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Embracing GenAI: A comparison of Italian and US households*

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Abstract

This paper explores the household adoption of Generative Artificial Intelligence (GenAI) in the United States and Italy, leveraging survey data to compare usage patterns, demographic influences, and employment sectoral composition effects. Our findings reveal higher adoption rates in the US, driven by socio-demographic differences between the two countries. Despite their lower usage of GenAI, Italians are more confident in its potential to improve their well-being and financial situation. Both Italian and US users tend to trust GenAI tools less than human-operated services, but Italians report greater relative trust in government and institutions when handling personal data with GenAI tools.

JEL Classification: O33, D10, J24.

Keywords: Generative Artificial Intelligence, Technology adoption, Cross-country comparison, Socio-demographic factors, Trust in technology, Cultural attitudes.

*Part of this research was conducted while Olivier Armantier was at the Federal Reserve Bank of New York. The views expressed herein are those of the authors and should not be attributed to the Bank of Italy, the Bank for International Settlements or the Federal Reserve Bank of New York.

1 Introduction

The development of Generative Artificial Intelligence (GenAI), particularly since the introduction of ChatGPT in late 2022, has marked a turning point in technology. GenAI can perform complex tasks, from generating human-like text to assisting with creative, educational, and professional activities. GenAI's ability to continuously learn, adapt, and generate content has contributed to its rapid diffusion that has outpaced previous waves of technology adoption, such as electricity, the computer, or the internet (Bank for International Settlements, 2024). ChatGPT alone, for instance, reached one million users in less than a week. Mirroring rapid adoption by users, firms have fast integrated GenAI in their daily operations in all sectors of economic activity (Singla et al., 2024).

Several studies have documented increases in productivity associated with the adoption of GenAI (Brynjolfsson et al., 2023, Noy and Zhang, 2023, Peng et al., 2023, Cui et al., 2024, Dell'Acqua et al., 2025). Despite its transformative potential, however, the adoption of GenAI varies significantly across countries, reflecting differences in digital infrastructures, income levels, human capital, cultural attitudes, and technological readiness (Liu et al., 2025, Calvino and Fontanelli, 2023). Understanding the factors that lead to the public's adoption of GenAI is critical for policymakers, businesses, and researchers, as they can reveal the underlying drivers of technological diffusion, as well as the barriers that might inhibit equitable access and utilization. Comparative studies that use surveys are especially valuable in this context, as they can highlight "directly" such differences without making particular assumptions, focusing on how diverse social and economic conditions may influence the integration of GenAI into everyday life.

This paper is the first to compare GenAI adoption among households in two advanced economies, drawing on comparable survey data from the United States and Italy. The two countries provide a compelling contrast: the U.S. stands as a global leader in AI innovation and rapid technological adoption, while Italy experiences a more gradual digital transformation

We find that GenAI usage, whether one-off or more regular over the past year, is higher in the U.S. than in Italy. The difference is entirely driven by the heterogeneous socio-demographic composition. Looking into factors potentially explaining current and future use of GenAI tools, we find that Italians, despite lower usage, express more optimistic expectations about GenAI's impact on their well-being and wealth, and report greater trust in government and institutional data handling. These findings highlight the influence of cultural, economic, and demographic factors on GenAI adoption patterns.

The structure of the paper is as follows. Section 2 describes the data sources and methodology used in the analysis. Section 3 examines adoption rates and their demographic and sectoral determinants. Section 4 explores differences in perceptions and trust in GenAI between the two countries. Section 5 concludes with policy implications and suggestions for future research.

2 Data

We use data from two surveys, the Survey of Consumer Expectations (SCE) carried out by the Federal Reserve Bank of New York in February 2024 and the Household Outlook Survey (HOS) conducted by the Bank of Italy in August and September 2024. The two surveys share a set of socio-demographic variables (age group: under 40 years, between 40 and 60 years, over 60 years; employment status: employed, retired, other non-employed; gender; education: holding a college degree) and a special GenAI module. The module, addressed only to respondents and not to entire households, gathered detailed information on the frequency of use of GenAI, on how respondents perceive its impact on their job prospects, and on their concerns regarding trust and data privacy. The full set of questions can be found in the Appendix B for the SCE and in Appendix C for the HOS[1]. Importantly, the subset of questions used for this paper were asked to respondents of the HOS and SCE surveys using the same (translated) wording, sequence, and grading scales, thus ensuring comparability of responses.

To conduct our analysis, we merge the two surveys into a single dataset using the population weights provided by each[2]. We further calibrate the weights so that the proportions of respondents by age group, gender, education and employment status match the official data on the adult population provided by the United States Census Bureau and the Italian National Institute of Statistics[3].

2.1 The Survey of Consumer Expectations (SCE)

The SCE is a monthly, internet-based survey produced by the Federal Reserve Bank of New York. Launched in 2013, it has become a valuable resource for researchers and policymakers to understand how expectations are formed and their impact on consumer behaviour. The SCE uses a 12-month rotating nationally representative panel of approximately 1,300 U.S. household heads. New respon-

[1]For the HOS, Loschiavo and Moscatelli (2025) provides a detailed analysis of the module.

[2]This is possible because the two surveys refer to disjoint populations.

[3]This adjustment is necessary because the surveys are calibrated to match the socio-demographic composition at the household level rather than at the respondent level, which is the unit of analysis used in this study and consists only of the adult population.

dents are drawn each month to match demographic targets from the American Community Survey, and they remain in the panel for up to 12 months before being replaced.

2.2 The Household Outlook Survey (HOS)

The Household Outlook Survey[4] (HOS) is an online biannual survey conducted by the Bank of Italy since 2024[5]. To meet Bank of Italy's informational needs, the HOS is designed to track the evolution of households' economic conditions in the years when the main Bank of Italy's Survey on Household Income and Wealth (SHIW) is not conducted. Although the HOS is carried out online, the target sample is selected from the respondents to the previous SHIW wave which is instead performed through in-person interviews[6]. This sampling approach offers two key advantages: i) it enhances representativeness compared to typical online surveys, since it allows to correct part of the bias introduced by the online data collection method by leveraging the characteristics of SHIW households that participated and those that did not; ii) it provides a richer set of household information, as detailed data from the previous SHIW wave can complement the more focused HOS questions. The HOS wave conducted in August and September 2024 included 1,916 households.

3 The adoption of GenAI in the United States and in Italy

First, we investigate differences in the proportion of people that have used GenAI at least once in the previous year (generic use); then, we focus on the differences in the share of people that have used GenAI at least once a week over the past 12 months (regular use). The distinction between regular and generic use allows us to differentiate between a sustained engagement with the technology and a more generic exposure, which may also include brief engagements driven by curiosity or one-off needs. We recall that, since the questions in the GenAI module are addressed only to the people that answer the survey, and not to their entire household, the reference population of the analysis is solely the adult population.

Based on the results of the SCE conducted in February 2024, the share of U.S. people reporting generic GenAI use was 36.4 per cent, compared to 31.0 per cent of Italian people according to the HOS held in August-September 2024. When we focus on regular use, the values become 13.7

[4] `https://www.bancaditalia.it/statistiche/tematiche/indagini-famiglie-imprese/indag-cong-fam-ita/index.html`

[5] Two pilot editions were conducted in June-July 2022 and in August–September 2023.

[6] For a detailed description of the SHIW methodology, see Loschiavo et al. (2025).

and 11.7 per cent, respectively[7].

