AI at Work: Use, Complementary Technologies, and Task Reallocation

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Abstract

We provide evidence from a 2025 survey of individuals in Spain on workplace use of artificial intelligence (AI) and other modern digital technologies. AI use is already economically meaningful but far from pervasive, with about 16% of workers reporting AI use. Its adoption is highly uneven across workers and jobs, with strong gradients by education, age, earnings, and firm size and scope, as well as substantial within-occupation heterogeneity. AI use is strongly correlated with the use of other modern technologies, which accounts for a larger share of variation than any worker or job characteristic considered separately, including occupational exposure measures. The purposes of AI use also vary markedly across demographic groups and jobs. Users report predominantly positive productivity effects in abstract cognitive tasks, together with limited but systematic time reallocation across tasks.

Keywords: AI at Work, Complementary Technologies, Task Reallocation, Productivity

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1 Introduction

Artificial intelligence (AI) and other modern technologies, such as automation and robotics, cloud services, the Internet of Things, big data analytics, augmented and virtual reality, 3D printing, and digital collaboration tools, have become increasingly prominent in the workplace. Yet systematic evidence on the use of these technologies, and how their adoption and purposes vary across workers, jobs, and firms, remains limited, particularly outside the United States. We provide new descriptive evidence from a bespoke survey fielded in Spain in 2025 that measures workplace technology use at the individual level.

The survey covers approximately 10,000 respondents. A key design feature of the survey is a conceptual separation between individual use of AI and other modern technologies at the workplace. The technology module asks respondents which technologies they use in their current job and which technology they perceive as the most important/significant in their job. In the AI module, we separately elicit the respondent's purposes of AI use and perceived impacts of AI on productivity and time allocation across job tasks.

Workplace use of modern technologies is widespread but uneven across technology types. About 16% of respondents report using AI at work, compared with roughly 35% for cloud services and digital collaboration tools. The use of automation and robotics and of big data analytics is somewhat lower, at about 10%, while augmented and virtual reality and 3D printing are used by only around 2% of respondents. Meanwhile, about 40% of respondents report that they use none of the listed technologies in their job.

The use of these technologies varies by gender and, more significantly, by education, age, and occupation. Descriptive tabulations show that women use cloud services more frequently and men use automation and robotics more often, while revealing no gender gap in AI use. Adoption of these technologies is generally higher among younger, highly educated, managerial, and professional workers, and lower among older workers and those in agricultural, manufacturing, and elementary occupations.

There is also substantial heterogeneity in how AI is used across groups. The most common reported application is generating written content, with women more frequently using AI for text and multimedia creation and men more frequently using it for analysis

and insights, automation, and decision-making support. More highly educated and older workers use AI more often for text generation and analysis and insights, whereas less-educated and younger workers report greater use for customer interaction and learning new skills unrelated to AI.

About 7% of respondents identify AI as the most significant workplace technology, compared with approximately 20% for each of cloud services and digital collaboration tools and 8% or less for each of the remaining technologies. Other modern technologies are also the strongest predictors of AI use, contributing more to explained variation than occupations and tasks, occupational AI exposure, or other worker and job characteristics. These patterns indicate that AI has already reached a non-negligible share of workers. Moreover, its early diffusion is more closely associated with the broader workplace technology environment than other work characteristics in isolation.

These descriptive tabulations may mask important compositional differences across groups. We complement them with regressions that condition on a rich set of covariates, including education and age categories, earnings brackets, job-task shares, firm size and scope of operations, and industry and occupation fixed effects. The main patterns persist, with a few exceptions. For example, women become slightly but significantly less likely than men to report using AI. In addition, workers in larger firms report lower AI use but greater use of automation and robotics, big data, and collaboration tools. AI, cloud services, and digital collaboration tools are also more prevalent among individuals whose jobs involve larger shares of abstract and interactive tasks. The main differences in the purposes of AI use likewise persist in regressions conditioning on these covariates.

Respondents who use AI report predominantly positive effects on perceived productivity for abstract cognitive tasks. For cognitive routine tasks, reported perceived productivity changes are smaller. Joint responses on perceived productivity changes and time reallocation also indicate limited but systematic task reallocation, with AI augmenting abstract cognitive tasks while reported effects are less pronounced and more mixed for other activities.

A separate module elicits respondents' subjective beliefs about two very near-term

labor-market outcomes: receiving a job offer and being unemployed during the following month. In regressions controlling for a rich set of covariates, we relate these beliefs to the technology that respondents identify as the most important in their work. Workers who identify AI as the most important technology report significantly higher subjective probabilities of both receiving a job offer and becoming unemployed within the next month. No other technology exhibits the same pattern of positive and statistically significant associations with both outcomes. Taken together, these results suggest a wider distribution of perceived near-term labor-market outcomes among workers for whom AI is central to their jobs.

Finally, we show that the ranking of occupation-level use of AI is sensitive to sample composition in terms of demography and technology co-use. It also aligns with the occupational exposure measures of Eloundou et al. (2024), Gmyrek et al. (2025), and Felten et al. (2021), though not perfectly.

2 Related Literature

A growing literature uses worker surveys to measure the diffusion and intensity of use of AI at work and outside of work. Bick et al. (2026a) document rapid adoption in nationally oriented US surveys (Bick and Blandin, 2023) and emphasize heterogeneity by education, occupation, and earnings. Bick et al. (2026a) also ask workers which activities AI assists and where it is most helpful. A distinctive contribution of their measurement approach is to elicit intensity of use and self-reported time savings, which they combine with information on hours and wages to bound the share of work hours assisted by AI and infer potential productivity gains from current adoption. Extending this evidence internationally, Bick et al. (2026b) combine comparable worker surveys from the US and six European countries with firm-level adoption data. They document higher AI adoption in the US, substantial variation within Europe, and an important role for worker characteristics and firm composition in explaining adoption gaps.

Our findings share several similarities with both studies. We also document rapid

but uneven early-stage adoption and strong gradients by education and wages. However, reported workplace AI use in Spain, at approximately 16%, is substantially below both the US rate and the 24.5% observed in Italy, the lowest-adoption country in the sample of Bick et al. (2026b). Our survey complements these studies by jointly examining AI and seven other modern workplace technologies and by eliciting the purposes of AI use and separate perceived productivity and time allocation changes across multiple tasks performed by the same worker. This allows us to document technology co-use, within-occupation heterogeneity, and task-level patterns of augmentation and adjustment.

Employer-side surveys provide complementary evidence. Bonney et al. (2024) document low but rising firm adoption in the United States, with substantial variation across sectors and firm sizes. Surveys of corporate executives similarly indicate heterogeneous AI investment, modest realized productivity gains, limited aggregate employment effects, and larger expected impacts (Baslandze et al., 2026, Yotzov et al., 2026). Using data from 15 OECD countries, Calvino et al. (2026) further show that AI and other advanced technologies build on complementary digital infrastructure and are associated with higher productivity, although the AI premium weakens after accounting for human and technological capital.

A related strand of work develops occupation-level measures of "AI exposure" by mapping AI capabilities to occupational task or ability content, often using US-based occupational taxonomies.[1] Felten et al. (2021) construct AI Occupational Exposure by linking a set of AI applications to O*NET ability requirements and aggregating these links to occupations, industries, and geographies. Eloundou et al. (2024) instead score exposure at the task and detailed-work-activity level using a rubric for whether LLMs or LLM-powered software can materially reduce task time, and then aggregate task exposure to occupations. Gmyrek et al. (2025) develop a global task-based index of generative-AI exposure using the ISCO-08 classification, distinguishing different degrees of exposure and emphasizing the potential for job transformation rather than complete automation.

[1] These papers build on the methods employed in seminal works on automation and job polarization (e.g., Autor et al., 2003). This literature argues that computers have substituted for routine jobs (e.g., Autor and Dorn, 2013, Jerbashian, 2019).

