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Inequalities in the Use of Generative Artificial Intelligence and Barriers to Adoption: Evidence from Household Survey Data

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Abstract

This paper examines the socioeconomic, demographic, digital, and labour-market factors associated with Generative Artificial Intelligence (GAI) adoption and the barriers that prevent its use. Using nationally representative data for Spain from the 2025 Survey on Equipment and Use of ICT in Households, we distinguish between private, work-related, and educational uses of GAI and analyse the heterogeneous reasons for non-adoption. To account for the selective observation of barriers among non-users, we estimate a multivariate sample-selection model with valid exclusion restrictions. The results reveal significant inequalities in both GAI adoption and non-adoption barriers. GAI adoption is positively associated with human capital, digital resources, and technology-intensive work environments. Moreover, non-adoption barriers vary substantially across population groups, with older, less educated, and female individuals facing primarily skill- and information-related constraints, while more educated and digitally connected individuals are more likely to question the relevance of these technologies. The findings suggest that the emerging GAI divide reflects both traditional forms of digital inequality and heterogeneous informational, capability-related, and attitudinal barriers. Policies aimed at promoting inclusive GAI adoption should therefore combine digital-skills development, awareness-raising initiatives, and measures to strengthen trust in AI technologies.

Keywords: Generative artificial intelligence; Digital divide; Technology adoption; Digital inequalities; Barriers to adoption.

JEL Codes: O33, J24, C34

1. Introduction

The rapid expansion of generative artificial intelligence (GAI) has renewed concerns about the emergence of a new layer of digital inequality, known as the "GAI divide". This "GAI divide" can be understood as a new dimension of digital inequality associated not only with access to and use of GAI technologies, but also with the capacity to integrate them effectively into everyday activities and derive meaningful benefits from their use. Effective use requires individuals to recognise potential applications, formulate well-designed prompts, critically evaluate AI-generated outputs, and develop sufficient trust in these technologies while understanding their

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limitations. In addition, because many of the expected benefits of GAI are linked to productivity enhancement, learning, and task automation, opportunities for adoption are likely to differ according to educational pathways, occupational characteristics, and workplace environments. As a result, the emergence of GAI may not only reproduce existing patterns of digital inequality but also create new forms of stratification.

Differences across socioeconomic and demographic groups in both the adoption of GAI and the barriers to its use may translate into unequal returns from the technology, with implications for productivity, learning outcomes, and access to information. Thus, understanding the factors that drive GAI adoption is essential not only for documenting emerging patterns of digital inequality, but also for identifying the mechanisms through which these inequalities may develop and persist. Importantly, the determinants of GAI use are unlikely to be homogeneous across domains, as the incentives, skills, opportunities, and constraints shaping its adoption may differ between professional, educational, and private contexts. Examining these dimensions separately can provide a more nuanced understanding of the sources of the emerging GAI divide and help identify the population groups most at risk of exclusion from the benefits associated with these technologies. Such evidence is crucial for the design of targeted policy interventions aimed at fostering inclusive adoption, enhancing digital and AI-related skills, and preventing the emergence of new forms of socioeconomic inequality linked to the diffusion of GAI.

However, analysing who adopts GAI technologies is only one part of the picture. Identifying the mechanisms that prevent adoption is equally important for assessing the nature and policy implications of the emerging GAI divide. Individuals may refrain from using GAI for very different reasons, including a lack of awareness, insufficient skills, concerns about privacy and security, or the perception that these tools are not relevant to their needs. These barriers reflect distinct underlying processes and may therefore require different policy responses. While informational and skill-related constraints may call for investments in awareness initiatives, digital education, and training, attitudinal barriers may persist even among individuals who possess adequate skills and access to technology. Distinguishing between these barriers is therefore essential for understanding observed adoption gaps and for designing effective interventions aimed at reducing emerging forms of digital exclusion.

The contribution of this paper to the emerging literature on inequalities in the adoption of GAI is fourfold. First, it provides an integrated analysis of the sociodemographic, socioeconomic, digital, and labour-market factors associated with GAI use, allowing us to assess the extent to which the emerging “GAI divide” reproduces established patterns of digital inequality. Rather than treating adoption as a homogeneous phenomenon, the analysis distinguishes between personal, professional, and educational uses of GAI, thereby capturing potential differences in the determinants of engagement across usage contexts. Second, it explicitly examines the role of labour-market positioning and work organisation, with particular attention to employment in ICT (Information and Communication Technologies) related occupations and teleworking arrangements, as potential sources of differential exposure to and engagement with GAI technologies. The analysis also explores whether the relationship between these labour-market characteristics and GAI use differs by gender. Third, the paper goes beyond observed adoption gaps by examining the specific barriers reported by non-users. By distinguishing between lack of perceived need, lack of awareness, insufficient skills and privacy and security concerns, the analysis provides a more nuanced understanding of the heterogeneous factors preventing individuals from engaging with GAI. Fourth, the paper contributes methodologically by estimating a multivariate sample-selection model with valid exclusion restrictions, which allows us to jointly analyse multiple, non-mutually exclusive reasons for non-adoption while correcting for the potential selection bias arising from observing these barriers only among GAI non-users.

For the purposes of the paper, we use microdata from the 2025 Survey on Equipment and Use of ICT in Households (ICT-H), produced by the Spanish National Statistics Institute (INE). The survey, harmonised with Eurostat, is nationally representative and provides detailed information on ICT use and, for the first time, on the use of GAI tools. Importantly, it allows us to identify GAI use for different purposes – private, work-related, and education or training – as well as the self-reported reasons for non-use. Combined with detailed information on sociodemographic characteristics, digital resources, employment status, occupation, and teleworking, these data provide a particularly rich setting for examining both inequalities in GAI adoption and the heterogeneous barriers underlying non-adoption in Spain.

Our results reveal substantial sociodemographic and labour-market inequalities in both GAI adoption and non-adoption barriers. Adoption is strongly associated with age, education, access to digital technologies, and exposure to technology-intensive work environments, while the barriers to adoption vary considerably across population groups. In particular, older, less educated, and female individuals are more likely to face skill-related, informational, or trust-related constraints. Taken together, these findings suggest that the emerging "GAI divide" combines traditional dimensions of the digital divide with additional inequalities associated with labour-market exposure and heterogeneous informational, capability-related, and attitudinal barriers. Thus, policies designed to foster GAI use should move beyond uniform approaches and instead address the distinct constraints faced by different population groups.

The remainder of the article is organised as follows. Section 2 reviews the main literature on inequalities in the adoption of digital technologies. Section 3 describes the dataset and the main variables used. Section 4 presents the empirical strategy, Section 5 discusses the main results, and Section 6 concludes.

2. Literature Review

The analysis of inequalities in the adoption and use of digital technologies has been a central topic in the digital economy literature for decades. Early studies on the digital divide mainly focused on inequalities in access to ICT. However, subsequent research has shown that the most persistent inequalities are not limited to physical access to the internet. Current empirical studies based on large-scale survey data consistently identify education and age as important sociodemographic predictors of differences in ICT adoption and advanced forms of technology use (Dewan and Riggins, 2005; van Deursen and van Dijk, 2014; Cruz-Jesús et al., 2016). Gender-based differences in ICT adoption have also been widely documented, although their magnitude varies across contexts and tends to be more pronounced in specific domains such as digital skills, technical use, or participation in technology-related activities (OECD, 2018). Moreover, while the gender gap in overall ICT adoption has narrowed considerably in many developed European economies (Bucea et al., 2021), persistent disparities remain in particular dimensions of digital engagement. In Spain, women continue to exhibit lower participation rates in online commercial activities, highlighting the multidimensional nature of digital inequality (López-Martínez et al., 2021). Previous research has also highlighted the role of labour market structures and occupational characteristics in technology adoption. In particular, exposure to digitally intensive environments and the nature of occupational tasks are important correlates of ICT use (Acemoglu and Restrepo, 2019; Caunedo et al., 2023).