Table 1: Socio-demographic composition and GenAI use in U.S. and in Italy

	Share of population			Generic use			Regular use		
	U.S.	IT	Diff.	U.S.	IT	Diff.	U.S.	IT	Diff.
Total	100.0	100.0	0.0	36.4	31.0	5.4	13.7	11.7	2.0
Male	49.0	48.4	0.6	40.0	37.4	2.6	15.2	12.3	2.9
Female	51.0	51.6	-0.6	33.0	25.1	7.9	12.3	11.2	1.1
Under 40 years	37.6	27.5	10.1	46.6	63.4	-16.9	17.2	22.6	-5.4
40–60 years	33.3	37.3	-4.1	36.9	25.9	11.0	16.4	10.4	6.1
Over 60 years	29.1	35.1	-6.0	22.8	11.1	11.7	6.1	4.6	1.5
Graduate	33.3	16.0	17.3	52.4	60.4	-8.1	16.5	16.4	0.1
Non graduate	66.7	84.0	-17.3	28.4	25.4	3.0	12.3	10.8	1.5
Employed	62.3	48.7	13.6	41.6	42.1	-0.5	14.2	13.9	0.3
Retired	19.6	32.1	-12.5	19.8	9.0	10.7	6.8	4.5	2.4
Other	18.1	19.2	-1.2	36.6	39.8	-3.2	19.5	18.2	1.3

Notes: The population considered in the sample includes only the respondents to the sample and not their family members, hence these are individuals aged 18 and above. “Generic use” indicates the proportion of individuals who used GenAI at least once in the previous year; “Regular use” indicates the proportion of individuals who used GenAI at least once a week during the previous year. The “Other” class for employment status includes all individuals who are not employed or retired, thus encompassing unemployed and inactive population not receiving retirement pension but possibly enrolled in other types of social assistance. All statistics are weighted using population weights.

Table 1 shows the composition and the adoption of GenAI by socio-demographic groups in the two countries. In line with their overall higher usage rate, the U.S. have a larger share of population in groups associated with a greater use of GenAI, such as individuals under 40 years, university graduates, and employed individuals[8]. When we compare within-group usage, however, we do not observe a uniformly higher GenAI use in the U.S.. For example, young Italians use GenAI more, both generically and regularly, while graduates and employed individuals have larger generic use in Italy and comparable regular usage rates; on the other hand, the use of GenAI among older

[7]Given the rapid growth of the adoption and the fact that the U.S. survey was conducted about six months earlier than the Italian one, the difference is possibly underestimated.

[8]Aldasoro et al. (2024) showed that GenAI adoption varies significantly in the U.S. across socio-demographic dimensions, with respondents that are younger, males, and college graduates being more likely to use GenAI.

individuals, those with lower levels of education, and retirees is less common in Italy than in the U.S..

Higher GenAI use in the U.S. may therefore arise from two sources: (i) a higher representation of high-use demographic groups in the U.S. (socio-demographic composition effect); (ii) a lower use of GenAI in Italy by certain socio-demographic groups, likely related to unobserved factors (within-group differences effect). To isolate how much of the cross-country difference is to be attributable to the different demographic composition, we use the Blinder-Oaxaca decomposition (Jann, 2008). We employ this technique because it accounts for the correlation among socio-demographic variables, thereby enabling the estimation of the joint compositional effect across categories such as gender, age, education, and occupation. For example, if the largest usage among youths only reflects the fact that GenAI is mostly used by employed individuals, the Blinder-Oaxaca decomposition would correctly attribute the effect only to the employment status, thus avoiding duplications.

3.1 Socio-demographic decomposition of the GenAI adoption gap

The probability that individual i uses GenAI is modeled, separately for each country $c \in \{IT, US\}$, as a linear function of its demographic characteristics:

$$AI_{i,c} = \beta_c^0 + \sum_d \beta_c^d X_{i,c}^d + \varepsilon_{i,c}$$

where $AI_{i,c}$ takes value 1 if individual i, in country c, uses GenAI tools and 0 otherwise, $X_{i,c}^d$ are binary socio-demographic variables, and $\mathbb{E}[\varepsilon_{i,c}] = 0$. Specifically, the model includes binary indicators for age (under 40, between 40 and 60, with over 60 as the reference group), educational attainment (college degree), gender (female), and employment status (employed and retired, with other non-retired statuses such as unemployment or inactivity as the reference group).

The difference in GenAI usage between the U.S. and Italy can then be decomposed as

$$\mathbb{E}[AI_{US} - AI_{IT}] \quad = \quad \underbrace{\sum_d \beta_{IT}^d \cdot (\pi_{US}^d - \pi_{IT}^d)}_{\text{Socio-demographic component}} \quad + \quad \mathcal{U},$$

where $\pi_c^d = \mathbb{E}[X_{i,c}^d]$ denotes the proportion of the population in group d within country c. The first term on the right-hand side — commonly referred to as the *explained* component in Blinder–Oaxaca decompositions — captures the portion of the observed difference in GenAI use attributable to differences in the two socio-demographic compositions. It represents the gap we would observe if the

U.S. group-level usage rates were equal to the Italian ones, while the socio-demographic compositions remained the ones we actually observe[9]. While the choice of reference categories may affect the individual estimated coefficients β_c^d, it does not influence the value of the explained component. The residual term $\mathcal{U}$, or *unexplained* component, captures the portion of the gap attributable to unobserved factors, and accounts for within-group differences in Generative AI usage.[10].

Table 2 reports, for both generic and regular use, the decomposition of the usage gap between the U.S. and Italy into the socio-demographic component and the unexplained component, as well as point estimates and standard errors for each individual socio-demographic variable (the overall product $\beta_{IT}^d \cdot (\pi_{US}^d - \pi_{IT}^d)$ of the formula above).

The socio-demographic differences play a crucial role in explaining the 5.4 percentage point gap in generic GenAI usage between the U.S. and Italy (Column (1)). Fixing group-level (conditional) usage rates in both countries to those observed in Italy, the implied gap would exceed 10 percentage points. This reflects the results in Table 1 where we showed that, among the socio-demographic groups with higher GenAI adoption, usage was greater in Italy than in the U.S.; if U.S. college graduates, for instance, not only outnumbered their Italian counterparts but also used GenAI at significantly higher rates, we would expect a gap larger than 5.4 percentage points. Differences in age structure, education levels, and the share of retirees contribute substantially to the observed gap, even after accounting for correlations among them. The effect of education is particularly pronounced, reflecting the large cross-country gap in the share of college graduates — a group with high GenAI adoption — at 33.3 per cent in the U.S. versus 16 per cent in Italy (Table 1). In contrast, within-group differences tend to *reduce* the overall usage gap, meaning that group-level differences that widen the gap (e.g., among older and non-graduates individuals) are more than offset by those that narrow it (e.g. among youths and graduates).

Of course, increasing the number of university graduates in Italy may not automatically lead to a 4.4 percentage point increase in GenAI usage (as suggested in Table 2), since usage behaviour of additional graduates might differ from the one we currently observe. Nonetheless, the exercise indicates that policies focused on increasing adoption among already-educated individuals may yield limited returns, as their usage rates are already high.

[9] Assuming that changing the demographic composition of the country does not affect group-level GenAI usage, this component would also reflect how the usage rate changes in Italy if it shared the same demographic structure as the U.S.