Svanberg et al. (2024) use an end-to-end cost model for computer vision automation and show that many exposed tasks are not economically attractive to automate at firm scale even when technically feasible. Gathmann et al. (2024) combine patent-based exposure measures with task survey data and administrative career histories. They document that AI and robots shift task content within detailed occupations and induce worker reallocation across jobs and industries. Finally, Lewandowski et al. (2025) adapt the Felten et al. (2021) exposure measure to worker task surveys to obtain country-specific, task-adjusted exposure measures. They highlight that within-occupation task variation is important for understanding cross-country differences in exposure.[2]

A parallel line of work uses task-based occupational exposure measures to assess broader reallocation and productivity implications at the macro level and to discipline quantitative predictions. Acemoglu (2025) combines task-based exposure estimates with feasibility and cost considerations to derive upper bounds on aggregate effects, concluding that the medium-run macroeconomic gains from current AI advances are likely to be positive but modest. He further argues that aggregate wage gains may be limited, the capital share may rise, and inequality can increase even when low-skill workers benefit in specific tasks.[3]

Our paper contributes to the literature by linking workplace AI use, occupational exposure, and task-level adjustment. Our survey measures individual AI use jointly with seven other modern technologies and shows that realized adoption is strongly embedded in a broader digital technology environment. Among AI users, the survey records purposes of use and perceived changes in productivity and time allocation across several tasks. We document significant heterogeneity in the purposes of AI use across demographic, job, and firm characteristics. Our findings also suggest that AI may systematically augment particular cognitive tasks while producing more mixed perceived effects for other activities, including manual and interactive tasks.

[2] An emerging literature links AI-related task capabilities and occupational exposure measures to realized workplace outcomes. Brynjolfsson et al. (2025a,b) find that AI assistance raises productivity in customer support, while employment declines among junior workers in AI-exposed occupations.

[3] More remotely related papers study the effects of AI on growth, knowledge accumulation and welfare (e.g., Acemoglu et al., 2026, Jones, 2024, 2025, Jones and Tonetti, 2026).

Finally, we show that occupational rankings in realized AI use are sensitive to demographic composition and technology co-use and align only imperfectly with the occupational exposure measures of Eloundou et al. (2024), Gmyrek et al. (2025), and Felten et al. (2021). Together with relatively limited contribution of these measures to explaining realized use, this indicates that occupational exposure and current adoption capture related but distinct dimensions of AI use/diffusion, particularly when adoption depends on complementary technologies and implementation conditions. Exposure measures nevertheless provide valuable proxies for where AI capabilities may transform or substitute for occupational tasks, and especially when direct measures of use are unavailable. These findings caution against interpreting either occupational exposure or realized use in isolation as a shock to occupational labor demand, particularly at an early stage of diffusion.

3 Data Sources and Measurement

Our empirical analysis is based on a unique survey of individuals in Spain, designed by the authors and fielded online by Netquest, a professional, ISO-certified provider of online access panels. Fieldwork was conducted between February and April 2025 and implemented in two main waves. The first wave yielded approximately 2,500 completed interviews and the second approximately 7,500, for a total of about 10,000.

The sample is constructed using quota-based stratification by territory and major demographic groups. The sample distributions closely match the corresponding quota targets. To further align the sample with the Spanish adult population, we construct calibration weights using the 2024 Spanish labor force survey and the iterative proportional fitting (raking) algorithm (Deming and Stephan, 1940). The baseline weights adjust the survey distribution by sex, age, and educational attainment to match the corresponding population margins. We use these weights throughout the workplace analyses.[4]

The survey, sampling procedures, data-quality checks, and weighting methodology are documented in the Appendix: Additional Survey Details. The variable definitions are

[4] Although the weighted sample is representative along several dimensions, selection on unobserved characteristics correlated with the outcomes of interest may remain. Bick et al. (2026a,b) use a similar survey and calibration methodology.

provided in the Appendix: Data and Variables.

3.1 Individual, Job, Employment, and Firm Characteristics

The survey records standard individual characteristics, including sex, age, educational attainment, and marital status. It records current labor-market status, distinguishing full-time employment, part-time employment, unemployment, self-employment, and non-participation.

For employed individuals, the survey measures usual weekly hours and net wage income in brackets. It records employer size in broad employment bins and measures the scope of firm operations on an ordered scale from local to international reach. It records occupation using the 2-digit ISCO-08 occupational classification and industry using the 1-digit NACE Rev.2 classification.

The survey measures job task content using broad categories that cover abstract analytical activities, routine cognitive activities, routine and non-routine manual activities, and interactive activities with clients and coworkers. Respondents report the share of working time allocated to each category in a typical workweek. These task measures are intended to capture broad differences in job content rather than precise time allocation.[5]

3.2 Technology Use at Work

The survey elicits whether a list of modern technologies is used in the respondent's job. The list includes AI, automation and robotics, cloud services, Internet of Things (IoT), augmented and virtual reality (AR/VR), big data analytics, 3D printing, and digital collaboration tools. Respondents can select multiple technologies, and the survey also allows respondents to report that none of the listed technologies are used.

To minimize ambiguity in how respondents interpret the technology categories, each option in the adoption question is accompanied by a short, plain-language description and at least one concrete example. Artificial intelligence is described as computer-based sys-

[5]Table F1 in the Appendix: Additional Results reports the share of working time allocated to each task category in 1-digit ISCO-08 occupations, ranking of occupations within the task categories, alongside the average wage bracket and weekly hours of work.

tems that simulate aspects of human intelligence and can perform tasks such as learning, reasoning, problem solving, perception, and decision support, with examples that include widely known conversational and content-generation tools. Automation and robotics is described as the use of technology and robots to carry out tasks with minimal human intervention, with examples that include industrial robots, automated chat systems, and autonomous vehicles. Cloud services are described as the delivery of computing services over the internet that provide access to servers, storage, software, and analytics on demand, with examples that include widely used cloud-based storage platforms. Digital collaboration tools are described as software applications that facilitate communication and teamwork, with examples that include video-conferencing platforms. The Internet of Things is described as networks of physical objects equipped with sensors and software that connect and exchange data. Augmented and virtual reality is described as technologies that overlay digital content on the real world or provide immersive simulated environments. Big data and analytics is described as the analysis of large and complex datasets to uncover patterns and inform decision-making. Three-dimensional (3D) printing is described as additive manufacturing that creates objects layer by layer from a digital model.

Further, the survey asks whether any of the technologies used at the workplace were introduced in the recent past. It also identifies the single technology that has the most significant impact on the respondent's work. For this specific technology, the survey measures the frequency of its use by the respondent using an ordered scale ranging from daily use to less-than-monthly use.

3.3 AI-Specific Measurement

The survey includes a dedicated module focused on the purposes of workplace AI use. Respondents who report using AI at work may select multiple applications, including (1) generating written content such as reports, articles, or emails; (2) analyzing data and producing insights; (3) automating repetitive tasks such as programming or data entry; (4) improving customer interactions through tools such as chatbots or virtual assistants;

(5) supporting decision-making; (6) creating multimedia content; and (7) acquiring skills unrelated to AI.

The module measures the frequency with which respondents use AI at work. For respondents who do not report AI use at the workplace, the survey elicits expectations about whether they expect to use AI at work in the next three months. It also records whether the opportunity to use AI was suggested by the employee or by the employer.

3.4 Measurement of Impacts on Work

The survey measures perceived impacts of technology, eliciting information regarding its impact on productivity and time allocation across tasks. For the technology identified as most significant for the respondent's work, response options indicate whether time and perceived productivity in each task category increased, did not change, or decreased. When AI is used in the workplace but is not selected as the most significant technology, the survey repeats the same questions specifically for it.[6]

4 Results

We begin by documenting the sample in Tables 1 and 2. The weighted distributions of gender, age, and education-level groups match the calibration margins in the Spanish labor force survey. The distribution across labor-market statuses is sensible, with full-time employees forming the largest group, followed by part-time employees and the self-employed. Average hours and wage brackets across groups also align well with standard labor-market patterns.[7]

We then document the overall prevalence of modern technologies used at work. As shown in Table 3, about 16% of respondents report that they use AI in their work. This is substantially lower than the reported use of cloud services and digital collaboration tools. Roughly 35% of the respondents report using them at work. By contrast, the use

[6] Appendix: Additional Survey Details offers further details about the survey and describes additional modules.