The emerging "GAI divide" does not appear to replace the "digital divide", but rather builds upon it. On the one hand, inequalities in the adoption and use of GAI technologies remain unevenly distributed across sociodemographic groups. Large-scale cross-country analyses reveal that women are less likely to use GAI tools than men across countries, sectors, and occupations, even when access barriers are reduced (Cranney et al., 2026). Similarly, other studies based on survey data and platform use show that male users tend to adopt and use GAI tools more intensively, resulting in larger productivity gains, thereby contributing to widening gender

disparities in outcomes (Tang et al., 2025). In the same vein, using data from the Survey of Consumer Expectations, Aldasoro et al. (2024 a) find significant gender differences in the use of these tools, confirming that men show higher adoption levels than women. The authors further argue that this gap is not explained solely by differences in access, but also by factors related to self-perceived technological competence, perceived usefulness, and concerns regarding privacy and AI-related risks. Differences in the adoption of GAI are not confined to gender but extend systematically to other sociodemographic characteristics. Consistent with the broader digital divide literature, early evidence indicates that age and education emerged as key predictors of GAI adoption. Younger and more highly educated individuals are substantially more likely to use these tools than their older and less educated counterparts (Gambacorta et al., 2025; Bick et al., 2026).

Beyond sociodemographic characteristics, labour-market position and occupational conditions may constitute an additional source of inequality in GAI adoption. The COVID-19 pandemic accelerated the digitalisation of work organisation and the expansion of teleworking. In this respect, some papers have provided evidence that occupations traditionally considered routine have experienced processes of cognitive complexification associated with the incorporation of digital technologies (Haslberger, 2022). Consequently, occupations intensive in cognitive and digital tasks are likely to provide greater incentives and opportunities for the adoption of GAI, whereas workers employed in less digitalised occupations may face lower levels of technological exposure. Thus, occupational inequalities and differences in work organisation may amplify pre-existing patterns of technological inequality.

Teleworking may be particularly relevant in this context because teleworkable jobs are concentrated in knowledge-intensive and digitally intensive occupations, which also tend to employ workers with higher educational attainment. The unequal distribution of teleworkable occupations therefore implies unequal opportunities for regular interaction with advanced digital tools, including AI-based technologies. Evidence from the EU also suggests that women are strongly represented in several teleworkable occupations (European Commission, 2020). This pattern raises the possibility that teleworkable employment may reshape gender differences in exposure to digital technologies and, potentially, in GAI adoption. Teleworking may thus represent an indirect channel through which pre-existing occupational, educational, and gender inequalities affect exposure to emerging technologies.

Finally, a growing body of research emphasises that GAI adoption is also shaped by behavioural and attitudinal factors: perceived usefulness, trust, ethical considerations, and concerns about privacy and security (Leschanowsky et al., 2024; Weis et al., 2026; Chen et al., 2026). Overall, these studies suggest that factors such as trust, social influence, and perceived usefulness positively shape individuals' intentions to use GAI technologies, whereas privacy and security concerns may act as barriers to adoption. These findings suggest that the emerging GAI divide incorporates a particularly relevant attitudinal dimension, in which behavioural factors play an increasingly important role compared with previous waves of technological diffusion.

In sum, the available evidence suggests that the emerging "GAI divide" does not only reproduce traditional patterns of digital inequality but, at the same time, incorporates additional dimensions related to social and attitudinal factors, such as openness to innovation and social engagement (Gambacorta et al., 2025).

However, several gaps in the related literature still remain, leaving scope for new empirical contributions. On the one hand, a substantial part of the existing empirical evidence is based on samples of digital-platform users, students, employees in particular organisations, or specific professional groups. By drawing on household survey data covering the general population and multiple domains of GAI use, our study provides a broader and more representative perspective on adoption patterns than previous research. On the other hand, existing studies have

emphasized the role of attitudinal factors in explaining GAI adoption, but do not put attention to the specific barriers associated with GAI non-adoption and on how these barriers vary across population groups. This study addresses this gap by analysing the self-reported reasons for non-adoption among non-users, allowing us to identify the specific constraints that hinder participation in the emerging AI ecosystem.

3. Dataset

This study uses microdata from the Survey on Equipment and Use of Information and Communication Technologies in Households (ICT-H) conducted annually since 2002 by the Spanish National Statistics Institute (INE). The survey is a nationally representative dataset covering individuals aged 16 to 74 residing in Spain, and follows Eurostat methodological standards, ensuring cross-country comparability within the European Union.

This survey is particularly well-suited to examine digital inequalities. Its primary objective is to collect detailed information on household ICT equipment and individual patterns of technology use, including internet use and digital services. We exploit the microdata of the 2025 wave of the ICT-H survey that contains, for the first time, detailed information on GAI adoption. Moreover, the database contains a rich set of socio-demographic and labour market characteristics. The latter, which encompasses not only employment status but also sector, occupation, ICT intensity, task content (manual vs. non-manual), and telework feasibility, expected to be important correlates of GAI divide.

The survey also identifies not only whether the individual has used GAI tools in the last three months, but also the main reasons for non-use. This allows us to identify self-reported barriers to GAI adoption that can be grouped into four main dimensions: i) low perceived usefulness ("*it was not necessary*"); ii) lack of awareness ("*did not know they existed*"); iii) insufficient skills ("*did not know how to use them*"); and iv) concerns related to trust ("*privacy, security, or data protection concerns*". An additional residual category captures other idiosyncratic constraints. This information enables an empirical assessment of the relative importance of informational, capability-related, and trust-based barriers shaping the adoption of GAI technologies.

4. Empirical Approach

This section describes the empirical strategy used to analyse both the determinants of GAI adoption and the barriers underlying its non-adoption. Our empirical approach is motivated by two key features of the data. First, individuals may use GAI for multiple purposes—private, work-related and educational – so that these adoption decisions are likely to be interdependent rather than independent. Second, individuals who do not use GAI may report several reasons for non-adoption simultaneously, implying that the reported barriers are not mutually exclusive. To account for these features, we estimate multivariate econometric models that explicitly allow for the correlation across both adoption decisions and reported barriers.

4.1 Determinants of GAI adoption

We first examine the determinants of the GAI divide by jointly analysing its use across three domains – private, work-related, and educational – thereby providing a comprehensive account of the multidimensional nature of GAI adoption.

For that purpose, we estimate a multivariate probit model that jointly considers three binary outcomes: $GAI_i^{private}$, GAI_i^{work}, and $GAI_i^{education}$, indicating whether individual $i$has used generative AI for private, work-related, and educational purposes, respectively. These observed outcomes are assumed to be generated by the following latent propensity equations:

$$\begin{aligned} GAI_i^{private*} &= \alpha_1 + \beta_1 X_i + \varepsilon_{1i} \\ GAI_i^{work*} &= \alpha_2 + \beta_2 X_i + \varepsilon_{2i} \\ GAI_i^{education*} &= \alpha_3 + \beta_3 X_i + \varepsilon_{3i} \end{aligned} \quad (1)$$

where X_i is a vector of explanatory variables and $\varepsilon_{ji} (j = 1,2,3)$ are error terms. Thus, the observed binary outcomes are defined as

$$
\begin{aligned}
GAI_i^{private} &= \begin{cases} 1 & \text{if } GAI_i^{private*} > 0 \\ 0 & \text{otherwise} \end{cases} \\
GAI_i^{work} &= \begin{cases} 1 & \text{if } GAI_i^{work*} > 0 \\ 0 & \text{otherwise} \end{cases} \\
GAI_i^{education} &= \begin{cases} 1 & \text{if } GAI_i^{education*} > 0 \\ 0 & \text{otherwise} \end{cases}
\end{aligned}
\tag{2}
$$

The error terms $(\varepsilon_{1i}, \varepsilon_{2i}, \varepsilon_{3i})$ are assumed to follow a trivariate normal distribution with zero means, unit variances, and pairwise correlations ρ_{12}, ρ_{13}, and ρ_{23}. These parameters capture the extent to which unobserved characteristics – such as digital literacy, attitudes towards innovation, or access to complementary resources, among others – simultaneously influence different types of GAI use, after conditioning on observed factors. Positive and statistically significant correlation coefficients would suggest complementarity across uses – i.e., unobserved factors that increase the probability of using GAI in one domain also increase it in others – while negative correlations would indicate substitution patterns.

