steep decline as age increases. This is confirmed both at the intensive margin (frequency of use) and extensive margin (days of use).

Figure 2 illustrates the relation between AI knowledge and use across different levels of educational attainment. The graph shows that individuals with higher education levels (especially those with a college degree) are more likely to know and adopt AI, as expected. Figure 3 depicts the relationship between AI awareness and use and family income. While the data indicate a positive correlation between higher income levels and AI adoption, the strength of the relation appears modest. The correlation is stronger when focusing on AI intensity use. This evidence suggests that while income may influence access to AI tools, other factors like education and age could play a more substantial role in adoption, as shown in previous figures. These findings imply that efforts to address income disparities in AI access should also consider educational and generational factors.

Looking at the prospective use, Figure 4 presents respondents' plans to use AI in various contexts over the next year. The histograms reveal that a significant portion of respondents (30%) do not plan to use AI in any of the suggested contexts. The highest intentions are concentrated in education, training and leisure purposes, while very few respondents foresee using gen AI in the context of medical and financial advice, which represents more critical domains.

3. Determinants of AI awareness and use

Table 2 presents regression analyses examining various factors associated with awareness and use of gen AI, based on demographic and socio-economic characteristics. The reported estimates represent marginal effects (evaluated at the mean values of each variable) from probit regressions. In these regressions, the dependent variables are binary indicators: AI awareness (columns 1 and 2) and AI use (columns 3 and 4). The analysis of AI awareness uses the entire sample of respondents, while the analysis of AI use is restricted to the sub-sample of respondents for whom the AI awareness indicator equals one.

The estimates reveal that the effect of the gender dummy is positive and statistically significant, indicating that, on average, males are about 7 percentage points more likely to be aware of AI than females. This gender difference is significant across all models. The gap between males and females in AI usage is also strong and significant, suggesting that AI awareness among males translates somewhat into actual usage. These findings align with recent studies highlighting a gen AI gender gap across different samples and countries (Aldasoro et al., 2024a; Bick et al., 2024; Otis et al., 2024). Potential reasons for these gender differences could include differing levels of interest in technology, access to resources, and societal norms. Addressing this gender gap is crucial for ensuring equitable access to AI benefits.

Higher education levels are associated with greater awareness and use of AI. Specifically, respondents with a high school diploma or college degree are approximately 10 and 16 percentage points more likely, respectively, to be aware of gen AI than those with lower education levels. Additionally, having a college degree significantly increases the likelihood of AI use, conditional on awareness. This suggests that individuals with higher education may possess both knowledge of AI and the practical skills or opportunities to use it. These findings underscore the importance of educational initiatives in promoting AI literacy and adoption, highlighting the need for targeted AI training programs in educational institutions.

Awareness and use of AI are strongly correlated with age. Taking the oldest group (65+ years) as the baseline, the youngest cohort (18–34 years) exhibits the largest differences, with an 11 percentage points higher probability of being aware and a 30 percentage points higher probability of using AI, conditional on awareness. Younger individuals are thus both more aware of AI and more likely to use it. The coefficients for middle-aged groups (35–44 and 45–54 years) are significant but lower than for the youngest cohort, while the oldest group (55–64 years) shows very low levels of awareness and usage. These results highlight a substantial generational gap in AI awareness and adoption, likely due to greater exposure to technology and digital literacy among younger individuals.

Occupational differences further support these findings. Students exhibit significantly higher levels of awareness and usage of AI, likely due to the educational context and greater openness to new technologies associated with their age group. Teachers, on the other hand, display lower levels of AI awareness, although these differences are not statistically significant. However, when conditioning on awareness, teachers exhibit significantly higher usage coefficients, suggesting that once aware, they are more likely to adopt AI in practice.

The coefficients for log income suggest that higher income levels are positively associated with both AI awareness and use. However, the effects are modest, indicating a gradual increase in awareness and usage as income rises. Interestingly, the coefficient for AI use is smaller than for awareness, implying that income may influence access to AI but not necessarily its practical adoption. These findings are consistent with McKinsey & Company (2021) which highlight that actual usage and integration of AI into daily life depend on other factors than income, such as education, digital literacy, and personal interest.

Living in medium or large cities does not significantly predict differences in AI awareness or adoption compared to smaller cities, suggesting that gen AI adoption is not strongly segmented by urbanization levels. In columns 2 and 4, three additional variables — Risk Innovation, Social Activities, and Trust — are included, using data from a subset of respondents who participated in precedent survey waves. Risk Innovation, a proxy for openness to innovation or risk, is positively associated with AI awareness and use, but the coefficients are generally not statistically significant. By contrast, the coefficient attached to Social Activities is positively and significantly associated with both AI awareness and use, suggesting that greater social exposure may facilitate AI adoption. The coefficient for Trust is positive for AI awareness but negligible for AI use, indicating that trust influences awareness but has little impact on usage.