[10] Formally, $\mathcal{U} = \beta_{\mathrm{US}}^0 - \beta_{\mathrm{IT}}^0 + \sum_d (\beta_{\mathrm{US}}^d - \beta_{\mathrm{IT}}^d) \cdot \pi_{\mathrm{US}}^d$

Table 2: Oaxaca-Blinder decomposition of the difference in GenAI use between U.S. and Italy

	(1) Generic Use	(2) Regular Use
U.S.:	36.4	13.7
Italy:	31.0	11.7
Difference US-IT:	5.4	2.0
- Socio-demographic component:	10.1	2.0
- Unexplained component:	-4.7	0.0
Individual demographic components:		
Age: <40	3.6**	1.5*
	(1.70)	(0.91)
Age: 40-60	0.1	-0.1
	(0.25)	(0.19)
College	4.5***	0.5
	(1.18)	(0.76)
Female	0.1	0.0
	(0.55)	(0.11)
Work status: employed	-0.5	-0.7
	(1.20)	(1.10)
Work status: retiree	2.4**	0.9
	(1.20)	(0.80)

Notes: The "Individual demographic components" panel displays the contribution of each demographic characteristic to the socio-demographic component of the decomposition. The reference category for the age variables are individuals above age 60, while the reference category for the employment variables is any employment status other than being employed or retired, such as unemployment or inactivity. All estimates are made using population weights. Robust standard errors for the contribution of different variables of the demographic components reported in parenthesis. ***, **, and * denote significance at 1, 5, and 10 per cent, respectively.

Column (2) examines cross-country differences in regular GenAI use. Again, the overall difference is totally explained by the demographic composition — in this case especially due to the younger age profile of the U.S. population. Because a relatively high share of young Italians use GenAI regularly (22.6 per cent, compared to 17.2 per cent for young Americans; see Table 1), assigning a higher youth share to Italy substantially increases its predicted usage. Within-group differences do not contribute meaningfully to the gap, in either direction.

A notable finding of Table 1, confirmed by the small estimates of the unexplained components in Table 2, is the small difference in GenAI usage among employed individuals across countries. Given that GenAI adoption differs markedly across sectors (see, e.g., Loschiavo and Moscatelli, 2025), and that countries exhibit very different industrial structures, one might have expected employment-related differences to account for a significant share of cross-country variation. This can be attributed to a still limited on-the-job adoption, which does not make job-related use of GenAI a determinant factor for cross-country differences. Still, in Appendix A we investigate the potential role of sectoral composition on widening the usage gap. We combine cross-sector differences in usage reported by Italian respondents with cross-country variation in sectoral composition — sourced from official statistics — to conduct a simple counterfactual exercise. The results suggest that the differences in the sectoral composition can indeed expand the cross-country usage gap among employed individuals, by about 20 per cent. Such increase, however, becomes negligible once we mediate sectoral effects by the socio-demographic composition — for example, sectors more prevalent in Italy, such as manufacturing, tend to consist of older and less-educated individuals, who are generally less likely to use GenAI.[11]

4 Embracing GenAI: A Comparison Between the United States and Italy

So far, we have discussed current differences in GenAI use between the U.S. and Italy. But what about the future? The data allow us to investigate additional factors that may influence future adoption of this technology in both countries. In particular, respondents to the surveys were asked about: i) their intended use of GenAI tools over the next year in different domains (job, finances, education, leisure); ii) the impact of GenAI on their well-being, wealth, and access to information; iii) their relative trust in GenAI-based services vs. human-operated ones (in banking, policymaking, education, information provision); and iv) their trust in the ability of government, financial

[11] At the same time, socio-demographic factors influence sectoral composition itself, potentially reinforcing cross-country differences.

intermediaries, and tech companies to securely store personal data when providing GenAI-based services.[12]

Respondents rated each of these domains on a 1-7 scale (where, depending on the question, 1 meant very unlikely/worse/no trust, and 7 meant very likely/better/full trust). On average, Americans appear to be more likely than Italians to use generative AI tools in the near future, with the notable exception of work-related applications, where the difference between the two groups is minimal (Table 3).

Table 3: In GenAI we (do not) trust

Country	**Future use**			
	On the job	**For financial advice***	**For Education***	**For leisure***
Italy	2.6	1.5	2.5	2.5
US	2.7	2.1	2.9	3.1
Total sample	2.7	2.0	2.8	3.0
Country	**Impact**			
	On wellbeing*	**On wealth***	**On obtaining information**	
Italy	3.9	3.8	4.5	
US	3.4	3.4	4.5	
Total sample	3.5	3.4	4.5	
Country	**Relative trust GenAI vs humans**			
	AI vs Bankers	**AI vs Policy interventions***	**AI vs Information provision**	**AI vs Education**
Italy	2.6	2.8	3.3	3.4
US	2.8	2.5	3.4	3.6
Total sample	2.8	2.6	3.4	3.6
Country	**Trust data store**			
	Government*	**Financial institutions**	**Big Tech companies**	
Italy	3.3	3.1	2.6	
US	2.9	3.1	2.3	
Total sample	3.0	3.1	2.4	

Weighted means, using population weights, of the respondents ranking on a 1-7 scale (where, depending on the domain, 1 means very unlikely/worse/no trust, and 7 means very likely/better/full trust). * denotes that the difference in means between the two countries is statistically significant at 5% significance level. Sources: Bank of Italy, Household Outlook Survey; Federal Reserve Bank of New York, Survey of Consumers Expectations.

In contrast, Italians express greater optimism about the potential of generative AI to

[12]See the questionnaires in Appendix B (questions 3, 4, 12 and 13) for the SCE and in Appendix C (questions 5, 6, 15 and 16) for the HOS.

enhance their overall well-being and financial outcomes. When it comes to relative trust in GenAI-based services vs. human-operated ones, both Italian and U.S. users generally place less confidence in generative AI tools across all domains. Trust in GenAI is especially low in sensitive areas such as banking and public policy. Assuming that greater relative trust encourages wider adoption, these trends suggest that, at least in the short term, GenAI tools are more likely to gain traction in fields like education and information (Aldasoro et al., 2024), where trust levels tend to be higher.

Trust in how AI tools handle personal data varies depending on the institution providing the service. In the U.S., respondents express the highest level of trust in traditional financial institutions (particularly for managing data such as bank transaction history, geolocation, or social media activity), whereas in Italy, respondents show greater trust in government agencies. Yet, in Italy the level of trust in traditional financial institutions is not significantly lower than in the U.S. In both countries, trust is the lowest for big tech companies (e.g., Apple, Meta, or Google). This result may be linked to concerns about security and privacy when engaging with major digital platforms (Aldasoro et al., 2024, Loschiavo and Moscatelli, 2025).

4.1 Socio-demographic factors and GenAI intended use

The previous section showed that demographic differences across countries have shaped current GenAI use patterns. Similarly, such heterogeneity may also play a role in influencing future adoption.

To dig further into this, we examine the data with an econometric model that controls for demographic differences between the two countries. More specifically, for each question on intended use, expected impact and trust we group responses into three categories:[13] 'negative' (1-3), 'neutral' (4) and 'positive' (5-7) and run ordered probit regressions to compare U.S. and Italian views, controlling for country, gender, age, employment status, education, and AI awareness.

Specifically regarding AI knowledge, it is important to stress that this set of questions were asked to all participants in both surveys, regardless of their declared familiarity with GenAI tools. Notably, a significantly larger share of Italian respondents reported being unfamiliar with GenAI compared to their American counterparts. This gap in awareness may turn out in a differentiated propensity between the two countries to express a non-neutral opinion on the potential impacts of GenAI. To take this aspect into account, we complement the analysis on the full sample with estimates that include a dummy variable set to 1 for respondents reporting no knowledge of GenAI

[13] While this aggregation makes the tables and figures easier to interpret, the results remain substantially unchanged when the regressions are estimated using the full 1-7 response scale.

tools, and 0 otherwise; this helps us capture the impact of self-reported knowledge of GenAI on the phenomenon under study.