[7] All further reported results exclude respondents who are unemployed or inactive. Table 2 and regression samples are further restricted to respondents who report their wage bracket.

of automation and robotics, as well as big data analytics, is about 10%, while the use of augmented and virtual reality (AR/VR) and 3D printing is rare at around 2%. The use of these technologies is highly correlated as shown in Table 4. Finally, about 40% of respondents report that they use none of the listed technologies in their job, underscoring that diffusion remains incomplete.

The descriptive tabulations in Table 5 show that the use of these technologies varies by gender and, more significantly, by education, age, and occupation. Men report using automation and robotics technologies more often than women, 10% versus 5%, while the use of cloud services is slightly higher among females, 37% versus 33%. There is no gender gap in the use of AI in the workplace in these tabulations. The education gradient is especially pronounced for AI, cloud services, and collaboration tools. Among respondents with a school-leaving certificate, reported AI use is 8%, compared with 37% among those with a master's or doctorate. The corresponding figures are about 23% versus 61% for cloud services and collaboration tools, for example. Reported AI use is 27% among respondents aged 18–34 and falls to 10% among those aged 50 or older, while the share reporting use of "none of these technologies" rises from 26% to 43% across the same age range. Occupational differences are similarly pronounced. Managers, professionals, and associate professionals report the highest use of AI and most other modern technologies, whereas automation and robotics are more prevalent in manufacturing and agricultural occupations. Elementary occupations report the highest incidence of using none of these technologies.

Table 6 reports Shorrocks-Shapley decompositions across worker demographics, firm characteristics, wage brackets, occupation and industry groups, other workplace technologies, task content, and occupational AI-exposure measures. The entries report each block's average incremental contribution to R-squared as a share of total explained variation. Other modern technologies emerge as the dominant predictor, accounting for approximately one-third of explained variation, followed by industry at about one-fifth. The exposure block combines the measures of Eloundou et al. (2024), Gmyrek et al. (2025), and Felten et al. (2021), aggregated to 2-digit occupations. These measures account for

only 8-9% of explained variation, even when the occupation block is excluded in column 2. Column 3 adjusts the AI-use indicator for the frequency and number of reported uses, with little effect on the relative importance of the different blocks of variables.[8] These results suggest that AI use is embedded in a broader digital technology environment and the relevant unit for understanding early AI diffusion is not the isolated technology or occupation, but the broader workplace technology environment.

Table 7 shows that cloud services and digital collaboration tools are the technologies most frequently identified as having the greatest significance at work, each accounting for about 20% of responses. IoT follows at 8% and AI at 7%. Automation and robotics, big data and analytics, 3D printing, and AR/VR each account for less than 4% of responses. Among AI users, 45% identify AI as the most significant technology, while about 21% report that cloud services and another 20% report that digital collaboration tools are the most significant technologies. Conversely, for example, over 53% of cloud-services and collaboration-tools users identify the corresponding technology as most significant, while about 10% select AI. Figure 1 also shows that differences in composition by sex are generally modest, although cloud services and collaboration tools have somewhat higher female shares, while automation and robotics and big data analytics have a higher male share among the most significant workplace technologies. Given that AI is a relatively new technology, its 7% share is not negligible and points to its rapid emergence as an important technology.

As shown in Figure 2, written-content generation is the most frequently reported purpose of workplace AI use, followed by automation, multimedia creation, and data analysis and insights. The subgroup patterns in Table 8 indicate considerable heterogeneity in how AI is used across demographic and occupation groups. For example, women report higher AI use for written and multimedia content creation, whereas men report higher use for data analysis and insights, automation, and decision support. The corresponding differences range from 6 percentage points for multimedia creation to 13 percentage

[8] Table F2 shows that the dominant contribution of other workplace technologies is robust to using 2-digit occupations. The technology block also remains one of the largest contributors to explained variation in AI use after excluding technology categories and AI uses with the greatest potential for conceptual overlap.

points for data analysis and insights. In turn, less-skilled and younger workers are also more likely to report using AI to acquire new skills unrelated to AI.

Conditional on reporting AI use at work, the intensity of use is remarkably similar across gender, age, education, and wage groups. As shown in Table 9, roughly one quarter of AI users report daily use and about two-fifths report using AI several times in a week across essentially all groups. In addition, 52% of employees report that they initiated its use, while 45% report that its use was suggested by the employer.

Among those who did not use AI at the time of the survey, 11% expected to use it during the next 3 months, 55% did not expect to do so, and another 35% could not say, reflecting the novelty and uncertainty surrounding these technologies (Table 10). There is considerable heterogeneity in these expectations, with higher expectations for use among younger, more educated, and higher wage individuals.

These descriptive tabulations can mask important compositional differences across groups. We complement them with regressions that condition on a rich set of covariates, including education and age categories, earnings brackets, job task shares, firm size and scope of operations, and industry and occupation fixed effects. The regressions use calibration weights multiplied by respondents' usual weekly working hours, giving greater weight to workers who work a higher number of hours. Table 11 reports the results. Females are significantly less likely than males to report use of AI and automation/robotics at the workplace after including the controls. The estimated female differential is -2.9 for AI and -3.8 percentage points for automation/robotics. They are more likely to report use of cloud services and Internet of Things than males, with estimated differentials of 3.0 and 3.5 percentage points for the corresponding technology.

Significant educational and age gradients across technologies persist. Relative to holding a school-leaving certificate, holding a postgraduate and PhD degree is associated with 12 percentage points increase in the likelihood of use of AI and more than 16 percentage points increase in the likelihood of use of cloud services and collaboration tools. In turn, older workers are significantly less likely than younger workers to use AI and several other modern technologies.

Firm characteristics are also strongly correlated with the reported use of these technologies at the workplace. We find that being employed in a firm with less than 11 employees, compared to being employed in a firm with 50 or more employees is associated with a 3.5 percentage points higher likelihood of using AI. It is associated with approximately 4 percentage points lower use of automation and robotics and big data analytics, and 7 percentage points lower use of collaboration tools. Compared to firms serving primarily local markets, being employed in a firm with international scope is associated with a 12 percentage points higher reported use of AI. It is also associated with approximately 16 percentage points higher use of cloud services and digital collaboration tools, and a 10 percentage points higher use of big data and analytics.

AI use is positively and significantly correlated with earnings. Individuals in higher wage brackets are significantly more likely to report using AI at work than those in lower wage brackets. The corresponding earnings gradients are also sizable for cloud services and collaboration tools. These correlations suggest that early diffusion of AI and the use of related digital technologies is concentrated among higher-earning workers.

We also relate workplace technology exposure to the task content of jobs. Individuals whose jobs involve a greater share of abstract cognitive tasks are significantly more likely to report using AI, cloud services, and digital collaboration tools. Those whose jobs involve greater interactive tasks are also significantly more likely to use cloud services and collaboration tools. In contrast, workers reporting larger shares of these tasks are generally less likely to use automation and robotics. These patterns are consistent with a task-based interpretation of AI and other workplace technology use.

Significant differences in the purposes of AI use persist after controlling for a rich set of covariates as shown in Table 12. For example, women are 7 percentage points more likely than men to use AI for generation of written content, while they are 7 percentage points less likely to use it for data analysis and insights or for automating repetitive tasks, and 10 percentage points less likely to use it for decision support. Workers in firms with 50 or more employees are more than 10 percentage points less likely than those in firms with fewer than 11 employees to use AI for written content generation, decision support, and

multimedia creation. Overall, they also report a significantly lower number of purposes of AI use. Conversely, workers in internationally oriented firms are more likely than those in locally oriented firms to use AI for generation of written content and data analysis and insights. Finally, respondents who received AI training report a broader range of AI uses and are significantly more likely to use AI for data analysis, automation, decision support, and acquisition of new skills not related to AI.