Table 3 examines the intensity of AI use, measured by the number of days AI tools were used in the past year. Columns (1) and (2) present OLS estimates. They show that males, on average and after controlling for other factors, used gen AI tools about four more days per year than females. A similar difference is observed for respondents with a college degree compared to those without a high school diploma. The coefficients for age groups confirm earlier findings: younger individuals use AI tools more intensively, with usage declining as age increases. Students and respondents with higher levels of social interaction also report more intensive use of AI tools. To ensure robustness, columns (3) and (4) report Tobit estimates, which account for the censored nature of the data and confirm the statistical significance conclusions from the OLS models. These findings suggest that certain demographic groups not only adopt AI but also engage with it more deeply.

Table 4 shifts the focus to the determinants of prospective AI use in various contexts, including work, medical and financial advice, education/training, and leisure. The dependent variables measure respondents' likelihood of using AI in these contexts on a scale from 1 (very unlikely) to 7 (very likely). The results, based on OLS regression models, show that males are consistently more likely to use AI across all contexts, with the strongest effect observed for financial advice (coefficient: 0.062).

Educational attainment also plays a role in prospective AI use. While the coefficients for high school education are small and generally insignificant, respondents with a college degree show positive and significant effects in most contexts, particularly for job-related (0.068) and leisure (0.035) activities. In contrast, college education has negligible or insignificant effects on obtaining medical and financial advice, reflecting variability in AI's relevance across different domains. Age has a strong, positive, and diminishing effect on prospective AI use. Younger cohorts (18–34 years) exhibit the largest and most significant coefficients across all categories (average: 0.178), while the oldest group (55–64 years) shows smaller but still significant effects (average: 0.048). These results reaffirm that younger individuals are more likely to use AI tools in the future, probably due to greater familiarity with technology and higher digital literacy. Occupational differences are also evident: students and teachers display higher prospective AI use, particularly in job-related and educational contexts. Income effects are consistent but modest, with coefficients ranging from 0.014 to 0.030 across contexts. Finally, city size shows only weak and marginally significant effects, suggesting limited variation in prospective AI use by urbanization level.

4. The returns to AI

In this section, we estimate the effect of AI use on earnings using the Mincer-type earnings function — a standard framework in labor economics that relates wages to human capital, typically measured by education and work experience. The model is specified in log-linear form, allowing the estimated coefficients to be interpreted as approximate percentage changes in earnings associated with an additional year of education, an additional year of experience, or the use of AI at work.

We preliminarily check that AI does not affect employment probabilities. We then focus on a sample of 2,700 employed respondents aged 18-64, using the log of respondents' earnings as the dependent variable. Table 5 reports the results. In the baseline specification, we control for standard determinants of earnings, including high school and college dummies, age, gender, city size. In the other regressions, we also control for sector fixed effects (column 2), type of occupation effects (column 3), and both sector and occupation effects (column 4). All regressions, including the baseline, control for regional fixed effects.

Across all specifications, the gender earnings premium is around 15% and remains highly significant. Controlling for occupation and sector fixed effects slightly reduces the estimated “male premium”. Completing high school is associated with a 2.8% to 4.1% increase in earnings relative to individuals without a high school diploma, while completing college increases earnings by about 18% to 20%, in line with existing empirical evidence on the returns to education in Italy.[4] Note, however, that the sample includes a higher share of college graduates relative to the population. The age coefficients indicate that younger workers (18–34) earn about 3% less than the reference group (aged 55+), consistent with lower level of labor market experience. For the 35-44 age group the effect is smaller (about 2%) but remains statistically significant. Finally, coefficients for medium and large cities are close to zero and not significant across all specifications. Including occupation and sector fixed effects slightly reduces the estimated returns to both high school, and college education, suggesting that part of the observed earnings differences is attributable to sorting into higher-paying occupations and sectors.

Most importantly for the purpose of this paper, the use of gen AI tools is associated with a 1.8-2.2% increase in earnings, holding other factors constant.[5] This effect is not economically negligible, as it is comparable to the returns from an additional half-year of education and represents around 10% of the returns to computer use observed in the early 90s (Di Nardo and Pischke, 1997). These findings suggest that AI adoption can enhance productivity and earnings, highlighting the potential economic benefits of integrating AI tools into the workforce.

We acknowledge that our estimates do not necessarily identify a causal relationship between AI use and earnings. Establishing causality remains challenging due to potential endogeneity and self-selection into AI adoption. However, the observed association is consistent with a growing body of micro-level evidence on the productivity-enhancing effects of AI. Instrumental variable approaches may help address the endogeneity problem, but they require strong assumptions that are difficult to verify. Nonetheless, recent experimental and quasi-experimental studies suggest substantial gains in task-level productivity following AI adoption. For instance, Gambacorta et al. (2024) document a 55% productivity gain in coding tasks. A randomized controlled trial involving 96 Google software engineers shows that access to AI tools reduces time on task by 21%. Similarly, Cui et al. (2024) report up to 26% gains in

[4] Algan et al (2021) report that in Italy, the average internal rate of return on a higher education degree relative to an upper secondary diploma is about 10%, placing this effect at the lower end of OECD estimates.