The model allows us to estimate the likelihood that a respondent falls into each ordered category. Full regression results are reported in Tables A.2 to A.5. Panels A display coefficients and panels B average marginal effects. In the following, we summarize the most relevant results for understanding potential future adoption trends.

When asked about the likelihood of using GenAI for financial advice in the next 12 months, Italians are 6.1 percentage points less likely to respond positively compared to Americans, and 9 percentage points more likely to say that such use is improbable (Figure 1).

By contrast, once demographic characteristics are accounted for, no significant cross-country differences emerge in the intended use of GenAI for work, education, or leisure. This aligns with the broader finding that socio-demographic factors are key to explaining variation in adoption patterns between countries.[14] In fact, consistently with our findings on reported GenAI adoption, the coefficients in Table A.2 show that similar demographic factors influence both current usage and future intentions. In particular, respondents under 40 are generally more likely to report future use of GenAI tools for leisure, educational, and work-related activities. Likewise, individuals with a college degree are more inclined than those with a lower educational attainment to use GenAI for work purposes within 12 months of the interview.

[14] Restricting the analysis to respondents who have already reported some use of GenAI tools we do not find systematic differences between American and Italian users over all the domains, including for financial advice future use.

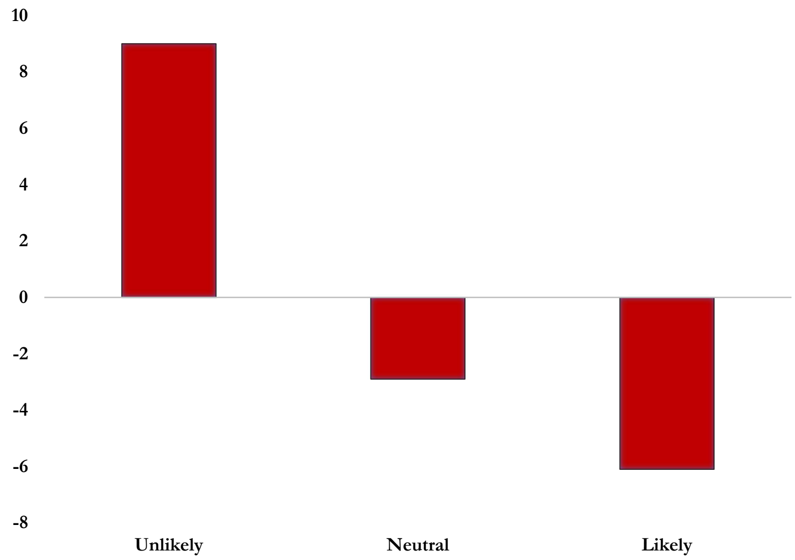

Figure 1: Italians vs Americans predicted probability of using GenAI

Average marginal effects from ordered probit models showing the predicted probability of using GenAI for obtaining financial advice. Bars represent the difference between Italian and American respondents, controlling for age, gender, education, and GenAI awareness.

4.2 Conditional differences in opinions about GenAI

Interestingly, and despite no reported differences in intended use, Italians show a more favourable outlook on the potential of GenAI to improve their personal outcomes. As shown in Figure 2, they are significantly more likely to believe that GenAI will improve their own well-being (+17.1 percentage points), financial wealth (+13.9 percentage points) and access to information (+10.2 percentage points), even after controlling for other factors.[15] While Italians exhibit greater optimism than Americans regarding the potential of generative AI to enhance financial wealth, they are, as noted above, less likely to report intentions to employ such technologies for financial advice in the short term. This apparent discrepancy may be interpreted in several ways. One possibility is that Italians may perceive the direct use of GenAI for financial advice as too risky without the oversight of professional human advisors, reflecting cultural preferences for personalised interaction in sensitive domains such as finance. At the same time, respondents may place relatively greater confidence in the ability of financial intermediaries to integrate GenAI into their service offerings in a controlled

[15] Results on well-being and financial wealth remain consistent when running regressions on the subset of individuals reporting generic use of GenAI, while no differences are observed in access to information within this group.

and regulated manner, thereby improving financial outcomes for clients via supply-side channels rather than through individual experimentation. Another interpretation is that the expected impact of GenAI on financial wealth is not necessarily linked to its direct use by households, but rather to broader, economy-wide spillover effects (Aldasoro et al. (2024)). Specifically, respondents may anticipate that the widespread diffusion of AI technologies will generate financial benefits indirectly, by fostering higher productivity, accelerating innovation, and sustaining long-term economic growth. Such developments could in turn translate into higher aggregate demand, rising household incomes, and improved asset valuations. In this sense, optimism about financial wealth may reflect expectations of structural gains at the macroeconomic level, even if individuals remain hesitant to rely on GenAI directly for financial advice in the short run.

Italians also demonstrate higher relative trust than Americans when it comes to public policy interventions. Furthermore, they express greater trust in both government institutions and, to a lesser extent, big tech companies, to safely store their personal data when they offer them services that require the use of GenAI (Figure 3). One possible explanation is that, in Europe, privacy protections and data handling are perceived to be more strictly governed - through laws such as the General Data Protection Regulation (GDPR)[16] - and more embedded in the public's everyday experience.[17]

[16]The GDPR is a comprehensive privacy and data protection law enacted by the European Union that came into effect on May 25, 2018. For more details, see Voigt and von dem Bussche (2017) and Aldasoro et al. (2024).

[17]When limiting the analysis to those who have used GenAI tools at least once in the past 12 months, Italians continue to show higher trust in government data storage than Americans. However, differences in trust towards public policy interventions disappear in this subsample.

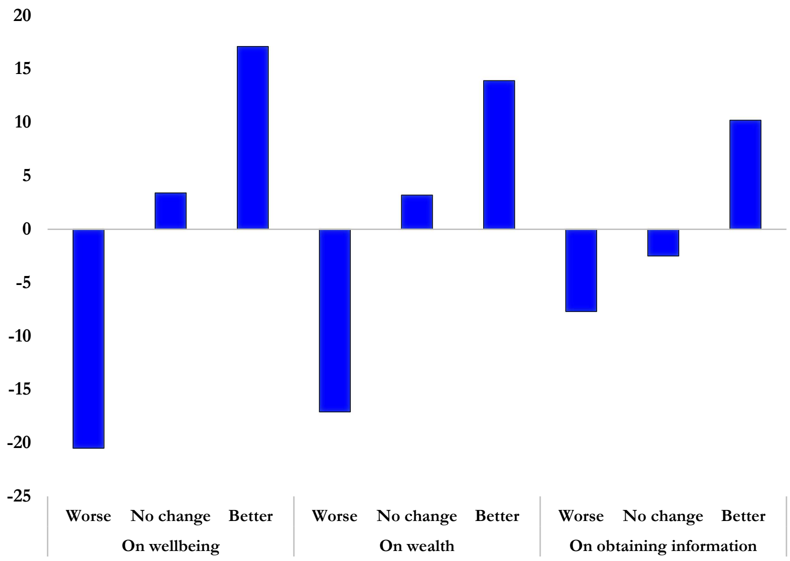

Figure 2: Italians vs Americans predicted probability that GenAI will improve well-being and wealth
Average marginal effects from ordered probit models showing the predicted probability that GenAI will improve well-being (left), wealth (middle panel) and information gathering (right). Bars represent the difference between Italian and American respondents, controlling for age, gender, education, and GenAI awareness.