Table 13 reveals substantial heterogeneity in the perceived effects of AI across job tasks. For abstract tasks, 60% of respondents report perceived productivity gains and 35% report increased time allocation. Notably, 29% report both outcomes simultaneously, a pattern consistent with productive task augmentation.[9] The corresponding shares for routine cognitive tasks are much lower at 46%, 29%, and 22%, respectively. Reported productivity gains are less common for manual and interactive tasks, where no changes in either productivity or time are more prevalent. This pattern is particularly pronounced for interactive tasks, for which close to half of respondents report no change in either dimension. Overall, these patterns are consistent with AI systematically augmenting particular cognitive tasks while having more limited perceived effects on other activities.[10]

In a separate module, we elicit respondents' subjective expectations regarding two near-term labor-market outcomes: receiving a job offer and being unemployed during the following month. Table 14 relates these expectations to the technology identified as most significant at work, controlling for a rich set of covariates. Respondents identifying AI as the most significant workplace technology report 9.2 percentage points higher perceived probability of receiving a job offer and 2.9 percentage points higher perceived probability of being unemployed during the following month. No other technology exhibits the same combination of associations. These results suggest that AI use is associated with a wider range of perceived labor-market outcomes rather than uniformly more favorable or less

[9] Admittedly, respondents might not fully distinguish between changes in task efficiency and changes in the amount of time devoted to the task. We offer further insights on these and other limitations in the Appendix: Discussion of Limitations.

[10] The Appendix: Elasticity of Substitution Between Abstract Tasks and AI illustrates how the survey responses can discipline a task-based production framework. The results consistently imply labor-AI complementarity in abstract tasks ($\varepsilon_A < 1$) and a larger effective AI weight in abstract tasks than in routine cognitive tasks.

favorable expectations.

Finally, we examine the use of AI at the occupational level and how the relative ranking of occupations changes once we account for the use of other modern technologies and for compositional differences in gender, age, and education within occupations.[11] We also examine how this relative ranking of occupations correlates with exposure measures commonly used in the literature.

Table 15 reports raw and composition-adjusted AI use shares across 1-digit ISCO-08 occupations, together with occupational AI exposure measures, in Panel A. The corresponding rankings are reported in Panel B.[12] In raw data, professionals report the highest AI use, followed by associate professionals and managers. Clerical support, service and sales, skilled agricultural, and craft and related trades workers fall in the middle of the distribution. Plant and machine operators/assemblers and elementary occupations record the lowest levels of AI use.

Adjusting for the use of other modern technologies and for demographic composition substantially compresses differences in AI use across occupations. It also produces changes in their relative ordering. Adjusting for technology co-use reverses the positions of managers and associate professionals and reshuffles several occupations in the middle of the distribution. Adjusting for demographic composition alone only reverses the positions of managers and associate professionals. The joint adjustment combines these patterns and further changes the positions of clerical support workers, craft and related trades workers, and elementary occupations. Nevertheless, professionals remain the highest-ranked occupation and plant and machine operators and assemblers the lowest-ranked under all specifications. Therefore, composition affects the relative ordering of occupations, particularly in the middle of the distribution.

The correlations between observed AI use and the exposure measures are generally strong and positive but sensitive to the adjustment applied. This imperfect alignment

[11] Conditioning on the use of other technologies is particularly relevant, as technology uses tend to be correlated and often complementary. For example, Jerbashian (2026) estimates the elasticity of substitution between ICT and intellectual property capital and finds that these technologies are gross complements.

[12] The Appendix: Composition Adjusted AI Use by Occupation describes the adjustment procedure. Table F5 presents results for 2-digit ISCO-08 occupations.

is unsurprising because the exposure indices capture the potential applicability of AI to tasks within occupations, whereas the survey measures actual occupational use, which also depends on demographic composition, complementary technologies, and, potentially, on implementation frictions.[13]

Overall, this evidence cautions against interpreting either raw occupation-level use or occupational exposure as a stand-alone shock to labor demand at this early stage of adoption, when realized use remains uneven and substantially heterogeneous within occupations.

5 Conclusions

This paper provides new evidence on workplace AI use, complementary technologies, and task-level adjustment using a bespoke individual-level survey fielded in Spain in 2025. AI use is already economically meaningful but remains far from universal. Around 16% of respondents report using AI at work, compared with roughly 35% reporting cloud services or digital collaboration tools, while about 40% report using none of the listed technologies.

AI use varies substantially across workers, jobs, and firms, and this heterogeneity extends beyond adoption to the purposes for which AI is used. Adoption increases with education and earnings and declines with age, while managers, professionals, and associate professionals report substantially higher use than workers in elementary occupations. Text generation is the most common application. Women are more likely to report using AI for text generation, but less likely to use it for data analysis, automation, and decision support. These patterns remain after conditioning on a rich set of worker, job, and firm characteristics.

Technology co-use is the largest contributor to explained variation in AI use, exceeding the contributions of worker characteristics, occupation, and occupational exposure measures. This finding suggests that early AI adoption is embedded in a broader digital

[13] As AI technologies continue to evolve, new exposure measures are being developed. While these measures provide useful benchmarks, their sensitivity to underlying assumptions underscore the importance of complementing them with direct evidence on actual workplace use.

technology environment rather than occurring in isolation.

The perceived effects of AI on job tasks are meaningful but nuanced. Respondents report predominantly positive productivity effects for abstract and routine cognitive tasks, while the effects on manual tasks are smaller and more mixed. Joint responses on perceived productivity and time allocation also indicate limited but systematic task reallocation, with AI augmenting abstract tasks while perceived effects are more limited and mixed for manual and interactive activities.

The expectations modules reveal considerable uncertainty about future AI adoption together with a mix of favorable and unfavorable expectations about near-term labor-market outcomes. Finally, occupational rankings in realized AI use are sensitive to technology co-use and demographic composition and align only moderately with occupational exposure measures. This distinction cautions against interpreting either measure as a stand-alone indicator of labor-demand effects, especially at an early stage of diffusion characterized by continuously evolving technical capabilities, uneven adoption, and substantial within-occupation heterogeneity.

6 Tables

Table 1: Sample Composition

Sex	Share	Wage Bracket, EUR	Share
Male	0.49	<1500	0.39
Female	0.51	1500-2500	0.31
		>2500	0.31
Age Bracket		**Firm Size**	
18-34	0.21	1 to 10 people	0.27
35-49	0.27	11 to 49 people	0.18
50+	0.53	50 people or more	0.55
Education Level		**Firm Scope**	
School Certificate	0.56	Local	0.34
Undergrad & Prof. Tr.	0.30	Regional	0.21
Master's & PhD	0.14	National	0.27
		International	0.17
Labor Status			
Full-Time	0.61		
Part-Time	0.12		
Unemployed	0.08		
Self-Employed	0.08		
Inactive	0.10		

This table reports percentages of sex, age bracket, education level, labor-market status, net monthly wage bracket, firm size, and firm scope for respondents interviewed in Spain in 2025. Entries are adjusted using calibration weights derived from the Spanish labor force survey. Quality-control procedures exclude entries that took too little or too much time and reduce the sample size from 10,000 to 9295 in the first column. Column 2 excludes entries from most of the unemployed and inactive, except those who report wage brackets and firm size and scope from the most recent job. The sample size is 8346.