[5] This effect is larger than that estimated by Humlum and Vestergaard (2025) for the use of AI chatbots. Using a difference-in-differences approach that exploits variation in employer policies as a quasi-experiment, they find only modest effects on earnings and recorded working hours across occupations, with confidence intervals that rule out impacts exceeding 1%.

software development tasks. Brynjolfsson et al. (2023) find that AI improves customer service performance by 14%, as measured by issues resolved per hour. These studies suggest that the productivity effects of AI are particularly pronounced in specific sectors (e.g., services) and for tasks such as coding and customer support.

Importantly, these micro-level productivity gains do not always translate into large aggregate effects. At the macroeconomic level, recent estimates suggest only modest contributions of AI to total factor productivity (TFP) growth. For instance, Acemoglu (2025) estimates a 0.07 percentage point increase in US TFP growth attributable to AI. Bergeaud (2024) reports a 0.29-point increase for the euro area, while Filippucci et al. (2024) estimate a range of 0.24-0.64 points for the US. Reconciling these micro- and macro-level findings requires further analysis, particularly on how AI adoption diffuses across the broader population and varies by demographic groups, sectors and occupations, especially those more exposed to automation.

Figure 5 presents the estimates of the effects of AI across different population subgroups, based on the regression model reported in column 4 of Table 5, which includes occupation and sector fixed effects. First, we split the sample by gender and highlight that the estimated returns to gen AI use are larger and more precisely estimated for males. While the coefficients are not statistically different from each other, the results suggest that AI use may contribute to amplify the male gender premium in the labor market. Second, using the aggregate measures of sectoral exposure to gen AI developed by Aldasoro et al. (2024c),[6] we classify individuals in our sample as working in high- or low-exposure sectors. High-exposure sectors include finance, real estate and business services, professional activities and public administration. The estimates in Figure 5 indicate that returns to gen AI use are somewhat larger for individuals employed in these high-exposure sectors.

To further explore heterogeneity, we restrict the sample to employed individuals (excluding the self-employed) and categorize them by occupational exposure. High-exposure occupations include teachers, managers, senior officials, university lecturers, and judges. Again, we find that the returns from gen AI use are higher and more precisely estimated for those in more exposed occupations, although the difference relative to less exposed groups is modest. This limited variation may reflect the fact that returns to AI use are shaped not only

[6] This measure is based on the dataset by Felten et al. (2021), which maps occupational, industry, and geographic exposure to AI in the US.

by occupational or sectoral exposure, but also by individual characteristics such as skills, familiarity with technology, and learning capacity.

Consistent with this interpretation, we observe more pronounced differences in estimated returns among younger individuals (aged 18-44) and college graduates, two groups that, as shown in previous analyses, report significantly higher awareness and adoption of gen AI tools.

Overall, these results are aligned with recent studies documenting positive income returns for AI adopters. They help bridge the gap between large microeconomic effects — often focused on specific groups or sectors — and the more modest macroeconomic estimates of gen AI on aggregate income. Importantly, beyond average effects, our findings indicate the need to address potential sources of inequality in outcomes to ensure equitable access to the economic benefits of AI adoption.

5. Conclusions

The adoption of gen AI tools is transforming industries, economies, and societies in profound ways. Our study provides valuable insights into the determinants of gen AI awareness and use among Italian households, as well as the economic returns associated with gen AI adoption.

We find significant gender, age, and educational disparities in AI awareness and use. Men, younger individuals, and those with higher education levels are more likely to be aware of and use gen AI tools. These disparities suggest that targeted efforts are needed to bridge the digital divide and ensure that all segments of the population can benefit from AI advancements. Additionally, the modest impact of income on AI use indicates that while higher income facilitates access to AI tools, other factors — such as education and digital literacy — play a more substantial role in practical adoption.

The economic benefits of AI adoption are evident in our findings, with AI use being associated with a 2% increase in earnings. This gain is comparable to the returns from half a year of additional education, highlighting the potential of AI to enhance productivity and income. However, the larger returns to AI use observed among males suggest that AI adoption may amplify existing gender disparities in the labor market.

To address the disparities in AI awareness and use, policymakers should invest in digital literacy programs and integrate AI training into educational curricula. These initiatives should target all age groups, with a particular focus on older individuals and those with lower educational attainment, to bridge the digital divide. Programs could include targeted outreach, mentorship opportunities, and support networks for women in technology fields. Finally, workforce training programs should focus on developing AI-related skills. This includes upskilling and reskilling initiatives that prepare workers for the evolving demands of the labor market. Policies should consider the specific needs of different sectors and occupations in promoting AI adoption. Tailored training programs and support for AI integration across industries can help ensure that the benefits of AI are widely distributed throughout the economy.