Ultimately, the analysis points to a potential for growing acceptance of GenAI among Italian households, particularly in terms of perceived benefits and trust in institutions. However, greater acceptance does not necessarily translate into higher intended use, especially once socio-demographic factors are taken into account. Actual future adoption will likely depend on multiple interacting factors — such as digital literacy, labour market context, and sectoral relevance — which are also impacted by structural countries' characteristics.

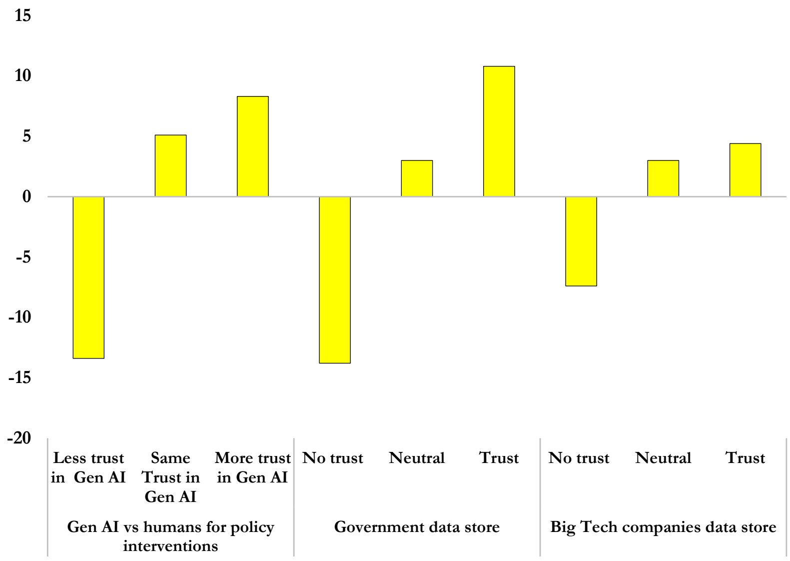

Figure 3: Italians vs Americans predicted probability of trust in GenAI

Average marginal effects from ordered probit models showing the predicted probability to express a higher relative trust in AI tools over traditional human-operated for public policy interventions (left); of trusting how government agencies (middle panel) and big tech companies (right) store their personal data when using AI tools. Bars represent the difference between Italian and American respondents, controlling for age, gender, education, and GenAI awareness.

5 Conclusions

This paper provides a comparative analysis of GenAI adoption among households in the U.S. and Italy, using survey data collected in 2024. We document a significantly higher uptake of GenAI in the U.S., both in terms of generic and regular use.

Through decomposition techniques, we show that differences in socio-demographic composition — particularly age, education and the proportion of retirees — play a major role in explaining the cross-country gap in both current and intended future GenAI use[18]. Importantly, the analysis also highlights that Italians, despite lower usage rates, express more optimistic expectations about GenAI's impact on their well-being and wealth, and report greater trust in government and

[18]The strong role of age further suggests that older cohorts may face greater hurdles in adapting to new technologies, with potential consequences for their labour market opportunities. Evidence from previous studies on digitalization and software adoption supports this interpretation, showing that older workers often experience greater difficulties in adjusting to technological change (Barth et al., 2020).

institutional data handling.

Future adoption trends, and the related benefits in terms of economic growth and overall well-being, will likely depend not only on digital infrastructure and skills, but also on how societies perceive and govern this rapidly evolving technology. Our findings underscore the importance of demographic, sectoral, and attitudinal factors in shaping the diffusion of GenAI technologies.

Looking ahead, the results of the analysis point to the need for tailored policy responses, especially if the aim of policymakers is to foster adoption and maximize the productivity-enhancing potential of these technologies. In Italy, where trust in GenAI is relatively higher but usage remains low, efforts should focus on increasing digital skills and access to the technology. In the U.S., where usage is higher but scepticism persists, priorities may include strengthening trust, data protection, and ethical oversight.

References

Aldasoro, I., O. Armantier, S. Doerr, L. Gambacorta, and T. Oliviero (2024). Survey evidence on Gen AI and households: job prospects amid trust concerns. BIS Bulletins 86, Bank for International Settlements.

Aldasoro, I., S. Doerr, L. Gambacorta, and D. Rees (2024). The impact of artificial intelligence on output and inflation. BIS Working Papers 1197, Bank for International Settlements.

Aldasoro, I., L. Gambacorta, A. Korinek, V. Shreeti, and M. Stein (2024). Intelligent financial system: how AI is transforming finance. BIS Working Papers 1194, Bank for International Settlements.

Bank for International Settlements (2024). *Artificial Intelligence and the economy: implications for central banks*. BIS Annual Economic Report.

Barth, E., J. C. Davis, R. B. Freeman, and K. McElheran (2020). Twisting the demand curve: Digitalization and the older workforce. NBER Working Paper w28094, National Bureau of Economic Research.

Brynjolfsson, E., D. Li, and L. R. Raymond (2023). Generative AI at work. Working Paper 31161, National Bureau of Economic Research.

Calvino, F. and L. Fontanelli (2023). A portrait of AI adopters across countries: Firm characteristics, assets' complementarities and productivity. OECD Science, Technology and Industry Working Papers 2023/02, OECD Publishing.

Cui, Z. K., M. Demirer, S. Jaffe, L. Musolff, S. Peng, and T. Salz (2024). The effects of Generative AI on high skilled work: Evidence from three field experiments with software developers. *Available at SSRN 4945566*.

Dell'Acqua, F., C. Ayoubi, H. Lifshitz, R. Sadun, E. Mollick, L. Mollick, Y. Han, J. Goldman, H. Nair, S. Taub, et al. (2025). The cybernetic teammate: A field experiment on Generative AI reshaping teamwork and expertise. Technical report, National Bureau of Economic Research.

DiNardo, J., N. Fortin, and T. Lemieux (1995). Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach.

Jann, B. (2008). The Blinder–Oaxaca decomposition for linear regression models. *The Stata Journal 8*(4), 453–479.

Liu, Y., J. Huang, and H. Wang (2025). Who on Earth Is Using Generative AI ? Global Trends and Shifts in 2025. Policy Research Working Paper Series 11231, The World Bank.

Loschiavo, D., G. M. Mariani, M. Moscatelli, A. Neri, E. Porreca, and F. Tullio (2025). Enhancing the SHIW weighting methodology with external data sources. Forthcoming.

Loschiavo, D. and M. Moscatelli (2025). Adoption and expected impact of Generative AI: evidence from Italian households. *Bank of Italy occasional papers 929*.

Noy, S. and W. Zhang (2023). Experimental evidence on the productivity effects of Generative Artificial Intelligence. *Science 381*(6654), 187–192.

Peng, S., E. Kalliamvakou, P. Cihon, and M. Demirer (2023). The impact of AI on developer productivity: Evidence from github copilot. *arXiv preprint arXiv:2302.06590*.

Redding, S. (2002). Specialization dynamics. *Journal of International Economics 58*(2), 299–334.

Singla, A., A. Sukharevsky, L. Yee, M. Chui, and B. Hall (2024). The state of AI in early 2024: Gen AI adoption spikes and starts to generate value. Technical report, McKinsey.

Voigt, P. and A. von dem Bussche (2017). *The EU General Data Protection Regulation (GDPR): A Practical Guide*. Cham: Springer International Publishing.