Table 2: Wage Bracket by Group

Sex	Wage	Hours	Labor Status	Wage	Hours
Male	1.86	36.79	Full-Time	1.77	37.08
Female	1.52	32.58	Part-Time	1.14	22.12
			Self-Employed	1.98	35.90
Age Bracket			Firm Scope		
18-34	1.53	32.32	Local	1.50	32.09
35-49	1.70	35.26	Regional	1.77	35.72
50+	1.76	35.42	National	1.74	35.43
			International	1.90	37.46
Education Level			Firm Size		
School Certificate	1.53	33.73	1 to 10 people	1.55	32.24
Undergrad & Prof. Tr.	1.76	35.48	11 to 49 people	1.61	34.25
Master's & PhD	2.09	36.30	50 people or more	1.79	35.97

Note: This table reports mean monthly net wage bracket (coded as 1 for <1500, 2 for [1500,2500], and 3 for >2500 euros) and usual weekly hours across key demographic and job groups. Wage and hours refer to the respondent's current job. The sample excludes unemployed and inactive respondents. Entries are weighted averages based on calibration weights derived from the Spanish labor force survey.

Table 3: Technology Use at the Workplace

N. Obs.	8085	Introduced Last 3 Months
	Share	Share
1. AI	0.16	0.52
2. Automation and Robotics	0.08	0.27
3. Cloud Services	0.35	0.18
4. IoT	0.19	0.19
5. AR / VR	0.02	0.32
6. Big Data	0.08	0.14
7. 3D Printing	0.02	0.23
8. Collaboration Tools	0.35	0.17
9. None	0.37	

Note: This table reports the share of respondents reporting use of each modern technology category in the respondent's job and the share of respondents reporting that the technology was introduced in the recent past (during the last 3 months). Technology-use indicators are based on the multiple-response question on whether the technology is used in the respondent's job, with an additional option indicating that none of the listed technologies are used. Entries are weighted using calibration weights derived from the Spanish labor force survey. The sample excludes unemployed and inactive respondents.

Table 4: Correlations Between Technologies Used at the Workplace

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1. AI							
2. Automation and Robotics	0.09***						
3. Cloud Services	0.28***	0.04***					
4. IoT	0.08***	0.12***	0.17***				
5. AR / VR	0.14***	0.12***	0.07***	0.08***			
6. Big Data	0.23***	0.14***	0.24***	0.14***	0.11***		
7. 3D Printing	0.14***	0.13***	0.08***	0.08***	0.25***	0.10***	
8. Collaboration Tools	0.25***	0.03**	0.39***	0.16***	0.06***	0.25***	0.05***

Note: This table reports pairwise correlations between technology use indicators. Correlations are weighted using calibration weights derived from the Spanish labor force survey. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Technology Use at the Workplace by Groups

Sex	(1) AI	(2) Automation and Robotics	(3) Cloud Services	(4) IoT	(5) AR / VR	(6) Big Data	(7) 3D Printing	(8) Collaboration Tools	(9) None
Male	0.16	0.10	0.33	0.18	0.02	0.10	0.03	0.35	0.38
Female	0.16	0.05	0.37	0.19	0.02	0.07	0.02	0.36	0.36
Education Level									
School Certificate	0.08	0.07	0.23	0.17	0.01	0.04	0.02	0.23	0.49
Undergrad & Prof. Tr.	0.17	0.08	0.41	0.20	0.02	0.10	0.03	0.41	0.30
Master's & PhD	0.37	0.08	0.60	0.22	0.05	0.17	0.04	0.61	0.15
Age Bracket									
18-34	0.27	0.11	0.42	0.18	0.04	0.13	0.03	0.40	0.26
35-49	0.18	0.09	0.36	0.19	0.02	0.10	0.03	0.38	0.36
50+	0.10	0.05	0.31	0.19	0.01	0.06	0.02	0.32	0.43
Occupation 1D									
1 Managers	0.24	0.12	0.45	0.23	0.04	0.14	0.03	0.42	0.26
2 Professionals	0.31	0.08	0.50	0.22	0.04	0.13	0.04	0.53	0.21
3 Associate Professionals / Technicians	0.25	0.06	0.55	0.23	0.02	0.15	0.02	0.54	0.20
4 Clerical Support Workers	0.11	0.05	0.40	0.20	0.01	0.06	0.01	0.37	0.33
5 Service and Sales Workers	0.08	0.03	0.21	0.17	0.01	0.06	0.01	0.22	0.53
6 Skilled Agricultural Workers	0.12	0.12	0.12	0.10	0.00	0.08	0.03	0.13	0.59
7 Craft and Related Trades Workers	0.09	0.17	0.16	0.19	0.01	0.04	0.05	0.22	0.48
8 Plant and Machine Operators / Assemblers	0.02	0.22	0.10	0.15	0.02	0.01	0.03	0.11	0.55
9 Elementary Occupations	0.05	0.08	0.07	0.08	0.02	0.02	0.02	0.12	0.69

Note: This table reports the share of respondents reporting use of each modern technology category in the respondent's job by sex, education, age, and occupation groups. Technology-use indicators are based on the multiple-response question on whether the technology is used in the respondent's job, with an additional option indicating that none of the listed technologies is used. The means are calculated using calibration weights derived from the Spanish labor force survey.

Table 6: Shorrocks-Shapley Decomposition of Explained Variation in AI Use

Blocks	(1) Baseline	(2) No Occupations	(3) Frequencies and Number of Uses
Sex	0.00	0.01	0.01
Education Level	0.07	0.08	0.05
Age Bracket	0.05	0.06	0.02
Firm Size	0.01	0.01	0.01
Firm Scope	0.06	0.06	0.07
Wage Bracket	0.05	0.06	0.05
Occupation 1D	0.08		0.07
Industry 1D	0.19	0.22	0.12
Technologies	0.34	0.36	0.47
Tasks	0.06	0.07	0.05
Exposure Measures	0.08	0.09	0.08
R2	0.23	0.22	0.17
N. Obs.	6253	6253	6253

Note: This table reports Shorrocks-Shapley decompositions of the R^2 for observed workplace AI use across variable blocks for sex, education, age, firm size, firm scope, wages, 1-digit occupation, 1-digit industry, other technologies, task content, and occupational AI exposure. Column (1) presents the full specification, column (2) excludes occupation fixed effects, and column (3) additionally adjusts AI use to account for AI-use frequency and the number of reported AI uses. Specifically, AI-use indicator is multiplied by the number of reported AI uses and a frequency measure ranging from 1 for daily use to 1/6 for use less than once a month and 0 for non-use. The values are each block's average incremental contribution to R^2 across all possible orderings and sum to 100% of explained variation. Other technologies include automation and robotics, cloud services, IoT, AR/VR, big data, 3D printing, and collaboration tools. The exposure block includes GPT-Human and GPT-Model (Eloundou et al., 2024), ILO GenAI (Gmyrek et al., 2025), and AIOE (Felten et al., 2021), aggregated to 2-digit occupations. The estimation sample excludes unemployed and inactive respondents and is restricted to respondents who report their wage bracket.

Table 7: The Most Significant Technology and Use of Technologies

		Use							
Most Important		(1) AI	(2) Automation and Robotics	(3) Cloud Services	(4) IoT	(5) AR / VR	(6) Big Data	(7) 3D Printing	(8) Collaboration Tools
1. AI	0.07	0.45	0.10	0.10	0.08	0.18	0.16	0.16	0.10
2. Automation and Robotics	0.04	0.03	0.58	0.03	0.05	0.06	0.05	0.08	0.03
3. Cloud Services	0.19	0.21	0.11	0.54	0.19	0.22	0.20	0.15	0.23
4. IoT	0.08	0.04	0.06	0.05	0.44	0.03	0.05	0.10	0.05
5. AR / VR	0.01	0.01	0.01	0.00	0.00	0.26	0.01	0.05	0.00
6. Big Data	0.02	0.04	0.04	0.04	0.03	0.03	0.30	0.05	0.04
7. 3D Printing	0.01	0.01	0.01	0.01	0.00	0.04	0.00	0.27	0.00
8. Collaboration Tools	0.19	0.20	0.10	0.23	0.19	0.17	0.23	0.14	0.53
9. None from the List	0.39	0.01	0.00	0.01	0.00	0.00	0.01	0.01	0.01
N. Obs.	8085	1613	674	3344	1611	204	858	232	3411

Note: This table reports the distribution of the technology that respondents identify as the most significant for their work. The first column reports the share of respondents selecting each technology as most significant. The "None from the List" option allows respondents to indicate that none of the 8 listed technologies is the most significant in their work. It also allows them to specify another technology that they consider most significant. The remaining columns report, for each technology-use group (e.g., AI users, cloud-services users), the share of respondents who select each technology as most significant. For example, the entry in the "AI" row and the "AI" column corresponds to the share of AI users who report AI as the most significant technology in their job, and the remaining entries in that column report which other technologies are reported as the most significant by AI users. The bottom row reports the number of observations for each technology-use group. The means are calculated using calibration weights derived from the Spanish labor force survey.