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Table 1. Descriptive statistics

	Mean	SD	N
AI Aware	.756	.43	5005
AI Use (0/1)	.357	.479	5005
AI use (days)	10.028	24.936	5005
AI Future Use (Job)	2.525	1.896	5005
AI Future Use (Financial advice)	2.398	1.75	5005
AI Future Use (Medical advice)	2.551	1.809	5005
AI Future Use (Education and training)	2.92	1.952	5005
AI Future Use (Leisure)	2.999	1.968	5005
AI Future Use (average)	2.678	1.599	5005
Male	.494	.5	5005
High school	.471	.499	5005
College	.217	.412	5005
Age (18-34)	.235	.424	5005
Age (35-44)	.16	.367	5005
Age (45-54)	.228	.42	5005
Age (55-64)	.223	.416	5005
Age (65-Over)	.154	.361	5005
Teacher	.023	.15	5005
Student	.039	.193	5005
North	.461	.499	5005
Centre	.198	.398	5005
South	.341	.474	5005
Log(income)	.678	.523	5005
Medium city	.223	.416	5005
Large city	.244	.429	5005
Risk of innovation	.405	.308	3743
Social activities	1.868	1.129	4218
Trust	5.265	2.281	4218

Note. The table reports the means and standard deviations of selected variables, using sample weights.

Table 2. Determinants of AI awareness and use

	AI Awareness	AI Awareness	AI Use	AI Use
Male	0.073	0.055	0.077	0.078
	(0.012)***	(0.016)***	(0.017)***	(0.021)***
High school	0.098	0.108	0.037	0.031
	(0.013)***	(0.016)***	(0.021)*	(0.026)
College	0.161	0.158	0.118	0.130
	(0.014)***	(0.018)***	(0.026)***	(0.032)***
Age (18-34)	0.113	0.092	0.366	0.336
	(0.018)***	(0.023)***	(0.026)***	(0.034)***
Age (35-44)	0.083	0.093	0.247	0.214
	(0.018)***	(0.022)***	(0.029)***	(0.037)***
Age (45-54)	0.054	0.060	0.191	0.177
	(0.018)***	(0.022)***	(0.028)***	(0.035)***
Age (55-64)	0.000	-0.001	0.088	0.100
	(0.019)	(0.023)	(0.030)***	(0.036)***
Teacher	-0.031	-0.054	0.125	0.123
	(0.047)	(0.060)	(0.056)**	(0.069)*
Student	0.084	0.075	0.208	0.155
	(0.032)***	(0.047)	(0.043)***	(0.063)**
Log(income)	0.038	0.041	0.031	0.021
	(0.012)***	(0.016)***	(0.017)*	(0.022)
Medium city	0.006	0.005	0.003	-0.011
	(0.015)	(0.020)	(0.022)	(0.027)
Large city	0.027	0.027	0.005	-0.032
	(0.015)*	(0.019)	(0.022)	(0.027)
Risk of innovation		0.007		0.038
		(0.025)		(0.036)
Social activities		0.015		0.033
		(0.007)**		(0.010)***
Trust		0.012		0.002
		(0.004)***		(0.005)
N	5,005	3,234	3,783	2,438

Note. The table reports marginal effects (evaluated at the mean values of each variable) from probit estimates with robust standard errors. The reported estimates represent marginal effects from probit regressions. In these regressions, the dependent variables are binary indicators: AI awareness and AI use. The analysis of AI awareness (columns 1 and 2) uses the entire sample of respondents, while the analysis of AI use (columns 3 and 4) is restricted to the sub-sample of respondents for whom the AI awareness indicator equals one. All regressions include region fixed effects. *** p-value ≤ 0.01; ** p-value ≤ 0.05; * p-value ≤ 0.1.

Table 3. Determinants of AI use (days)