APPENDIX

A The potential role of employment sectoral composition in widening the usage gap and additional tests

We assess the *potential* role of sectoral employment composition in explaining cross-country differences in GenAI adoption, with a simple counterfactual exercise. We observe the sector of employment only for individuals in the HOS. We aggregate the granular sectors available in the Italian survey so that, for each sector, we have enough workers to accurately compute the share that regularly uses GenAI. We assume that currently observed relative usage differences across sectors reflect differences in on-the-job use across sectors (we exploit the information on "regular use"). Although this is likely a strong assumption, the usage by sector, reported in column (4) of Table A.1, aligns well with the a priori expectation of a larger use in the ICT, administration, professional and education and health sectors. Based on this assumption, we simulate what GenAI usage for the Italian employed population would be if it had the same sectoral employment structure as the U.S., and compare to the one measured with the current Italian sectoral distribution. Specifically, we weight Italy's sector-specific GenAI usage rates using U.S. sectoral employment shares.[19] The results, shown in Panel (a) of Table A.1, suggest that GenAI use in Italy would rise by about 20% under the U.S. sectoral distribution, driven by higher employment shares in sectors like ICT, administrative and professional services, and education and health.[20]

We further examine the mediating role of socio-demographic factors. Sectors with greater weight in the Italian economy—such as manufacturing—tend to employ a higher share of workers with characteristics associated with lower usage rates, including older age and lower levels of education. Conversely, socio-demographic differences also influence the sectoral structure itself, potentially amplifying cross-country disparities in adoption. For instance, the relatively larger presence of service-oriented and innovation-intensive sectors in the U.S. economy, compared to many Euro-

[19] Sectoral employment shares are taken from official sources: for the U.S., from the Bureau of Labor Statistics ("Detailed industries: hours and employment"); for Italy, from Istat ("Employed (thousands): Ateco 2007 (detail) - professional position"). Both refer to 2023 averages. Letting $AI_{IT} = \sum_s AI^s_{IT} \cdot \pi^s_{IT}$ denote actual usage and $AI_{IT,secUS} = \sum_s AI^s_{IT} \cdot \pi^s_{US}$ the counterfactual (where s indicates the sector), we isolate the effect of sectoral composition.

[20] The survey-based GenAI usage rate for employed individuals differs from that in the table due to discrepancies between the survey's sectoral employment shares and national statistics, as the sample is not designed to be representative by sector.

pean countries, is partly driven by differences in the educational composition of the workforce (see, e.g., Redding, 2002). To account for these dynamics, we extend our analysis by controlling for cross-country differences in socio-demographic characteristics. Although the results should be interpreted with caution, this exercise highlights how individual-level attributes may mediate the influence of labour market composition on GenAI uptake.

Table A.1: Sectoral contribution to GenAI use

Sector	**Employment shares**			**GenAI Use**	**Contribution to overall GenAI use**		
	Italy	**U.S.**	**Difference**	**Italy**	**Actual**	**Counterfactual**	**Difference**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel (a): No Socio-Demographic Weighting						
Manufacturing	20.1	10.5	9.6	1.3	0.3	0.1	0.1
Trade	13.5	17.8	-4.3	3.3	0.4	0.6	-0.1
ICT	3.3	4.1	-0.8	79.7	2.6	3.3	-0.6
Finance	2.6	5.9	-3.3	9.0	0.2	0.5	-0.3
Admin. and Prof.	11.6	16.6	-5.0	20.3	2.4	3.4	-1.0
Education and Health	15.3	16.9	-1.6	19.5	3.0	3.3	-0.3
Others	33.6	28.1	5.5	7.9	2.7	2.2	0.4
Overall use					11.6	13.4	-1.9
	Panel (b): With Socio-Demographic Weighting						
Manufacturing	17.5	10.5	7.0	3.0	0.5	0.3	0.2
Trade	10.7	17.8	-7.1	3.7	0.4	0.7	-0.3
ICT	4.2	4.1	0.1	80.7	3.4	3.3	0.0
Finance	3.2	5.9	-2.7	12.4	0.4	0.7	-0.3
Admin. and Prof.	11.0	16.6	-5.6	17.7	1.9	2.9	-1.0
Education and Health	21.4	16.9	4.5	17.6	3.8	3.0	0.8
Others	32.0	28.1	3.9	8.1	2.6	2.3	0.3
Overall use					13.0	13.2	-0.2

Notes: employment shares for Italy are taken from "Employed (thousands): Ateco 2007 (detail) - professional position" from Istat - link: `http://dati.istat.it/Index.aspx?DataSetCode=DCCV_TAXOCCU1`. Employment shares for the U.S. are from "Detailed industries: hours and employment" from the Bureau of Labor Statistics - link: `https://www.bls.gov/productivity/tables/`. GenAI use refers to regular use and is taken from the HOS survey. Actual contribution multiplies the Italian GenAI use times the Italian employment share. Counterfactual contribution multiplies the Italian GenAI use times the U.S. employment share. Panel (b) mirrors panel (a), but Italian employment share and GenAI use are modified according to the new weights that equalize the distributions of socio-demographic characteristics in Italy and the U.S.

We follow the procedure outlined in DiNardo et al. (1995), where, prior to computing the counterfactual estimate, we calibrate the weights of the Italian survey through raking so that the socio-demographic distribution matches that of the U.S.[21] Under this approach, for example, older

[21] Since the sectoral employment composition for Italy is taken from Istat rather than directly from the survey, we estimate how this composition would shift if Italy had the same socio-demographic structure as the U.S. by computing,

Italian workers—overrepresented in manufacturing—receive a lower weight, reducing the effective weight of the manufacturing sector in the counterfactual economy (Panel (b), Column (1)). Similarly, the ICT employment share is comparable across the two countries, while the higher U.S. employment in Administration and Professional Services is offset by a larger share of Italian workers in Education and Health. As a result the average GenAI usage rate increases (Column (5)), indicating that nearly the entire gap observed in Panel (a) would vanish if Italy's socio-demographic structure—and the resulting sectoral composition—mirrored that of the U.S. We conclude that the role of sectoral composition, while potentially substantial, should be assessed in conjunction with other structural factors that are both correlated with sectoral structure and relevant for GenAI adoption.

The remaining part of this appendix presents a series of tests designed to check the robustness of cross-country comparisons (Italy vs. U.S.) by controlling for socio-demographic characteristics (age, gender, education, employment status, and GenAI awareness). In particular:

- **Table A.2** reports an ordered probit on intended future use of GenAI, showing Italians less inclined toward financial advice.
- **Table A.3** presents results on expected impacts of GenAI, with Italians more optimistic on well-being, wealth, and access to information.
- **Table A.4** examines relative trust in GenAI versus humans, finding Italians more trusting of AI compared with policy interventions.
- **Table A.5** analyses institutional trust in data storage, with Italians showing higher confidence in government agencies and Big Tech.

for each sector, the percentage change in its share in the HOS survey before and after reweighting, and then applying that change to the official Istat shares.