Table 8: The Purpose of AI Use at the Workplace by Groups

Sex	(1) Text	(2) Analysis and Insights	(3) Automation	(4) Customer Interactions	(5) Decision Making	(6) Multimedia Content	(7) New Skills	(8) Other
Male	0.55	0.39	0.43	0.20	0.26	0.33	0.30	0.03
Female	0.59	0.26	0.33	0.21	0.18	0.39	0.23	0.04
Education Level								
School Certificate	0.46	0.29	0.35	0.25	0.17	0.35	0.30	0.02
Undergrad & Prof. Tr.	0.59	0.31	0.38	0.21	0.22	0.32	0.27	0.04
Master's & PhD	0.64	0.37	0.41	0.17	0.25	0.40	0.23	0.04
Age Bracket								
18-34	0.53	0.31	0.39	0.22	0.22	0.39	0.27	0.03
35-49	0.56	0.30	0.39	0.19	0.20	0.33	0.27	0.04
50+	0.63	0.36	0.36	0.21	0.24	0.36	0.25	0.04
Occupation								
1 Managers	0.64	0.45	0.36	0.28	0.33	0.31	0.32	0.02
2 Professionals	0.66	0.31	0.38	0.13	0.23	0.43	0.26	0.04
3 Associate Professionals / Technicians	0.57	0.35	0.42	0.20	0.20	0.29	0.26	0.05
4 Clerical Support Workers	0.50	0.33	0.37	0.28	0.16	0.28	0.24	0.05
5 Service and Sales Workers	0.44	0.25	0.45	0.28	0.21	0.45	0.19	0.00
6 Skilled Agricultural Workers	0.63	0.22	0.23	0.19	0.16	0.06	0.02	0.00
7 Craft and Related Trades Workers	0.31	0.25	0.32	0.18	0.14	0.47	0.30	0.04
8 Plant and Machine Operators / Assemblers	0.25	0.00	0.53	0.47	0.00	0.00	0.53	0.00
9 Elementary Occupations	0.43	0.26	0.35	0.26	0.26	0.26	0.41	0.00

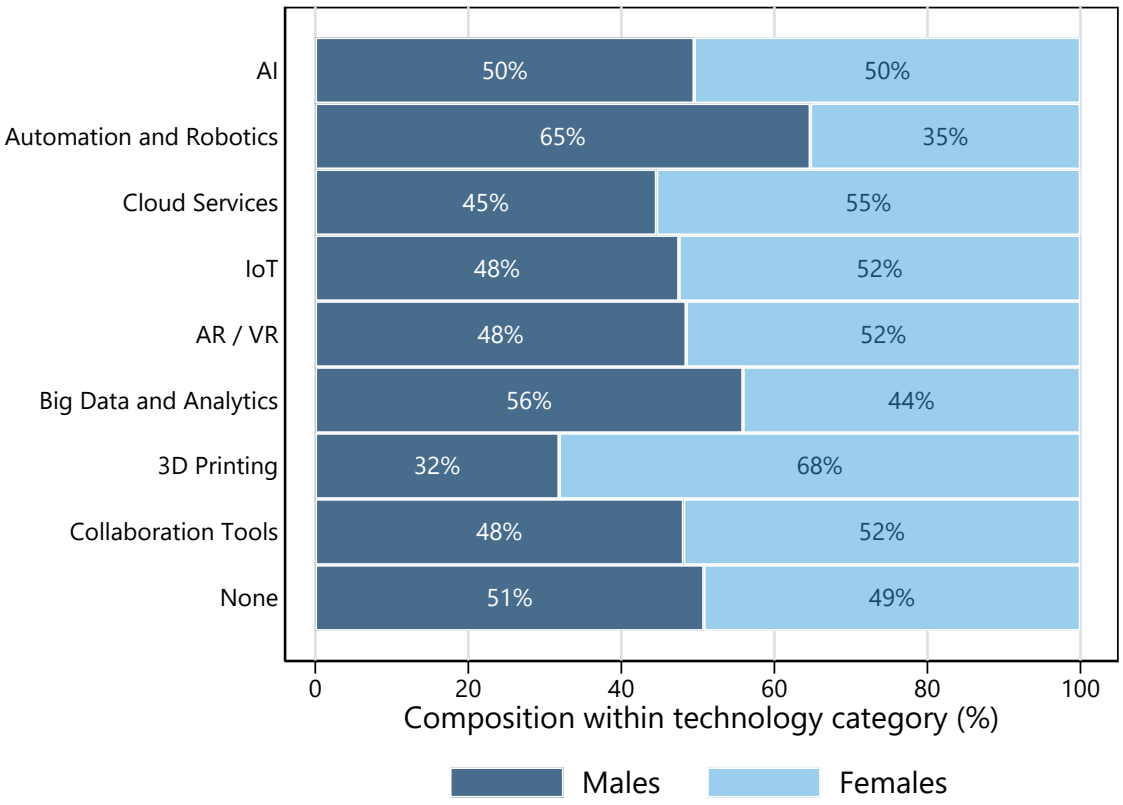
Note: This table reports the distribution of reported purposes of AI use among respondents in their job. Each column is a separate AI-use purpose, and responses are multiple-choice. The table reports subgroup means by sex, education, age, and occupation. The means are calculated using calibration weights derived from the Spanish labor force survey.

Table 9: Frequency of AI Use

		(1)	(2)		(3)	(4)	(5)
		Sex			Age Bracket		
		Male	Female		18-34	35-49	50+
Daily	0.24	0.26	0.22		0.24	0.23	0.25
Several Times in a Week	0.38	0.39	0.38		0.38	0.38	0.39
Once per Week	0.12	0.12	0.13		0.15	0.11	0.11
Several Times in a Month	0.14	0.14	0.14		0.14	0.15	0.14
Once per Month	0.04	0.03	0.04		0.04	0.03	0.04
Less than Once a Month	0.07	0.06	0.09		0.07	0.09	0.07
		(6)	(7)	(8)	(9)	(10)	(11)
		Education Level					
		School Certificate	Undergrad & Prof. Tr.	Master's & PhD	Wage <1500	1500-2500	>2500
Daily		0.21	0.26	0.24	0.22	0.26	0.26
Several Times in a Week		0.37	0.38	0.40	0.37	0.37	0.42
Once per Week		0.10	0.11	0.15	0.14	0.15	0.08
Several Times in a Month		0.19	0.12	0.12	0.16	0.13	0.15
Once per Month		0.02	0.06	0.03	0.03	0.03	0.05
Less than Once a Month		0.11	0.07	0.05	0.09	0.07	0.04

Note: This table reports the share of reported frequency of AI use at the job among respondents who report AI use. The table also tabulates frequency distributions by sex, age bracket, education level, and wage bracket. The frequencies are calculated using calibration weights derived from the Spanish labor force survey.