The covariate vector X_i is specified progressively across three alternative models. The baseline specification (M1) includes demographic, socioeconomic, regional, and digital-resource variables, covering gender, age, nationality, marital status, educational attainment, household structure, household income, computer availability, and regional fixed effects. The second specification (M2) additionally incorporates labour-market characteristics, specifically labour-market status and teleworking arrangements. The most comprehensive specification (M3) further includes interactions between gender and labour-market characteristics, allowing the relationship between employment conditions and GAI use to vary across men and women. Table 1 provides a detailed description of all explanatory variables, their coding, and corresponding reference categories.

[Insert Table 1]

Identification of the multivariate probit model relies on both distributional assumptions and the functional form underlying the latent variable specification. The model can be identified even when the set of explanatory variables is the same across the three equations. Thus, it does not require exclusion restrictions for identification. Nonetheless, from an empirical perspective, including variables that plausibly affect some outcomes but not others improves both interpretability and robustness of the estimation results. In our setting, we incorporate certain covariates in X_i that influence the use of GAI differentially across domains (e.g. occupation-specific characteristics affecting work-related use but not private use), thereby strengthening the credibility of the estimations.

4.2 Barriers to GAI adoption

The second part of the analysis examines the barriers to GAI adoption by analysing the reasons reported by individuals for not using these tools. The survey ICT-H allows respondents to indicate multiple, and not mutually exclusive, reasons. These include: (i) no perceived need, (ii) lack of awareness, (iii) lack of skills, and (iv) privacy and security concerns.[3] An important remark

[3] There is a fifth category "other reasons" that has not considered in the multivariate probit with sample selection analysis. This category reflects unspecified motives reported by respondents and, unlike the remaining barriers, lacks a clear conceptual interpretation, making the economic meaning of the corresponding estimates difficult to assess.

is that such reasons are only observed for individuals who do not use GAI, and therefore, the sample under analysis may be prone to selection bias.

To jointly account for the endogenous selection into non-use of GAI and the multidimensional nature of reported barriers, we estimate a multivariate probit model with sample selection. Formally, the selection equation governing GAI adoption, for at least one purpose, can be specified as:

$$GAI_i^{*any} = \pi + \lambda M_i \quad + \nu_i$$
$$GAI_i^{any} = \begin{cases} 1 & \text{if } GAI_i^{*any} > 0 \\ 0 & \text{otherwise} \end{cases} \qquad (3)$$

where GAI_i^{*any} is an unobserved latent propensity to use GAI for whatever reason. $M_i$is a vector of observed characteristics and ν_i captures unobserved determinants of GAI use.

Now, let $B_i^k, k = 1, \dots, K$, denote a set of binary indicators capturing whether individual i reports a given barrier to GAI adoption:

$$B_i^k = 1[\delta_k + \theta_k W_i \quad + \xi_{ki} > 0], k = 1, \dots, K$$

where each B_i^kcorresponds to a specific reported reason for not using GAI among the ones specified before. These outcomes are only observed for "non-users", that is whenever $GAI_i^{any} = 0$.

To achieve identification, the vector M_i in equation (3) is specified as $M_i = (W_i, Z_i)$, where Z_i denotes two instrumental variables included exclusively in the selection equation. These exclusion restrictions are assumed to influence GAI adoption but to have no direct effect on the reporting of barriers once the adoption decision has been accounted for. The rationale underlying these instruments is presented in Section 5.2.

Finally, the econometric model is completed by specifying a joint distribution for the error terms:

$$(\nu_i, \xi_{1i}, \dots, \xi_{Ki}) \sim \mathcal{N}(0, \Sigma)$$

where Σ is a covariance matrix with unit variances on the diagonal and unrestricted correlations across all equations. This structure allows for two distinct sources of dependence. First, correlations among ξ_{ki} capture the interdependence between reported barriers, reflecting the fact that unobserved characteristics, such as digital skills or attitudes towards technology, may simultaneously affect multiple constraints. Second, correlations between ν_i and ξ_{ki} account for selection effects, capturing the extent to which unobserved factors influencing GAI adoption also shape the reporting of barriers.

5. Results

5.1 Determinants of GAI adoption

The descriptive statistics of Table 2 reveal notable heterogeneity across different types of GAI use. Compared with private and education users, individuals using GAI for work purposes tend to be more highly educated, with over 70% holding a university degree, and are more frequently engaged in ICT occupations and teleworking arrangements. Across all use categories, users are predominantly young adults, live in relatively high-income households, and report widespread access to computers. Education-related use is somewhat more prevalent among women and foreign-born individuals, whereas work-related use is associated with stronger labour-market attachment and lower rates of unemployment and inactivity. Overall, the descriptive statistics suggest that educational attainment, digital resources, and labour-market characteristics are closely linked to the purposes for which GAI is adopted.

[Insert Table 2]

Having established the main descriptive patterns for the different purposes of GAI use, we next turn to a multivariate analysis to assess whether these associations persist once observable

characteristics are jointly taken into account and the correlation across different uses of GAI is explicitly modelled. Table 3 reports the results from the three alternative multivariate probit specifications for GAI use specified in Section 4.1 (Models M1-M3). In order to facilitate interpretation of how key covariates affect the joint and marginal likelihoods of GAI adoption across domains, in all cases we report marginal effects instead of estimated coefficients.

[Insert Table 3]

The first thing that is worth noticing is that the estimated cross-equation correlations are positive and statistically significant, providing strong support for multivariate specifications. This confirms that unobserved factors – such as digital skills or technology affinity – jointly influence GAI adoption decisions across domains.

Second, the estimates reported in Table 3 reveal substantial heterogeneity in GAI use across demographic, socio-economic, and labour-market groups. One of the most striking findings concerns age. Our findings indicate the existence of a pronounced generational divide in GAI adoption. Relative to individuals aged 16–24, the probability of using GAI declines steadily and significantly with age, particularly for private and work-related purposes. In our preferred specification (M3), individuals aged 25–34 are 6.8 pp less likely to use GAI for private purposes and 3.2 pp less likely to use it for work-related activities than those aged 16–24. These differences widen markedly across age groups: among individuals aged 65 or above, the corresponding gaps reach 21.1 pp for private use and 10.9 pp for work-related use. A modest age gradient also emerges for education and training, with individuals aged 65 or above being 7.0 pp less likely to use GAI for this purpose than the youngest age group. These results are consistent with previous evidence showing that age remains a key source of digital inequality (Bick et al., 2026; Gambacorta et al., 2025)

Gender differences are more nuanced. In the baseline model (M1), women are 5.9 pp less likely than men to use GAI for private purposes and 2.1 pp less likely to use it for work-related activities. However, once labour-market characteristics are incorporated in M2, the estimated gender gap in work-related use falls to only 0.5 pp and becomes statistically insignificant, suggesting that part of the initial disparity reflects gender differences in employment conditions and workplace exposure rather than gender differences per se. By contrast, in our preferred specification (M3), women display a significantly higher probability of using GAI for education and training purposes, with an estimated advantage of 2.5 pp relative to men. At the same time, women remain 5.2 pp less likely to use GAI for private purposes, whereas the gender difference in work-related use is small and statistically insignificant. Thus, our findings suggest, first, that, as was the case with traditional digital technologies (see van Deursen and van Dijk, 2014), gender disparities in GAI adoption increasingly depend on the specific purpose and context of technology use. Second, workplace organisation may be an important mechanism underlying gender inequalities in GAI use (Aldasoro et al., 2024 a). Finally, the broad stability of the marginal effects between M2 and M3 suggests that allowing the relationship between employment conditions and GAI use to vary by gender does not substantially alter the estimated overall patterns. Taken together, these results indicate that gender inequalities in GAI use may be partly driven by differential exposure to digital work environments, while also revealing a distinct female advantage in education- and training-related adoption.