Table A.2: **Panel A**: Future use of GenAI - ordered probit estimations

	(1) On the job	(2) For financial advice	(3) For education	(4) For leisure
Italian	0.079	-0.422***	0.023	-0.161
	(0.126)	(0.146)	(0.113)	(0.106)
Female	0.093	-0.052	0.048	-0.020
	(0.117)	(0.136)	(0.116)	(0.107)
Age < 40	0.516**	0.390**	0.668***	0.695***
	(0.216)	(0.195)	(0.175)	(0.177)
Age 40-60	0.486**	0.061	0.310**	0.438***
	(0.214)	(0.169)	(0.155)	(0.159)
Retirees	-6.352***	0.076	-0.202	0.194
	(0.143)	(0.221)	(0.204)	(0.189)
Other not employed	-0.015	-0.198	-0.094	0.070
	(0.184)	(0.177)	(0.146)	(0.147)
College	0.310***	-0.181	0.019	0.041
	(0.116)	(0.120)	(0.102)	(0.101)
Know nothing about Gen AI	-1.030***	-0.425**	-0.906***	-0.875***
	(0.157)	(0.179)	(0.162)	(0.138)
cut1	0.416***	0.450***	-0.158	-0.172
	(0.139)	(0.155)	(0.140)	(0.139)
cut2	0.694***	0.779***	0.193	0.178
	(0.137)	(0.161)	(0.145)	(0.137)
Observations	1720	2809	2807	2809
Pseudo-R^2	0.09	0.04	0.10	0.08
Panel B: Average marginal effects - Italians vs Americans predicted probability of using GenAI...				
Unlikely	-0.025	0.090***	-0.007	0.054
	(0.039)	(0.029)	(0.036)	(0.035)
Neutral	0.003	-0.029***	0.001	-0.008
	(0.005)	(0.010)	(0.005)	(0.006)
Likely	0.021	-0.061***	0.006	-0.046
	(0.034)	(0.020)	(0.031)	(0.030)

Notes: Panel A reports raw coefficients of ordered probit regressions. Panel B reports the corresponding average marginal effects for each category of the ordinal dependent variables indicated in columns. Weighted estimates with robust standard errors reported in parenthesis. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. Reference categories are: US respondents; males; older than 60; employee; undergraduate.

Table A.3: **Panel A**: Impact of GenAI - ordered probit estimations

	(1) On wellbeing	(2) On wealth	(3) On obtaining information
Italian	0.596***	0.462***	0.278***
	(0.094)	(0.094)	(0.095)
Female	-0.025	0.059	-0.146
	(0.097)	(0.104)	(0.105)
Age < 40	0.301**	0.293*	0.226
	(0.141)	(0.155)	(0.169)
Age 40-60	0.041	0.064	0.000
	(0.125)	(0.125)	(0.147)
Retirees	0.058	-0.017	-0.107
	(0.141)	(0.157)	(0.166)
Other not employed	-0.010	-0.164	-0.103
	(0.128)	(0.145)	(0.143)
College	0.172*	-0.048	0.076
	(0.095)	(0.100)	(0.100)
Know nothing about Gen AI	-0.453***	-0.324***	-0.671***
	(0.110)	(0.119)	(0.115)
cut1	-0.426***	-0.364***	-1.130***
	(0.131)	(0.140)	(0.149)
cut2	0.808***	0.678***	-0.451***
	(0.128)	(0.146)	(0.138)
Observations	2809	2808	2808
Pseudo-R^2	0.04	0.02	0.05
Panel B: Average marginal effects - Italians vs Americans predicted probability that GenAI will make situation...			
Worse	-0.205***	-0.171***	-0.077***
	(0.030)	(0.034)	(0.026)
No change	0.034***	0.032***	-0.025***
	(0.009)	(0.010)	(0.009)
Better	0.171***	0.139***	0.102***
	(0.027)	(0.027)	(0.034)

Notes: Panel A reports raw coefficients of ordered probit regressions. Panel B reports the corresponding average marginal effects for each category of the ordinal dependent variables indicated in columns. Weighted estimates with robust standard errors reported in parenthesis. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. Reference categories are: US respondents; males; older than 60; employee; undergraduate.

Table A.4: **Panel A**: Relative trust GenAI vs humans - ordered probit estimations

	(1)	(2)
	AI vs Bankers	AI vs Policy interventions
Italian	-0.009	0.372***
	(0.095)	(0.104)
Female	-0.070	-0.118
	(0.110)	(0.106)
Age < 40	0.086	0.149
	(0.204)	(0.210)
Age 40-60	-0.075	-0.075
	(0.183)	(0.185)
Retirees	0.005	-0.138
	(0.207)	(0.217)
Other not employed	-0.082	0.003
	(0.151)	(0.162)
College	-0.164*	-0.038
	(0.099)	(0.100)
Know nothing about Gen AI	-0.350***	-0.130
	(0.120)	(0.121)
cut1	0.057	0.339***
	(0.129)	(0.130)
cut2	0.768***	0.999***
	(0.129)	(0.135)
Observations	2807	2806
Pseudo-R^2	0.01	0.01
Panel B: Average marginal effects - Italians vs Americans predicted probability of relative trust...		
Less trust in GenAI	0.003	-0.134***
	(0.035)	(0.037)
Same level of trust	-0.001	0.051***
	(0.014)	(0.015)
More trust in GenAI	-0.002	0.083***
	(0.022)	(0.024)

Notes: Panel A reports raw coefficients of ordered probit regressions. Panel B reports the corresponding average marginal effects for each category of the ordinal dependent variables indicated in columns. Weighted estimates with robust standard errors reported in parenthesis. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. Reference categories are: US respondents; males; older than 60; employee; undergraduate.

Table A.5: **Panel A**: Trust data store - ordered probit estimations

	(1) Government	(2) Big Tech companies
Italian	0.358***	0.231**
	(0.100)	(0.110)
Female	0.024	-0.022
	(0.102)	(0.115)
Age < 40	0.032	0.455***
	(0.183)	(0.167)
Age 40-60	-0.158	0.081
	(0.166)	(0.151)
Retirees	-0.214	0.134
	(0.195)	(0.180)
Other not employed	-0.238*	-0.134
	(0.141)	(0.157)
College	0.087	-0.123
	(0.096)	(0.110)
Know nothing about Gen AI	-0.167	-0.082
	(0.113)	(0.129)
cut1	0.176	0.415***
	(0.126)	(0.151)
cut2	0.736***	1.002***
	(0.125)	(0.158)
Observations	2808	2807
Pseudo-R^2	0.01	0.02
Panel B: Average marginal effects - Italians vs Americans predicted probability of trusting data store by...		
No trust	-0.138***	-0.074**
	(0.038)	(0.036)
Neutral	0.030***	0.030**
	(0.008)	(0.015)
Trust	0.108***	0.044**
	(0.031)	(0.021)

Notes: Panel A reports raw coefficients of ordered probit regressions. Panel B reports the corresponding average marginal effects for each category of the ordinal dependent variables indicated in columns. Weighted estimates with robust standard errors reported in parenthesis. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. Reference categories are: US respondents; males; older than 60; employee; undergraduate.

B Artificial Intelligence module in the February 2024 SCE

1. How much do you know about artificial intelligence tools (such as ChatGPT, Google Bard, DALL-E, . . .) [**Q0**]

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

2. How often have you used artificial intelligence tools (such as ChatGPT, Google Bard, DALL-E, . . .) in the past 12 months? [**Q1new**]

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

3. Over the next 12 months, how likely are you to use an artificial intelligence tool in the following contexts? For each of them, please report the likelihood on a scale from 1 (very unlikely that you will use such tools) to 7 (very likely) [**Q2**]

	Very unlikely						Very likely
	1	2	3	4	5	6	7
In your Job							
To obtain financial advice							
To obtain medical advice							
For education or training							
For leisure activity (for example writing, drawing or creating videos)							

4. Do you think artificial intelligence tools will make your situation worse or better in the following areas? For each area, please report your answer on a scale from 1 (my situation will be much worse) to 7 (it will be much better). [**Q3**]

	Much worse			No change			Much better
	1	2	3	4	5	6	7
General well-being							
Financial wealth (for example through cheaper or better financial advice)							
Physical health (for example with targeted exercise recommendations)							
Mental health (for example through faster and targeted advice)							
Obtaining information (for example by quickly finding useful information on a topic)							