Figure 1: Most Significant Technology Used at the Workplace



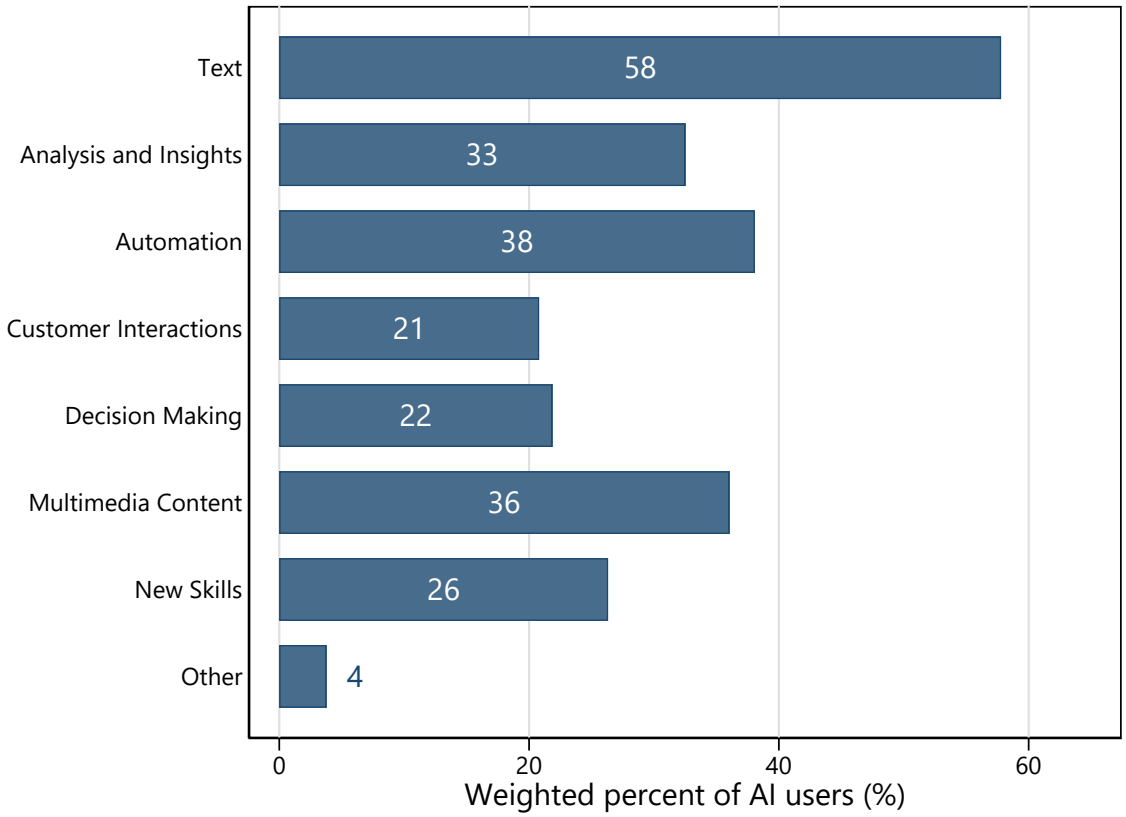
Note: This figure reports the distribution of the technology that respondents identify as the most significant for their work, by sex. Each bar shows the number of respondents selecting the corresponding category as most significant, separately for males and females. The calculations use calibration weights derived from the Spanish labor force survey.

Table 10: Expected Use of AI in the Next 3 Months

		(1)	(2)		(3)	(4)	(5)
		Sex			Age Bracket		
		Male	Female		18-34	35-49	50+
Yes	0.11	0.11	0.11		0.14	0.10	0.10
No	0.55	0.56	0.54		0.56	0.56	0.53
Don't Know	0.35	0.34	0.36		0.30	0.33	0.37
		(6)	(7)	(8)	(9)	(10)	(11)
		Education Level			Wage		
		School Certificate	Undergrad & Prof. Tr.	Master's & PhD	<1500	1500-2500	>2500
Yes		0.08	0.13	0.17	0.08	0.14	0.18
No		0.58	0.52	0.46	0.60	0.52	0.47
Don't Know		0.34	0.35	0.37	0.31	0.35	0.35

Note: This table reports expectations of starting to use AI at work within the next three months among respondents who do not report current AI use at work. The table also reports expectations by sex, age bracket, education level, and wage bracket. The computations use calibration weights derived from the Spanish labor force survey.

Figure 2: The Purpose of AI Use at the Workplace



Notes: This figure reports the distribution of reported purposes of AI use in the respondent's job. Categories correspond to the multiple-response AI purpose question (generating written content; performing data analysis and generating insights; automating repetitive tasks; improving customer interactions; supporting decision-making; designing/creating multimedia content; learning new skills unrelated to AI; and other). Category shares need not sum to one because responses are multiple choice. The shares are calculated using calibration weights derived from the Spanish labor force survey.

Table 11: The Use of Technologies at the Workplace

	(1) AI	(2) Automation and Robotics	(3) Cloud Services	(4) IoT	(5) AR / VR	(6) Big Data	(7) 3D Printing	(8) Collaboration Tools
Female	-0.029**	-0.038***	0.030*	0.035**	0.002	-0.018**	-0.008**	0.009
	(0.012)	(0.010)	(0.016)	(0.015)	(0.005)	(0.009)	(0.004)	(0.016)
Education Level								
Undergrad & Prof. Tr	0.030**	0.001	0.072***	0.002	0.002	0.023**	0.015***	0.081***
	(0.012)	(0.010)	(0.017)	(0.016)	(0.005)	(0.010)	(0.005)	(0.017)
Master's & PhD	0.116***	-0.015	0.163***	0.001	0.016*	0.069***	0.012	0.182***
	(0.020)	(0.015)	(0.024)	(0.022)	(0.009)	(0.016)	(0.008)	(0.024)
Age Bracket								
35-49	-0.079***	-0.021	-0.027	0.014	-0.012	-0.040***	-0.005	0.008
	(0.017)	(0.014)	(0.020)	(0.017)	(0.008)	(0.013)	(0.007)	(0.020)
50+	-0.133***	-0.072***	-0.056***	0.016	-0.023**	-0.067***	-0.012*	-0.016
	(0.018)	(0.014)	(0.021)	(0.018)	(0.009)	(0.013)	(0.007)	(0.020)
Firm Size								
11 to 49 people	0.001	0.024*	0.007	0.068***	-0.004	0.042***	0.002	0.057**
	(0.017)	(0.013)	(0.023)	(0.021)	(0.007)	(0.012)	(0.006)	(0.023)
50 people or more	-0.035**	0.045***	-0.022	0.030*	-0.005	0.040***	-0.001	0.066***
	(0.014)	(0.011)	(0.019)	(0.017)	(0.006)	(0.010)	(0.005)	(0.019)
Firm Scope								
Regional	-0.018	0.006	0.039*	-0.005	-0.003	0.018*	0.009	0.042**
	(0.013)	(0.011)	(0.020)	(0.018)	(0.006)	(0.011)	(0.005)	(0.020)
National	0.049***	0.018	0.093***	0.031*	0.010	0.039***	0.010***	0.083***
	(0.014)	(0.011)	(0.020)	(0.018)	(0.006)	(0.010)	(0.004)	(0.021)
International	0.118***	0.061***	0.165***	0.020	0.011	0.102***	0.023***	0.163***
	(0.018)	(0.016)	(0.023)	(0.022)	(0.008)	(0.015)	(0.008)	(0.023)
Wage Bracket								
1500-2500	0.022*	0.004	0.097***	0.038**	0.000	0.020**	0.004	0.087***
	(0.012)	(0.011)	(0.017)	(0.016)	(0.005)	(0.009)	(0.004)	(0.018)
2500+	0.108***	0.037**	0.139***	0.052**	0.019**	0.078***	0.020**	0.112***
	(0.019)	(0.016)	(0.023)	(0.022)	(0.008)	(0.016)	(0.008)	(0.024)
Tasks								
Abstract	0.186***	-0.096***	0.260***	0.056	-0.029*	0.078**	-0.023	0.301***
	(0.035)	(0.035)	(0.050)	(0.044)	(0.015)	(0.035)	(0.015)	(0.054)
Cognitive Routine	0.036	-0.104***	0.112**	0.026	-0.038***	-0.026	-0.004	0.070
	(0.028)	(0.036)	(0.045)	(0.041)	(0.013)	(0.028)	(0.015)	(0.049)
Manual Non-Routine	0.007	-0.104***	0.020	0.005	0.010	-0.023	-0.008	-0.038
	(0.026)	(0.039)	(0.051)	(0.044)	(0.017)	(0.028)	(0.015)	(0.056)
Inter. with Clients	0.046	-0.116***	0.102**	0.055	-0.024**	0.009	-0.014	0.141***
	(0.028)	(0.033)	(0.045)	(0.042)	(0.011)	(0.028)	(0.011)	(0.048)
Inter. with Coworkers	0.079***	-0.104***	0.080*	-0.010	-0.032**	-0.003	-0.023	0.127**
	(0.029)	(0.036)	(0.046)	(0.040)	(0.015)	(0.030)	(0.014)	(0.050)
Industry 1D FE	YES	YES	YES	YES	YES	YES	YES	YES
Occupation 1D FE	YES	YES	YES	YES	YES	YES	YES	YES
N. Obs.	6253	6253	6253	6253	6253	6253	6253	6253
R2	0.179	0.081	0.194	0.027	0.022	0.105	0.028	0.185