Education stands out as one of the strongest and most robust predictors of GAI adoption. A clear educational gradient is observed across all three dimensions of GAI use, with higher-educated individuals being substantially more likely to use GAI. Individuals holding a university degree or PhD are 23.7 percentage points more likely to use GAI for work-related purposes and 18.4 percentage points more likely to use it for private purposes than those with primary education or less. This pattern closely mirrors the evidence documented for ICT adoption more generally, where education has consistently been identified as a major source of digital inequalities.

Higher educational attainment not only facilitates the acquisition of the skills needed to cope with the complexity of emerging technologies (Rogers, 2003), but also increases exposure to digital tools in both workplace and everyday-life settings. As a result, education enhances both the capability and the opportunity to engage with GAI, helping to explain why human capital remains a central determinant of adoption (Rogers, 2003; Van Dijk, 2020; Helsper, 2021;).

Household composition appears to play only a limited role in explaining GAI adoption. The first thing that is worth noticing is that its influence is largely confined to private use. Relative to the reference household category (single-person households), individuals living in couples without children are approximately 3.0 pp less likely to use GAI for private purposes, while those living in couples with children exhibit an even larger reduction of around 3.5 pp. By contrast, respondents belonging to other household arrangements are about 8.2 pp more likely to use GAI for private purposes. In contrast, no significant differences emerge for work-related or education/training purposes, suggesting that household circumstances primarily shape discretionary or leisure-oriented engagement with GAI rather than more instrumental forms of adoption. Again, these results are in line with previous research highlighting that household characteristics are more closely associated with differences in discretionary technology use (van Deursen and van Dijk, 2014; Helsper, 2021)

Household income also contributes to explaining inequalities in GAI adoption, although its effects are more moderate than those associated with education. Individuals in the highest income category (€4,400 or more per month) are around 5.4 pp more likely to use GAI privately, 4.1 pp more likely to use it for work-related purposes, and 4.7 pp more likely to use it for educational purposes than those in the lowest income group. This positive association between economic resources and technology adoption has long been documented in the digital divide literature, where affordability constraints influence access to digital devices, internet services, and technological learning opportunities (Norris, 2001; DiMaggio and Hargittai, 2001). Interestingly, the relatively modest magnitude of the income effects compared with educational attainment suggests that financial constraints may be less important in determining GAI use than skills and knowledge barriers once basic access conditions are satisfied.

The importance of digital resources is further confirmed by the positive and statistically significant effect of having a computer available in the household. This finding echoes the traditional first-level digital divide literature, which emphasizes that access to technological infrastructure remains a fundamental precondition for benefiting from digital innovations (van Dijk, 2005; Ragnedda and Muschert, 2013). Although internet access has become nearly universal in many developed countries, the results indicate that disparities in access to appropriate digital equipment continue to shape participation in emerging technologies such as GAI.

Labour-market characteristics also play an important role. Individuals employed in ICT occupations are 17.5 pp more likely to use GAI for professional purposes, while teleworkers exhibit an increase of 13.2 pp. These effects are substantially larger than those observed for private use (10.3 pp and 6.1 pp, respectively). For education and training purposes, the effect of ICT occupation is negligible, while the positive effect of teleworking, although statistically significant, remains relatively modest compared with those observed for private and work-related use. Overall, these results suggest that exposure to digital work environments and the nature of individuals' jobs play a key role in explaining differences in the adoption of GAI, supporting the view that emerging GAI inequalities are closely linked to labour market positioning rather than to access alone. These findings are consistent with recent research arguing that workplaces characterized by high digital intensity create favourable environments for the adoption of new technologies and the accumulation of digital skills (Autor, et al., 2022; Greenan and Napolitano, 2024).

While the overall results are highly stable, Model M3 uncovers several noteworthy gender-specific patterns that are related to labour-market characteristics. First, the positive effect of employment in ICT occupations on private GAI use becomes smaller once the interaction with female status is introduced (marginal effects of 0.140 and 0.103, respectively), whereas the marginal effect associated with the interaction term Female × ICT occupation is positive and marginally significant (0.156). This would indicate that females employed in ICT occupations are more likely to use GAI for private purposes, partially offsetting the overall gender gap observed in the baseline estimates. Second, the positive association between teleworking and GAI use remains robust across all dimensions, but significant negative interaction effects emerge for women. For work-related use, teleworking is associated with a substantially higher likelihood of using GAI. However, the magnitude of this effect increases when we include interactions between gender and labour market characteristics. In Model M2, teleworkers are 11.0 pp more likely to use GAI for work-related purposes, and this effect increases to 13.2 pp in Model M3. However, the negative and statistically significant interaction between *Female* and *Teleworking* (-0.031) indicates that the positive association between teleworking and GAI use is weaker among women. A similar pattern emerges for educational use. This result indicates that although teleworking generally creates favourable conditions for experimentation with GAI tools, the gains associated with remote work appear to be weaker among women. Third, whereas inactivity is not significantly related to educational uses of GAI in Model M2, the interaction *Female* × *Inactive* is negative and significant in Model M3 (−0.038), suggesting that inactive women are less likely than comparable inactive men to use GAI for educational or training purposes. This result may reflect gender-specific constraints affecting participation in skill acquisition and digital learning activities outside the labour market.

5.2 Barriers to GAI adoption

We now turn to discuss the main results derived from estimating the multivariate probit model with sample selection for barriers to GAI adoption. The descriptive analysis of Table 4 already highlights marked differences in the profiles of non-users across barriers to GAI adoption. *Lack of awareness* and *lack of skills* are slightly concentrated among individuals with lower educational attainment, lower employment rates, and less access to digital equipment, suggesting that these barriers are closely linked to broader forms of digital disadvantage. In contrast, respondents reporting *no perceived need* tend to display relatively higher levels of education, employment, and computer ownership. *Privacy and security concerns* appear more evenly distributed across socio-economic groups. These patterns provide preliminary evidence that observed disparities in GAI adoption may reflect both resource constraints and differences in perceptions regarding the usefulness of this technology.

[Insert Table 4]

To determine whether these differences remain significant once observable characteristics are taken into account, Table 5 presents the results from the multivariate probit model with sample selection (Section 4.2, equation (3)). Our results reveal several robust and economically meaningful patterns in the perceived barriers among non-users.[4]

[Insert Table 5]

The first aspect that is worth mentioning is that our model specification explicitly accounts for the fact that barriers are only observed for individuals who do not use GAI, implying that the observed sample of non-users may not constitute a random subsample of the population. This concern is particularly relevant in the present context, since unobserved factors such as digital literacy, technological openness, confidence in digital tools, or risk perceptions may

[4] Again, we report average marginal effects instead of coefficients.

simultaneously affect both the probability of adopting GAI and the type of barrier reported by non-users.

The estimated selection correlation terms provide clear evidence that selection into non-use is not random and that unobserved factors affecting GAI adoption are also associated with several reported barriers. Significant selection correlations are found for *no perceived need* (Barrier 1), *lack of awareness* (Barrier 2), and *lack of skills* (Barrier 3), indicating that the propensity to remain a non-user is systematically related to the likelihood of reporting these obstacles. The positive and highly significant correlations for *no perceived need* (0.476) and *lack of awareness* (0.755) suggest that unobserved characteristics that reduce adoption are also associated with attitudinal and informational barriers. By contrast, the negative selection correlation estimated for *lack of skills* (-0.352) indicates a different mechanism, whereby unobserved factors associated with lower adoption propensity are linked to a lower probability of reporting skill-related constraints. However, the selection correlation for *privacy and security concerns* (Barrier 4) is not statistically significant, suggesting that this barrier is reported independently of the unobserved factors driving adoption decisions.