	OLS	OLS	Tobit	Tobit
Male	4.121	4.512	9.115	10.231
	(0.887)***	(1.038)***	(1.682)***	(2.131)***
High school	0.591	-0.078	3.161	1.880
	(0.938)	(1.080)	(2.109)	(2.560)
College	5.279	4.487	11.867	11.786
	(1.369)***	(1.582)***	(2.544)***	(3.083)***
Age (18-34)	14.256	11.588	37.263	32.237
	(1.442)***	(1.857)***	(3.081)***	(3.831)***
Age (35-44)	8.635	5.318	25.800	19.845
	(1.420)***	(1.682)***	(3.242)***	(3.924)***
Age (45-54)	5.489	3.446	18.958	15.474
	(1.212)***	(1.471)**	(3.080)***	(3.748)***
Age (55-64)	2.213	1.310	8.371	7.875
	(1.122)**	(1.319)	(3.195)***	(3.778)**
Teacher	3.540	9.260	9.403	16.027
	(3.374)	(4.453)**	(4.930)*	(6.340)**
Student	9.944	13.439	16.969	19.962
	(3.153)***	(4.792)***	(3.860)***	(5.923)***
Log(income)	1.106	0.546	2.713	1.648
	(0.943)	(1.115)	(1.720)	(2.175)
Medium city	1.956	2.079	2.197	2.087
	(1.183)*	(1.484)	(2.179)	(2.840)
Large city	1.246	0.237	1.513	-1.456
	(1.143)	(1.285)	(2.147)	(2.665)
Risk of innovation		0.764		2.774
		(1.786)		(3.633)
Social activities		1.305		3.465
		(0.505)***		(1.007)***
Trust		-0.101		-0.082
		(0.251)		(0.498)
N	3,783	2,439	3,783	2,439

Note. The table reports OLS estimates in columns (1) and (2) and Tobit estimates in column (3) and (4) with robust standard errors. All regressions include region fixed effects. *** p-value ≤ 0.01; ** p-value ≤ 0.05; * p-value ≤ 0.1.

Table 4. Plans to use AI

	Job	Financial advice	Medical advice	Education/ training	Leisure	Average
Male	0.058	0.062	0.035	0.050	0.056	0.052
	(0.007)***	(0.007)***	(0.007)***	(0.008)***	(0.008)***	(0.006)***
High school	0.005	-0.000	-0.007	0.011	0.014	0.004
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.007)
College	0.073	0.017	-0.010	0.054	0.048	0.037
	(0.011)***	(0.011)	(0.011)	(0.012)***	(0.012)***	(0.010)***
Age (18-34)	0.248	0.143	0.091	0.200	0.208	0.178
	(0.011)***	(0.012)***	(0.013)***	(0.012)***	(0.013)***	(0.010)***
Age (35-44)	0.189	0.109	0.064	0.143	0.160	0.133
	(0.012)***	(0.012)***	(0.013)***	(0.013)***	(0.013)***	(0.011)***
Age (45-54)	0.161	0.083	0.048	0.119	0.110	0.104
	(0.010)***	(0.011)***	(0.012)***	(0.012)***	(0.012)***	(0.010)***
Age (55-64)	0.083	0.031	0.010	0.055	0.063	0.048
	(0.010)***	(0.010)***	(0.012)	(0.011)***	(0.012)***	(0.009)***
Teacher	0.087	-0.025	-0.010	0.072	0.005	0.026
	(0.028)***	(0.025)	(0.026)	(0.028)***	(0.029)	(0.022)
Student	0.035	-0.019	-0.027	0.124	0.019	0.027
	(0.021)*	(0.019)	(0.020)	(0.022)***	(0.022)	(0.016)*
Log(income)	0.030	0.026	0.014	0.026	0.023	0.024
	(0.007)***	(0.007)***	(0.008)*	(0.008)***	(0.008)***	(0.006)***
Medium city	0.010	0.004	0.018	0.017	0.013	0.012
	(0.009)	(0.009)	(0.009)*	(0.010)*	(0.010)	(0.008)
Large city	0.017	0.002	0.007	0.008	0.009	0.009
	(0.009)*	(0.009)	(0.009)	(0.009)	(0.010)	(0.008)
N	5,005	5,005	5,005	5,005	5,005	5,005

Note. The table reports OLS estimates with robust standard errors. All regressions include region fixed effects. *** p-value ≤ 0.01; ** p-value ≤ 0.05; * p-value ≤ 0.1.

Table 5. Returns to AI

	Baseline	Occupation FE	Sector FE	Both FE
Male	0.155	0.155	0.145	0.148
	(0.007)***	(0.007)***	(0.007)***	(0.007)***
High school	0.040	0.027	0.039	0.027
	(0.009)***	(0.009)***	(0.009)***	(0.009)***
College	0.240	0.214	0.235	0.211
	(0.009)***	(0.011)***	(0.010)***	(0.011)***
Age (18-34)	-0.036	-0.036	-0.033	-0.035
	(0.010)***	(0.010)***	(0.010)***	(0.010)***
Age (35-44)	-0.022	-0.023	-0.020	-0.022
	(0.011)**	(0.011)**	(0.011)*	(0.011)**
Age (45-54)	-0.012	-0.014	-0.011	-0.013
	(0.010)	(0.010)	(0.010)	(0.010)
Medium city	-0.004	-0.006	-0.003	-0.005
	(0.008)	(0.008)	(0.008)	(0.008)
Large city	-0.002	-0.008	-0.001	-0.007
	(0.008)	(0.008)	(0.008)	(0.008)
AI Use (0/1)	0.023	0.020	0.022	0.019
	(0.007)***	(0.007)***	(0.007)***	(0.007)***
N	2,700	2,700	2,700	2,700

Note. The table reports OLS estimates with robust standard errors. All regressions include region fixed effects. The sample includes employed respondents aged 18-64. *** p-value ≤ 0.01; ** p-value ≤ 0.05; * p-value ≤ 0.1.