5. (**Only if the respondent is working or is actively looking for a job**) What do you think are the chances that artificial intelligence will increase your productivity at work? *Values: 0-100.* [**Q4_1**]
   ___%

6. (**Only if the respondent is working or is actively looking for a job**) What do you think are the chances that artificial intelligence will help you find new job opportunities? *Values: 0-100*[**Q4_2**]
   ___%

7. (**Only if the respondent is a worker**) What do you think are the chances that you will lose your current job because of artificial intelligence tools? *Values: 0-100* [**Q5_1**]
   ___%

8. (**Only if the respondent is a worker**) And what do you think are the chances that your salary in your current job will decrease because of artificial intelligence tools? *Values: 0-100* [**Q5_2**]
   ___%

9. 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 without your consent)? *Values: 1-7.* [**Q6_1**]

Decrease a lot						Increase a lot
1	2	3	4	5	6	7

10. 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 adds)? *Values: 1-7* [**Q6_2**]

Not concerned at all						Very concerned
1	2	3	4	5	6	7

11. Are you concerned that an increased reliance on artificial intelligence will have negative effects on human interactions or relationships? *Values: 1-7* [**Q6_3**]

Not concerned at all						Very concerned
1	2	3	4	5	6	7

12. In the following areas, would you trust artificial intelligence (AI) 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).*. [**Q7new**]

	Trust AI Much less Much less			Same level of trust			Trust AI 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 (such as summarizing news or scientific articles)							
Education and training (such as on-line courses)							

13. 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).* [**Q8**]

	No 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, ...)							

14. To what extent do you agree that there should be rules or restrictions on how individuals and firms can use artificial intelligence tools? *Please indicate your level of agreement on a scale from 1 (I totally disagree) to 7 (I totally agree).* [**Q9**]

	Totally disagree						Totally agree
	1	2	3	4	5	6	7
There should be rules or restrictions for individuals (for example when creating fake videos or aggregating news)							
There should be rules or restrictions for financial institutions (for example when approving loans)							
There should be rules or restrictions for firms and companies (for example when setting prices)							
There should be rules or restrictions for doctors and scientists (for example when doing research)							

C Artificial Intelligence module in the August-September 2024 HOS

1. How much do you know about GenAI tools? *Please score on a scale from 1 to 7, where 1 means "nothing at all" and 7 "a lot," and the intermediate numbers serve to graduate the response* [**AIKNOW**]

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

If AIKNOW> 1

2. How often have you used GenAI tools in the past 12 months? [**AIFREQ**]

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

If AIFREQ> 1

3. Which of these tools have you used in the last 12 months? (*More than one answer possible*) [**AITOOL1_4**]

   1 ChatGPT 2 Google Bard/Gemini 3 Dall-E 4 Other (please specify)

If AIFREQ> 1

4. For which of these purposes have you used GenAI in the last 12 months? (*More than one answer possible*) [**AIFIN1_7**]

   1 Search for information 2 Writing assistance 3 Programming assistance 4 Learning support 5 Creativity support 6 Entertainment 7 Other (please specify)

5. **(All respondents)** Over the next 12 months, how likely are you to use a GenAI tool in the following contexts? *For each of them, please report the likelihood on a scale from 1 (very unlikely that you will use such tools) to 7 (very likely).* [**AICONTEXT1_4**]

	Very unlikely						Very likely
	1	2	3	4	5	6	7
(**Only if the respondent is not retired**) In your Job							
To obtain financial advice							
For education or training							
For other purposes (for example, leisure activities such as drawing or creating ideos, to obtain medical advice)							

6. **(All respondents)** Do you think GenAI tools will make your situation worse or better in the following areas? *For each area, please report your answer on a scale from 1 (my situation will be much worse) to 7 (it will be much better).* [**AIOPP1_4**]

	Much worse			No change			Much better
	1	2	3	4	5	6	7
General well-being							
Work life balance							
Financial wealth (for example through cheaper or better financial advice)							
Obtaining information (for example by quickly finding useful information on a topic)							

7. (**Only if the respondent is not retired**) What do you think are the chances that the GenAI will increase your productivity at work? *Please report the likelihood on a scale from 0 to 100, where 0 means "certainly no" and 100 "certainly yes", and the intermediate numbers serve to graduate the response.* [**AJOBPROD**]
   ___%

8. (**Only if the respondent is not retired**) What do you think are the chances that the GenAI will help you find new job opportunities? *Please report the likelihood on a scale from 0 to 100, where 0 means "certainly no" and 100 "certainly yes", and the intermediate numbers serve to graduate the response.* [**AIJOBOPP**]
   ___%

9. (**Only if the respondent is a worker**) What do you think are the chances that the tasks you perform at your job will be influenced by GenAI tools? *Please report the likelihood on a scale from 0 to 100, where 0 means "I am sure my tasks will not be influenced" and 100 "I am sure my tasks will be influenced", and the intermediate numbers serve to graduate the response.* [**AIJOBTASK**]
   ___%

10. (**Only if the respondent is a worker**) What do you think are the chances that you will lose your current job because of GenAI tools? *Please report the likelihood on a scale from 0 to 100, where 0 means "I am sure I will not lose my job" and 100 "I am sure I will lose my job", and the intermediate numbers serve to graduate the response.* [**AIJOBLOSS**]
    ___%

11. (**Only if the respondent is a worker**) And what do you think are the chances that your salary in your current job will decrease or increase by less because of GenAI tools? *Please report the likelihood on a scale from 0 to 100, where 0 means "certainly my salary will not decrease" and 100 "certainly my salary will decrease", and the intermediate numbers serve to graduate the response.* [**AIWAGELOSS**]
    ___%

12. **(All respondents)** Are you concerned that sharing your personal information with GenAI tools will increase the risk of data breaches (that is, your data becoming publicly available without your consent)? *Please indicate your level of concern on a scale from 1 (not concerned at all) to 7 (very concerned).* [**AIRISK**]

Not concerned at all						Very concerned
1	2	3	4	5	6	7

13. **(All respondents)** Are you concerned that an increased reliance on GenAI will have negative effects on human interactions or relationships? *Please indicate your level of concern on a scale from 1 (not concerned at all) to 7 (very concerned).* [**AIWB**]

Not concerned at all						Very concerned
1	2	3	4	5	6	7

14. (**Only if the respondent is a worker**) Are you concerned that an increased reliance on GenAI will have negative effects on interactions or relationships with your colleagues or supervisors at your workplace? *Please indicate your level of concern on a scale from 1 (not concerned at all) to 7 (very concerned).* [**AIWBJOB**]

Not concerned at all						Very concerned
1	2	3	4	5	6	7

15. **(All respondents)** In the following areas, would you trust GenAI-based services less or more than traditional human-operated services? F*or each of them, please indicate your level of trust on a scale from 1 (much less trust than in a human) to 7 (much more trust in GenAI).* [**AIVSHUM1_4**]

	Much less trust in GenAI			Same level of trust			Much more trust in GenAI
	1	2	3	4	5	6	7
Banking (such as customer support or financial advice)							
Public policy interventions (such as economic and monetary policy measures)							
Information provision (such as summarizing news or scientific articles)							
Education and training (such as on-line courses)							

16. **(All respondents)** How much do you trust the following entities or firms to safely store your personal data when they offer you services that require the use of GenAI? *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).* [**AIDATATRUST1_3**]

	No trust at all						Complete trust
	1	2	3	4	5	6	7
Government agencies and public entities (such as the Revenue Agency or the National Social Welfare Institute)							
Traditional financial institutions (such as banks, insurers, ...)							
Large technology companies (such as Facebook/Meta, Google, Apple, ...)							

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