Moreover, the estimated cross-equation correlation parameters reveal that several barriers share common unobserved determinants. The correlation between *no perceived need* and *lack of awareness* is negative and statistically significant (-0.116), suggesting that unobserved factors increasing the propensity to report one of these barriers tend to reduce the likelihood of reporting the other. In contrast, *lack of awareness* exhibits positive and statistically significant correlations with both *lack of skills* (0.209) and *privacy and security concerns* (0.186), while *lack of skills* is also positively associated with *privacy and security concerns* (0.213). The remaining correlation terms involving *no perceived need* are not statistically different from zero. The estimated correlations point to a common latent dimension linking *lack of awareness*, *lack of skills*, and *privacy and security concerns*, suggesting that these barriers reflect related informational, capability, and risk-perception constraints. In contrast, *no perceived need* appears to represent a more distinct form of non-adoption behaviour, largely disconnected from the other reported obstacles

The instrument relevance test provides strong support for the identification strategy. *Per capita regional AI expenditure by firms with 10 or more employees* in 2025 and regional *Fiber To The Home (FTTH) coverage* in 2021are jointly significant in the selection equation ($\chi^2 = 29.14$, $p < 0.001$), rejecting the null hypothesis that the excluded instruments have no explanatory power for GAI adoption. Importantly, both variables exert a positive and statistically significant effect on the probability of GAI use, suggesting that exposure to a more developed regional AI ecosystem and better digital infrastructure facilitates adoption. These findings alleviate concerns about weak instruments and confirm that the excluded variables are sufficiently informative to identify selection into GAI use.

The choice of instruments is also theoretically well grounded. Per capita regional AI expenditure by firms with 10 or more employees captures differences in the local AI ecosystem, including investment in AI-related infrastructure, innovation capacity, and technological diffusion. Individuals living in regions with stronger AI-related investment are likely to face greater exposure to AI-related information, initiatives, and applications, which may increase their probability of its adoption. Regional FTTH coverage in 2021, in turn, captures the quality of broadband infrastructure and the availability of high-speed connectivity, which constitute enabling conditions for the use of data-intensive and cloud-based technologies such as GAI. Importantly, the instrument is measured in 2021, whereas AI adoption and non-adoption barriers are observed in 2025. This temporal separation reduces concerns that regional FTTH coverage directly affects the contemporaneous barriers reported by non-users, while preserving its role as a predictor of the underlying propensity to adopt GAI through differences in digital infrastructure and connectivity conditions. This interpretation is consistent with the broader

technology-diffusion and digital-divide literature, which emphasises that both innovation capacity and broadband infrastructure shape digital adoption and the ability to benefit from new technologies.

The validity of the exclusion restrictions is further supported by the equation-specific exogeneity tests reported in Table 5. The p-values for the five barrier equations are all well above conventional significance levels. These tests fail to reject the null hypothesis that the excluded instruments have no direct effect on each barrier equation among non-users. This provides supportive evidence for the exclusion restriction assumption: per capita regional AI expenditure by firms with 10 or more employees and FTTH coverage appear to affect reported barriers primarily through their influence on the initial probability of using GAI, rather than through an independent direct association with the barriers themselves. Although exogeneity cannot be proven definitively in sample-selection settings, the evidence is consistent with the validity of the identification strategy. The excluded instruments are jointly relevant in explaining GAI adoption, while the exogeneity tests fail to reject the null hypothesis that they exert no direct effect on any of the barrier equations. Combined with the underlying theoretical justification, these results support the plausibility of the exclusion restrictions.

Turning to the determinants of the reported barriers, the results reveal substantial heterogeneity across population groups. Gender differences are particularly informative. Women are 4.2 pp less likely than men to report *no perceived need* as the reason for not using GAI, but 3.8 pp more likely to report either *lack of skills* and *privacy and security concerns*. By contrast, no statistically significant gender difference emerges for *lack of awareness*. These findings suggest that women's lower adoption of GAI is not primarily driven by a perception that this technology lacks relevance or usefulness. Rather, non-use appears to be more closely associated with lower confidence in their ability to use this technology effectively and greater concerns about the risks related to AI systems. This pattern is broadly consistent with recent evidence on digital inequalities and the emerging gender gap in GAI adoption, highlighting the relevance of perceived knowledge and risk perceptions in adoption decisions even among individuals with comparable levels of access and awareness (Aldasoro et al., 2024a, 2024b).

Age emerges as one of the strongest predictors of the type of barriers reported by non-users of GAI. Older individuals are significantly less likely to report *no perceived need* and considerably more likely to report *lack of skills*, with the magnitude of the effects increasing markedly across age groups. For example, individuals aged 65 and over are 11.7 pp less likely than those aged 16–24 to report *no perceived need*, but 20.6 pp more likely to identify *lack of skills* as their main barrier to adoption. By contrast, age differences in *lack of awareness* are small and not statistically significant. Interestingly, individuals aged 65 and over are also significantly less likely to cite *privacy and security concerns* as a barrier, suggesting that older non-users are constrained primarily by capability-related factors rather than by concerns over the risks associated with AI systems. Overall, the results indicate that age-related inequalities in GAI adoption reflect differences in digital competencies more than differences in awareness or perceptions of technological risk.

Educational attainment plays a central and multidimensional role in shaping the perceived reasons for non-use. Among non-users, higher levels of education are associated with a substantially lower probability of reporting both *lack of awareness* and *lack of skills*. Individuals in the highest educational category are 7.7 pp less likely to report *lack of awareness* and 14.9 pp less likely to report *lack of skills* than those with the lowest level of education. At the same time, more educated individuals are significantly more likely to report *no perceived need* as a reason for non-adoption. For example, respondents in the highest educational category are 9.0 pp more likely to state that they do not perceive a need for GAI. Interestingly, intermediate and highly educated individuals are also more likely to report *privacy and security concerns*, suggesting a greater awareness of the potential risks associated with AI systems. Overall, these findings

indicate that, when highly educated individuals remain non-users, their non-adoption is less likely to be associated with lack of awareness or insufficient skills and more likely to be related to their perceived need for GAI and concerns about its potential risks. This interpretation is broadly consistent with the literature on second-level digital divides, which emphasizes the role of education and digital skills in shaping individuals' patterns of technology use and their ability to benefit from digital technologies (Helsper, 2021).

Household income exhibits a relatively weak and unsystematic relationship with the barriers to GAI adoption. While income plays an important role in explaining GAI use itself, it provides little explanatory power regarding the specific reasons reported by non-users. The only consistent pattern concerns *no perceived need*: individuals in the highest income category (EUR 4,400+) are 4.3 pp more likely to report that they do not perceive a need for GAI, whereas those in the EUR 1,400–2,199 income group are 4.9 pp less likely to cite this barrier compared with the lowest-income group. By contrast, no significant associations emerge between income and *lack of awareness*, *lack of skills*, or *privacy and security concerns*. These findings suggest that, once differences in education, digital resources, employment status, and other socio-economic characteristics are taken into account, financial resources play only a limited role in shaping the specific barriers underlying GAI non-adoption.

Access to digital resources remains an important factor in shaping the barriers to GAI adoption. Among non-users, computer access is associated with a substantially lower probability of reporting *lack of skills*, reducing the likelihood of citing this barrier by 9.4 pp. At the same time, individuals with access to a computer are 4.4 pp more likely to report *no perceived need* and 5.3 pp more likely to identify *privacy and security concerns* as reasons for non-adoption. No significant association emerges with *lack of awareness*. This pattern suggests that digital access influences non-adoption through two distinct channels. On the one hand, access to digital equipment facilitates the development of the skills required to engage with new technologies, thereby reducing capability-related barriers. On the other hand, greater exposure to digital environments may lead individuals to assess GAI more critically, either because they conclude that the technology offers limited additional value for their specific needs or because they are more aware of potential privacy, security, and data-related risks. Overall, the results indicate that digital access does not merely facilitate technology adoption but also shapes the way individuals perceive both the benefits and the potential drawbacks of emerging AI applications.

Finally, our findings suggest that labour-market participation may increase exposure to and opportunities for using AI technologies, thereby facilitating adoption, but does not systematically shape the reasons underlying non-adoption once individuals remain outside the user population.