Figure 1. AI knowledge and use, by age

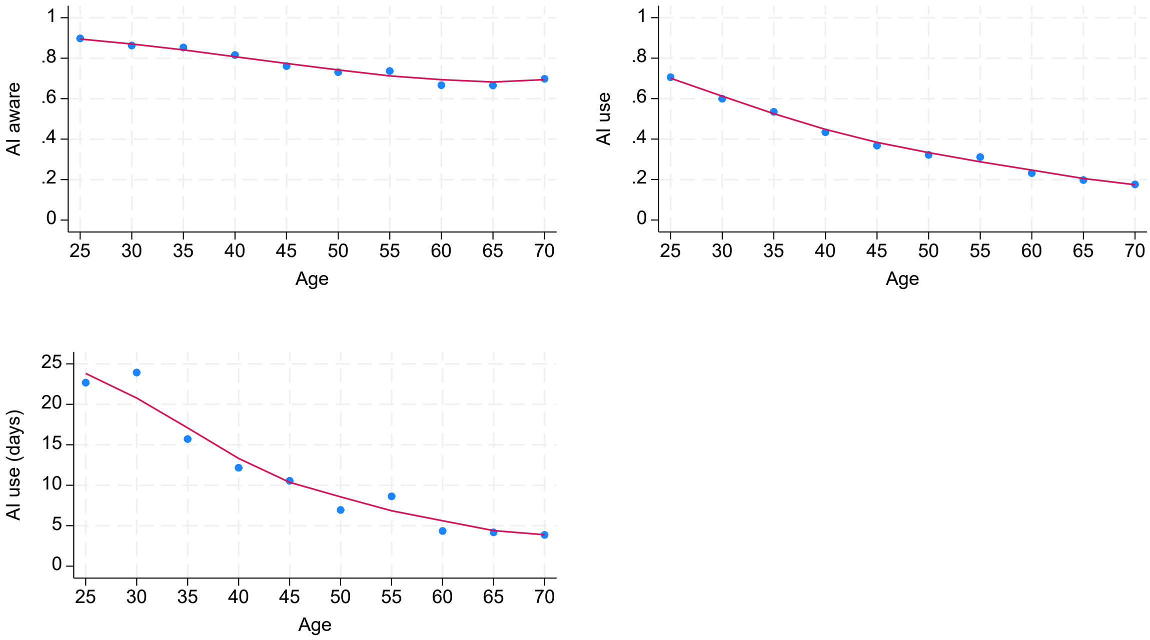


Figure 2. AI knowledge and use, by education

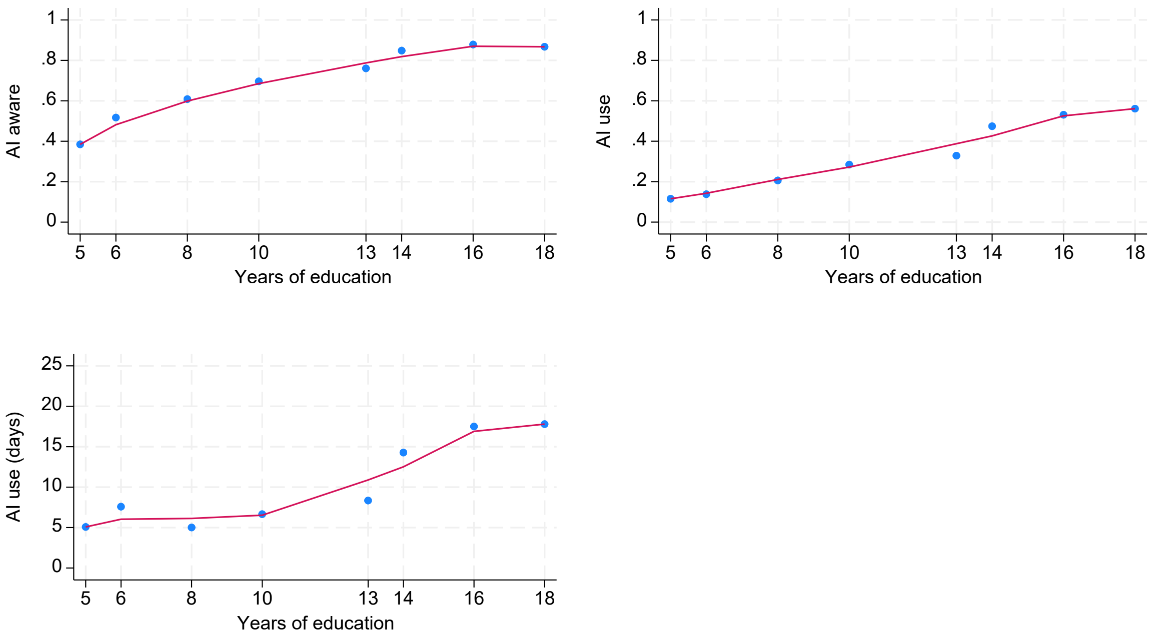


Figure 3. AI knowledge and use, by income

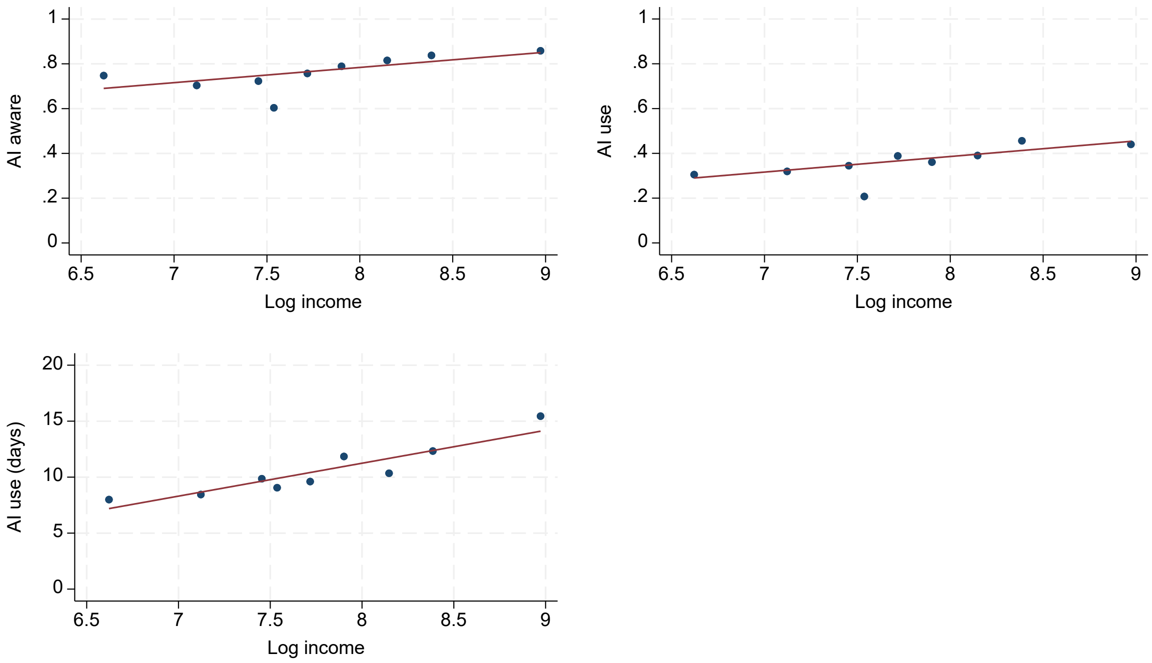


Figure 4. Plans to use AI in the next 12 months

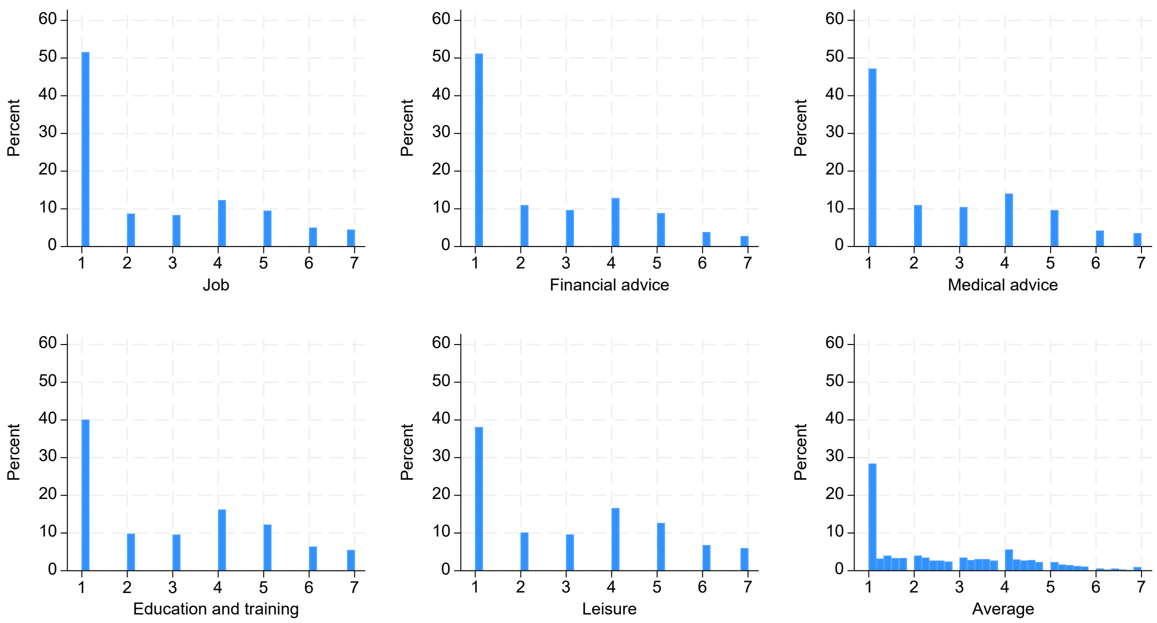
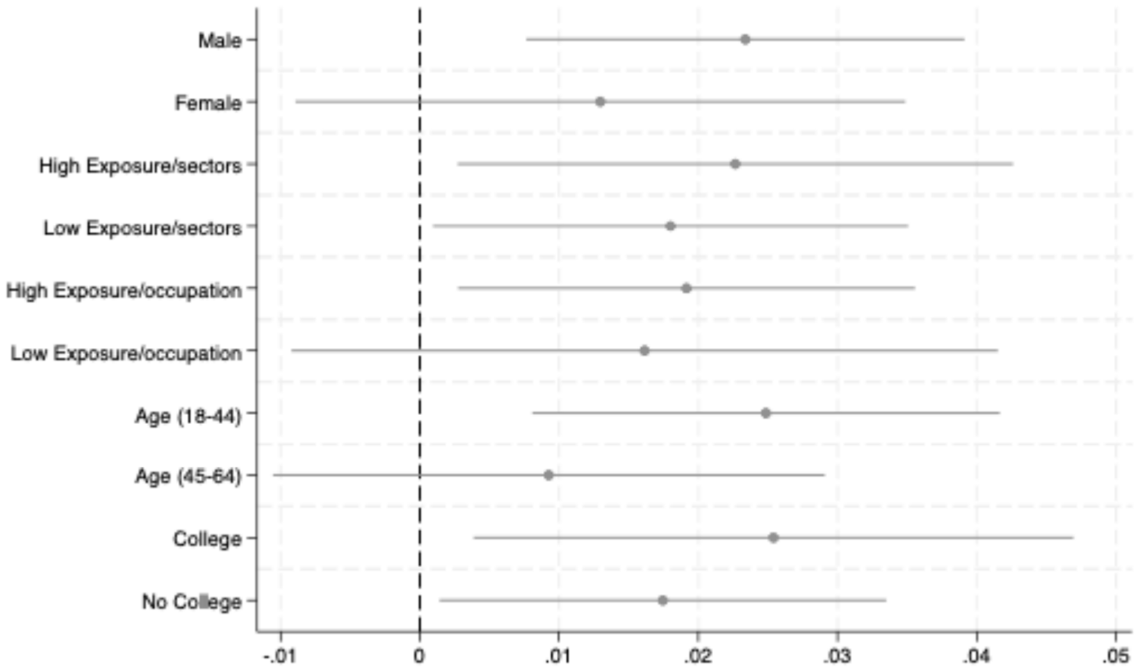


Figure 5. AI and Log Earnings: Heterogeneity analysis



Note. The figure reports OLS estimates of the variable "AI Use (0/1)" for different subgroups of individuals labeled on the y axis. 95% confidence intervals are reported using robust standard errors. All regressions include region, sector and occupation fixed effects.

APPENDIX A

1. Survey questions

H7. How much do you know about Artificial Intelligence tools (such as ChatGPT and Gemini)? Score your answer on a scale of 1 to 7, where 1 indicates "I know nothing" and 7 indicates "I know a lot"

1 “I know nothing”	2	3	4	5	6	7 “I know a lot”
○	○	○	○	○	○	○

H8. In the last 12 months, how often have you used an artificial intelligence tool (such as ChatGPT or Gemini)? *(one answer only)*

1. Never
2. Less than once a month
3. Once a month
4. Once a week
5. More than once a week

H9. In the next 12 months, how likely are you to use an Artificial Intelligence tool in the following contexts? For each, indicate the probability of use on a scale from 1 to 7, where 1 indicates "very unlikely" and 7 indicates "very likely". *(one answer per item, rotate items)*

	1 “very unlikely”	2	3	4	5	6	7 “very likely”
1. In your work	○	○	○	○	○	○	○
2. To get financial advice	○	○	○	○	○	○	○
3. To get medical advice	○	○	○	○	○	○	○
4. For education or training	○	○	○	○	○	○	○
5. For leisure activities (for instance drawing or creating videos)	○	○	○	○	○	○	○

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