In sum, the results indicate that demographic characteristics, educational attainment, and digital resources are considerably more important than labour-market or household characteristics in explaining the structure of barriers to GAI adoption

5. Conclusions

This paper has examined inequalities in the adoption of GAI in Spain using nationally representative microdata from the 2025 Survey on ICT Equipment and Use in Households (ICT-H). By jointly analysing the determinants of GAI adoption for different purposes and the barriers underlying its non-adoption, this study provides new evidence on the emergence of the so-called GAI divide and its relationship with traditional forms of digital inequality.

Our results reveal substantial sociodemographic and labour-market inequalities in GAI adoption. The probability of using GAI is significantly higher among younger and more highly educated individuals and among those with access to a computer. Labour market characteristics emerge as important correlates of GAI adoption. Our findings suggest that exposure to digital technologies in the workplace plays a central role in explaining the use of GAI.

In particular, employment in ICT-related occupations and engagement in teleworking are associated with a substantially higher likelihood of adoption, especially for professional purposes, highlighting the importance of technology-intensive work environments in fostering AI-related competencies and facilitating experimentation with these tools. By contrast, labour market inactivity is associated with a significantly lower probability of professional GAI use, reflecting the limited opportunities for acquiring and applying AI-related skills outside employment settings. Finally, it is worth noticing that gender differences in the use of GAI vary across domains. While women are consistently less likely to use it for private purposes, gender differences in professional use are largely explained by labour-market characteristics. In contrast, after accounting for these characteristics, women are more likely than men to use GAI for education and training purposes.

Our analysis of the barriers to adoption also highlights considerable heterogeneity across population groups. Among non-users, older individuals are significantly less likely to report no perceived need but considerably more likely to cite insufficient skills as a barrier to adoption, suggesting that non-adoption at older ages is primarily driven by capability constraints rather than by a lack of interest in the technology. This pattern highlights the importance of targeted policies aimed at strengthening digital and AI-related competencies among older population groups. Gender differences are also evident. Women are significantly more likely than men to report insufficient skills and privacy and security concerns as barriers to adoption, indicating that gender-related constraints continue to influence the uptake of generative AI, in line with broader evidence on digital technology adoption. Educational attainment is strongly associated with the type of barriers reported by non-users of GAI. Whereas lower-educated individuals face predominantly informational and skill-related barriers, non-adoption among highly educated individuals appears to be driven primarily by a lack of perceived usefulness.

Overall, our results suggest, on the one hand, that a one-size-fits-all approach to fostering GAI diffusion is unlikely to be effective. Instead, policies should be tailored to the specific context of use, combining digital skills development, workplace-oriented adoption strategies, and targeted interventions aimed at reducing barriers among socio-demographic groups with lower engagement. On the other hand, non-use cannot be understood as a single phenomenon but rather reflects a combination of informational, capability-related, and attitudinal barriers. Thus, interventions aimed at fostering the diffusion of GAI should move beyond broad measures designed to increase access alone. Instead, reducing the emerging GAI divide would require a combination of digital-skills initiatives and targeted outreach strategies tailored to the specific barriers faced by different population groups. In particular, our findings would suggest that policies targeting older adults and other vulnerable groups should prioritise the development of practical AI-related skills and digital capabilities, as capability deficits emerge as one of the most important barriers to adoption. At the same time, awareness and information campaigns may be particularly relevant for individuals with lower levels of education, helping to reduce informational barriers and improve understanding of the potential applications of GAI. In contrast, building trust through transparent governance frameworks, clear data-protection standards, and responsible AI practices may be equally important for encouraging informed and sustainable adoption among more educated people.

Notwithstanding the contributions to the literature, certain limitations of our study should be acknowledged. First, the cross-sectional nature of the data precludes causal interpretation of the estimated relationships. Second, both GAI use and the reported barriers are based on self-reported information and may therefore be affected by reporting bias. Third, the survey captures whether individuals report using GAI tools, but it does not provide information on the intensity, frequency, or quality of that use. Finally, given the rapid evolution of GAI technologies, the patterns documented in this study should be interpreted as evidence from an early stage of their diffusion. In this respect, future research should examine not only whether individuals adopt

GAI, but also how intensively and effectively they use these technologies and the extent to which GAI adoption translates into potential productivity gains, labour market outcomes and broader socioeconomic inequalities. Longitudinal data will be particularly valuable for understanding whether the AI divide widens or narrows as these technologies become more widespread.

Appendix

Table 1. Definition of Explanatory Variables

Panel	Variable Group	Variables Included	Reference Category	Models
Panel A. Demographic characteristics				
	Gender	Female	Male	M1–M3
	Age	25–34; 35–44; 45–54; 55–64; 65+	16–24 years old	M1–M3
	Nationality	Foreign nationality	Spanish nationality	M1–M3
	Marital status	Married; Widowed; Divorced/Separated	Single	M1–M3
Panel B. Socio-economic characteristics				
	Educational attainment	Lower secondary and intermediate vocational education; Advanced vocational education; University degree or PhD	Primary education or less	M1–M3
	Household type	Single-parent household; Couple without children; Couple with children; Other household types	Single-person household	M1–M3
	Household income	€1,400–€2,199; €2,200–€3,099; €3,100–€4,399; ≥ €4,400	< €1,400 per month	M1–M3
Panel C. Digital resources				
	Access to digital technologies	Computer available in the household	No computer available in the household	M1–M3
Panel D. Regional controls				
	Region	Autonomous Community fixed effects	Reference Autonomous Community	M1–M3
Panel E. Labour-market characteristics				
	Occupational status	ICT occupation; Unemployed; Inactive	Employed in a non-ICT occupation	M2–M3
	Work arrangement	Teleworking (partially or fully)	Not teleworking	M2–M3
Panel F. Gender interactions				
	Gender-specific labour-market effects	Female × ICT occupation; Female × Unemployed; Female × Inactive; Female × Teleworking	–	M3

Notes: This table reports the explanatory variables included in the multivariate probit specifications. Model M1 includes demographic, socio-economic, regional and digital-access variables; Model M2 additionally incorporates labour-market characteristics; and Model M3 further includes gender-by-labour-market interaction terms.

Table 2. Descriptive statistics by type of GAI use

Variable	Private use	Work use	Education use
Individual and Household characteristics			
Female	0.442	0.484	0.538
Age			
Age 25-34	0.343	0.372	0.417
Age 35-44	0.220	0.246	0.248
Age 45-54	0.097	0.063	0.063
Age 55-64	0.028	0.005	0.014
Age 65+	0.004	0.002	0.004
Foreign-born	0.122	0.139	0.179
Marital status			
Married	0.559	0.572	0.591
Widowed	0.011	0.006	0.009
Separated/divorced	0.077	0.060	0.084
Education			
Lower secondary education or intermediate vocational training	0.267	0.153	0.241
Advanced vocational training	0.176	0.135	0.158
University degree or doctorate	0.537	0.706	0.589
Household composition			
Single-parent household	0.113	0.097	0.122
Couple without children	0.155	0.146	0.118
Couple with children	0.528	0.567	0.580
Other household type	0.083	0.080	0.083
Household income			
Household income: EUR 1,400-2,199	0.111	0.093	0.108
Household income: EUR 2,200-3,099	0.157	0.151	0.181
Household income: EUR 3,100-4,399	0.236	0.228	0.252
Household income: EUR 4,400 or more	0.346	0.403	0.346
Digital resources and labour-market status			
Computer	0.939	0.952	0.959
ICT occupation	0.057	0.096	0.045
Unemployed	0.086	0.044	0.102
Inactive	0.107	0.020	0.094
Telework	0.369	0.556	0.358
Observations	**2,540**	**1,642**	**864**

Notes: The table reports weighted means for the estimation sample of model M4, separately for individuals using generative AI for private, work, and education purposes. For binary variables, means represent weighted proportions. The three user categories are not mutually exclusive. The omitted categories are not reported. Sampling weights are applied throughout the analysis. Observations are unweighted counts.

Table 3. Average marginal effects from multivariate probit models of GAI use

Variable	Private use			Work-related use			Education/training use		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
Panel A. Demographic characteristics									
Female	-0.059***	-0.052***	-0.052***	-0.021**	-0.005	0.012	0.008	0.008	0.025***
	(0.039)	(0.040)	(0.058)	(0.046)	(0.047)	(0.066)	(0.051)	(0.051)	(0.073)
25–34 years old	-0.067***	-0.067***	-0.068***	-0.030***	-0.032***	-0.032***	0.005	0.005	0.005
	(0.058)	(0.058)	(0.058)	(0.063)	(0.064)	(0.064)	(0.070)	(0.070)	(0.069)
35–44 years old	-0.151***	-0.147***	-0.148***	-0.078***	-0.071***	-0.071***	-0.033***	-0.033***	-0.033***
	(0.062)	(0.062)	(0.062)	(0.067)	(0.069)	(0.069)	(0.080)	(0.080)	(0.079)
45–54 years old	-0.203***	-0.185***	-0.187***	-0.153***	-0.112***	-0.113***	-0.070***	-0.069***	-0.070***
	(0.069)	(0.075)	(0.075)	(0.089)	(0.091)	(0.090)	(0.096)	(0.112)	(0.114)
55–64 years old	-0.214***	-0.189***	-0.192***	-0.169***	-0.120***	-0.122***	-0.073***	-0.071***	-0.072***
	(0.087)	(0.104)	(0.105)	(0.177)	(0.204)	(0.209)	(0.130)	(0.156)	(0.157)
65+ years old	-0.224***	-0.210***	-0.211***	-0.158***	-0.108***	-0.109***	-0.071***	-0.070***	-0.070***
	(0.160)	(0.167)	(0.169)	(0.291)	(0.310)	(0.310)	(0.271)	(0.283)	(0.285)
Foreign nationality	-0.043**	-0.038*	-0.038*	-0.005	0.004	0.004	0.021	0.021	0.021
	(0.081)	(0.081)	(0.081)	(0.092)	(0.094)	(0.094)	(0.102)	(0.102)	(0.102)
Married	-0.005	-0.003	-0.004	0.003	0.001	0.001	0.007	0.009	0.008
	(0.053)	(0.053)	(0.053)	(0.062)	(0.062)	(0.063)	(0.069)	(0.069)	(0.069)
Widowed	-0.026	-0.021	-0.014	-0.029	-0.013	-0.011	-0.008	-0.003	-0.001
	(0.113)	(0.111)	(0.112)	(0.152)	(0.158)	(0.160)	(0.190)	(0.190)	(0.192)
Divorced/Separated	0.039**	0.039**	0.040**	0.007	0.004	0.005	0.031**	0.032**	0.034**
	(0.073)	(0.072)	(0.072)	(0.078)	(0.082)	(0.082)	(0.097)	(0.096)	(0.096)
Panel B. Socio-economic characteristics									
Lower secondary and intermediate vocational education	0.060**	0.058**	0.057**	0.088***	0.066**	0.069**	0.062***	0.062***	0.062***
	(0.101)	(0.100)	(0.100)	(0.174)	(0.184)	(0.182)	(0.163)	(0.158)	(0.160)
Advanced vocational education	0.166***	0.152***	0.150***	0.196***	0.134***	0.136***	0.121***	0.119***	0.116***
	(0.110)	(0.109)	(0.109)	(0.179)	(0.188)	(0.187)	(0.171)	(0.166)	(0.168)
University degree or PhD	0.210***	0.186***	0.184***	0.317***	0.237***	0.237***	0.140***	0.137***	0.133***
	(0.103)	(0.103)	(0.103)	(0.172)	(0.183)	(0.182)	(0.163)	(0.158)	(0.160)
Single-parent household	-0.023	-0.023	-0.024	-0.016	-0.014	-0.015	0.009	0.008	0.006
	(0.069)	(0.070)	(0.070)	(0.080)	(0.084)	(0.085)	(0.095)	(0.094)	(0.094)
Couple without children	-0.032**	-0.030*	-0.030*	-0.011	-0.001	-0.001	-0.012	-0.012	-0.012
	(0.065)	(0.065)	(0.065)	(0.082)	(0.083)	(0.083)	(0.092)	(0.092)	(0.092)
Couple with children	-0.039**	-0.036**	-0.035**	-0.017	-0.005	-0.005	0.001	0.002	0.002
	(0.063)	(0.062)	(0.062)	(0.073)	(0.076)	(0.076)	(0.085)	(0.085)	(0.086)
Other household types	-0.084***	-0.081***	-0.082***	-0.049***	-0.042***	-0.043***	-0.019	-0.019	-0.020
	(0.083)	(0.084)	(0.084)	(0.097)	(0.102)	(0.102)	(0.109)	(0.109)	(0.109)
€1,400–€2,199	-0.008	-0.009	-0.010	0.014	0.012	0.011	0.024	0.024*	0.025*
	(0.074)	(0.074)	(0.073)	(0.089)	(0.096)	(0.096)	(0.102)	(0.101)	(0.101)
€2,200–€3,099	-0.014	-0.013	-0.013	0.013	0.006	0.006	0.030**	0.033**	0.033***
	(0.068)	(0.068)	(0.068)	(0.081)	(0.085)	(0.085)	(0.092)	(0.090)	(0.090)
€3,100–€4,399	0.015	0.016	0.014	0.027*	0.015	0.015	0.034***	0.037***	0.037***
	(0.066)	(0.066)	(0.066)	(0.077)	(0.080)	(0.081)	(0.088)	(0.086)	(0.086)
≥ €4,400	0.060***	0.055***	0.054***	0.068***	0.041***	0.041***	0.044***	0.046***	0.047***
	(0.066)	(0.066)	(0.066)	(0.076)	(0.079)	(0.079)	(0.092)	(0.091)	(0.091)
Panel C. Digital resources									
Computer available in the household	0.114***	0.108***	0.108***	0.055***	0.038***	0.037***	0.053***	0.051***	0.051***
	(0.063)	(0.062)	(0.062)	(0.080)	(0.081)	(0.081)	(0.091)	(0.091)	(0.091)
Panel D. Regional controls									
Autonomous Community fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel E. Labour-market characteristics									
ICT occupation		0.140***	0.103**		0.201***	0.175***		0.011	-0.001
		(0.128)	(0.146)		(0.146)	(0.176)		(0.155)	(0.188)

Unemployed		0.045**	0.019	-0.021	-0.004	0.035**	0.027
		(0.078)	(0.117)	(0.101)	(0.141)	(0.097)	(0.139)
Inactive		-0.032*	-0.014	-0.108***	-0.094***	0.001	0.029
		(0.070)	(0.087)	(0.115)	(0.155)	(0.102)	(0.134)
Teleworking		0.058***	0.061***	0.110***	0.132***	0.015*	0.039***
		(0.052)	(0.073)	(0.055)	(0.077)	(0.064)	(0.091)
Panel F. Gender interactions							
Female × ICT occupation			0.156*		0.078		0.038
			(0.290)		(0.271)		(0.334)
Female × Unemployed			0.045		-0.033		0.008
			(0.154)		(0.200)		(0.188)
Female × Inactive			-0.030		-0.033		-0.038**
			(0.100)		(0.196)		(0.154)
Female × Teleworking			-0.005		-0.031*		-0.036***
			(0.098)		(0.102)		(0.123)
Panel G. Cross-equation correlations							
atanh(ρ Work, Private)	0.828***	0.833***	0.835***				
	(0.035)	(0.036)	(0.035)				
ρ Work, Private	0.679***	0.682***	0.683***				
	(0.019)	(0.019)	(0.019)				
atanh(ρ Education, Private)	0.759***	0.752***	0.752***				
	(0.037)	(0.037)	(0.037)				
ρ Education, Private	0.641***	0.636***	0.637***				
	(0.022)	(0.022)	(0.022)				
atanh(ρ Education, Work)	0.781***	0.832***	0.832***				
	(0.040)	(0.044)	(0.043)				
ρ Education, Work	0.653***	0.682***	0.681***				
	(0.023)	(0.023)	(0.023)				
Panel H. Model statistics							
Observations	11722	11722	11722				
Log likelihood	-2.55e+07	-2.45e+07	-2.45e+07				

Notes: Average marginal effects are reported. Standard errors of the underlying coefficients are shown in parentheses. Estimates are computed using the survey sampling weights. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. Reference categories are defined in Table 1. Model M1 includes demographic, socio-economic, regional and digital-access variables; Model M2 additionally includes labour-market characteristics; Model M3 further includes gender-by-labour-market interaction terms. Panel G reports both Fisher-transformed cross-equation correlations (atanh(ρ)) and the corresponding correlations (ρ).

Table 4. Descriptive Statistics by reported barriers of non-users

Variable	Barrier 1 no perceived need	Barrier 2 lack of awareness	Barrier 3 lack of skills	Barrier 4 privacy and security concerns
Female	0.514	0.553	0.553	0.552
25-34	0.205	0.170	0.172	0.197
35-44	0.261	0.254	0.250	0.269
45-54	0.228	0.254	0.240	0.256
55-64	0.133	0.171	0.177	0.135
65+	0.043	0.062	0.060	0.034
Foreigner	0.143	0.144	0.148	0.129
Married	0.633	0.660	0.653	0.638
Widowed	0.056	0.081	0.075	0.062
Separated/Divorced	0.085	0.072	0.087	0.087
Education 2	0.475	0.531	0.510	0.520
Education 3	0.125	0.090	0.099	0.122
Education 4	0.275	0.175	0.216	0.245
Household size 2	0.099	0.092	0.091	0.096
Household size 3	0.224	0.238	0.251	0.234
Household size 4	0.416	0.376	0.377	0.406
Household size 5+	0.128	0.159	0.144	0.127
Income: EUR 1,400-2,199	0.154	0.181	0.184	0.164
Income: EUR 2,200-3,099	0.207	0.224	0.215	0.206
Income: EUR 3,100-4,399	0.229	0.229	0.214	0.232
Income: EUR 4,400+	0.216	0.170	0.189	0.205
Computer	0.776	0.699	0.706	0.780
Employed	0.548	0.445	0.473	0.528
Observations	**5732**	**2274**	**4059**	**3792**

Notes: The table reports weighted means of the explanatory variables among non-users who report each barrier. For binary explanatory variables, the means represent weighted proportions. The barrier categories are not mutually exclusive. Sampling weights are applied throughout the analysis. Observations are unweighted counts of individuals reporting each barrier.

Table 5. Average marginal effects from multivariate probit with sample selection for barriers of adoption

Variable	AI use	Barrier 1 no perceived need	Barrier 2 lack of awareness	Barrier 3 lack of skills	Barrier 4 privacy and security concerns
Female	-0.038*** (0.000)	-0.042*** (0.001)	0.009 (0.527)	0.038*** (0.009)	0.038** (0.016)
25-34	-0.068*** (0.000)	-0.039 (0.147)	0.024 (0.464)	0.040 (0.194)	0.026 (0.429)
35-44	-0.169*** (0.000)	-0.047* (0.089)	0.014 (0.714)	0.117*** (0.000)	0.052 (0.152)
45-54	-0.267*** (0.000)	-0.078** (0.011)	-0.021 (0.639)	0.141*** (0.000)	0.061 (0.148)
55-64	-0.325*** (0.000)	-0.078** (0.024)	-0.027 (0.586)	0.223*** (0.000)	0.013 (0.789)
65+	-0.412*** (0.000)	-0.117*** (0.006)	-0.039 (0.497)	0.206*** (0.000)	-0.114** (0.042)
Foreigner	-0.027 (0.179)	-0.012 (0.641)	-0.022 (0.486)	0.023 (0.454)	-0.049 (0.139)
Married	-0.008 (0.595)	-0.045** (0.026)	-0.006 (0.800)	0.007 (0.751)	-0.038 (0.112)
Widowed	-0.003 (0.907)	-0.004 (0.887)	0.026 (0.475)	0.048 (0.154)	0.050 (0.185)
Separated/Divorced	0.031 (0.112)	-0.004 (0.858)	-0.035 (0.226)	0.012 (0.662)	-0.013 (0.673)
Education 2	0.071*** (0.006)	0.004 (0.856)	-0.066*** (0.010)	-0.054** (0.031)	0.086*** (0.001)
Education 3	0.174*** (0.000)	0.054** (0.042)	-0.089*** (0.006)	-0.133*** (0.000)	0.069** (0.044)
Education 4	0.257*** (0.000)	0.090*** (0.000)	-0.077** (0.013)	-0.149*** (0.000)	0.053 (0.123)
Household size 2	-0.018 (0.344)	-0.023 (0.294)	0.001 (0.963)	0.004 (0.864)	-0.042 (0.128)
Household size 3	-0.018 (0.299)	0.008 (0.710)	-0.001 (0.982)	0.053** (0.028)	0.026 (0.333)
Household size 4	-0.033** (0.048)	0.009 (0.702)	0.019 (0.506)	0.059** (0.020)	0.009 (0.746)
Household size 5+	-0.075*** (0.000)	-0.039 (0.126)	0.027 (0.395)	0.072** (0.013)	-0.018 (0.564)
Income: EUR 1,400-2,199	0.011 (0.565)	-0.049** (0.025)	0.004 (0.858)	0.010 (0.681)	-0.011 (0.682)
Income: EUR 2,200-3,099	-0.011 (0.555)	-0.005 (0.788)	0.022 (0.359)	0.006 (0.790)	-0.006 (0.804)
Income: EUR 3,100-4,399	0.019 (0.275)	-0.001 (0.963)	0.017 (0.509)	-0.022 (0.334)	0.006 (0.816)
Income: EUR 4,400+	0.072*** (0.000)	0.043** (0.045)	0.018 (0.500)	-0.019 (0.434)	0.005 (0.864)
Computer	0.130*** (0.000)	0.044*** (0.007)	-0.003 (0.865)	-0.094*** (0.000)	0.053** (0.010)

Variable	AI use	Barrier 1 no perceived need	Barrier 2 lack of awareness	Barrier 3 lack of skills	Barrier 4 privacy and security concerns
Employed	0.046*** (0.002)	0.002 (0.892)	-0.028 (0.163)	-0.027 (0.159)	-0.018 (0.385)
Regional AI expenditure per inhabitant	0.001** (0.036)	—	—	—	—
Regional FTTH coverage 2021	0.002*** (0.010)	—	—	—	—
Model diagnostics					
Observations	11725	11725	11725	11725	11725
Excluded instruments		Regional AI expenditure per inhabitant; Regional FTTH coverage 2021			
Instrument relevance test, $chi^2(df)$			29.14 (2)		
Instrument relevance test, p-value			0.000		
Exclusion/exogeneity test, p-value	—	0.147	0.362	0.860	0.462
Selection correlation terms					
atanh(rho): selection–Barrier 1	—	0.476 (0.000)			
atanh(rho): selection–Barrier 2	—		0.755 (0.000)		
atanh(rho): selection–Barrier 3	—			-0.352 (0.006)	
atanh(rho): selection–Barrier 4	—				0.140 (0.261)
Cross-barrier correlation terms					
atanh(rho): Barrier 1–Barrier 2	—		-0.116 (0.001)		
atanh(rho): Barrier 1–Barrier 3	—			0.009 (0.777)	
atanh(rho): Barrier 1–Barrier 4	—				0.049 (0.137)
atanh(rho): Barrier 2–Barrier 3	—			0.209 (0.000)	
atanh(rho): Barrier 2–Barrier 4	—				0.186 (0.000)
atanh(rho): Barrier 3–Barrier 4	—				0.213 (0.000)

Notes: The table reports average marginal effects from the multivariate probit with sample selection. p-values are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The two regional variables enter only the AI-use selection equation as excluded instruments. The exclusion/exogeneity test is the equation-specific joint test that the excluded instruments have no direct effect in each barrier equation among non-users. Estimates are computed using the survey sampling weights. The category "other reasons" is excluded because it captures unspecified and conceptually heterogeneous motives and complicated model estimation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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