Note: This table reports regression results for workplace use of each technology. Each column corresponds to a separate binary dependent variable indicating whether the respondent reports use of the listed technology at work. The reference categories are male, age 18–34, firm size of 1–10 employees, local firm scope, a net monthly wage below €1,500, and routine manual tasks. All specifications use calibration weights derived from the Spanish labor force survey multiplied by respondents' usual weekly working hours and include 1-digit industry and occupation fixed effects. The estimation sample excludes unemployed and inactive respondents and is restricted to respondents who report their wage bracket. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12: The Purpose of AI Use at the Workplace

	(1) Text	(2) Analysis and Insights	(3) Automation	(4) Customer Interactions	(5) Decision Making	(6) Multimedia Content	(7) New Skills	(8) Number of AI Uses
Female	0.070**	-0.070**	-0.069**	-0.021	-0.097***	0.039	-0.039	-0.187**
	(0.035)	(0.033)	(0.034)	(0.029)	(0.028)	(0.032)	(0.030)	(0.094)
Education Level								
Undergrad & Prof. Tr	0.069	-0.017	0.021	-0.028	0.012	-0.006	-0.071	-0.021
	(0.055)	(0.053)	(0.051)	(0.047)	(0.045)	(0.050)	(0.053)	(0.154)
Master's & PhD	0.093	0.034	0.025	-0.019	0.048	0.018	-0.136**	0.062
	(0.059)	(0.058)	(0.056)	(0.049)	(0.052)	(0.055)	(0.059)	(0.169)
Age Bracket								
35-49	0.080**	-0.044	0.019	-0.004	-0.097***	-0.048	-0.064*	-0.157
	(0.038)	(0.035)	(0.038)	(0.033)	(0.032)	(0.037)	(0.036)	(0.109)
50+	0.113**	-0.030	-0.005	-0.010	-0.072*	0.043	-0.088**	-0.048
	(0.044)	(0.042)	(0.043)	(0.040)	(0.039)	(0.046)	(0.041)	(0.131)
Firm Size								
11 to 49 people	0.010	-0.068	-0.034	0.042	-0.183***	-0.080	-0.029	-0.341**
	(0.054)	(0.051)	(0.054)	(0.050)	(0.046)	(0.056)	(0.050)	(0.154)
50 people or more	-0.122***	-0.049	0.028	0.001	-0.105***	-0.136***	0.016	-0.366***
	(0.045)	(0.041)	(0.046)	(0.042)	(0.040)	(0.045)	(0.040)	(0.122)
Firm Scope								
Regional	0.060	0.064	-0.037	0.032	0.019	0.001	0.016	0.154
	(0.053)	(0.046)	(0.054)	(0.044)	(0.043)	(0.052)	(0.049)	(0.142)
National	0.065	0.090**	-0.005	-0.005	0.007	-0.037	0.019	0.134
	(0.049)	(0.045)	(0.050)	(0.042)	(0.039)	(0.047)	(0.046)	(0.137)
International	0.104**	0.144***	-0.010	0.002	0.010	-0.076	-0.004	0.170
	(0.050)	(0.048)	(0.051)	(0.045)	(0.042)	(0.049)	(0.048)	(0.124)
Wage Bracket								
1500-2500	0.087**	0.089**	-0.012	-0.004	0.023	0.021	0.016	0.219*
	(0.043)	(0.041)	(0.043)	(0.038)	(0.033)	(0.042)	(0.037)	(0.124)
2500+	-0.035	0.105**	-0.023	-0.012	0.098**	0.034	0.086*	0.252*
	(0.050)	(0.046)	(0.049)	(0.044)	(0.041)	(0.052)	(0.046)	(0.130)
Training	-0.006	0.102***	0.075**	0.049	0.084***	0.049	0.111***	0.465***
	(0.034)	(0.034)	(0.034)	(0.030)	(0.031)	(0.035)	(0.034)	(0.101)
Tasks								
Abstract	0.186	0.203	-0.031	-0.080	0.166	-0.184	0.114	0.373
	(0.166)	(0.140)	(0.193)	(0.123)	(0.110)	(0.166)	(0.156)	(0.407)
Cognitive Routine	0.433**	-0.005	-0.218	0.004	0.212*	-0.022	0.086	0.490
	(0.170)	(0.141)	(0.203)	(0.145)	(0.123)	(0.185)	(0.166)	(0.440)
Manual Non-Routine	-0.118	-0.048	-0.116	0.151	0.143	-0.001	0.136	0.146
	(0.239)	(0.195)	(0.263)	(0.180)	(0.164)	(0.253)	(0.226)	(0.610)
Inter. with Clients	0.373**	0.070	-0.263	0.092	0.179	-0.286*	-0.037	0.128
	(0.164)	(0.133)	(0.193)	(0.132)	(0.118)	(0.171)	(0.146)	(0.387)
Inter. with Coworkers	0.152	-0.075	-0.104	-0.025	0.056	-0.090	0.048	-0.039
	(0.171)	(0.141)	(0.197)	(0.136)	(0.113)	(0.170)	(0.161)	(0.410)
Industry 1D FE	YES	YES	YES	YES	YES	YES	YES	YES
Occupation 1D FE	YES	YES	YES	YES	YES	YES	YES	YES
Freq. Use FE	YES	YES	YES	YES	YES	YES	YES	YES
N. Obs.	1275	1275	1275	1275	1275	1275	1275	1275
R2	0.136	0.164	0.131	0.096	0.140	0.115	0.084	0.220

Note: This table reports separate linear probability models for the purposes of AI use among AI users in columns 1-7. The dependent variable in each column is a binary indicator equal to one if the respondent reports using AI for the indicated purpose. Respondents could report more than one purpose. Column 8 reports estimates for the number of reported AI uses, constructed as the sum of the seven purpose-specific indicators. The reference categories are male, age 18–34, firm size of 1–10 employees, local firm scope, a monthly net wage below €1,500, and routine manual tasks. The regressions use calibration weights derived from the Spanish labor force survey multiplied by respondents' usual weekly working hours. All specifications include 1-digit industry and occupation fixed effects and AI-use frequency fixed effects. The estimation sample excludes unemployed and inactive respondents and is restricted to respondents who report their wage bracket. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 13: The Perceived Effect of AI on Productivity and Reported Effect on Time Allocation

Abstract				Cognitive Routine			
	Time				Time		
Productivity	Increased	No Change	Decreased	Productivity	Increased	No Change	Decreased
Increased	0.29	0.10	0.22	Increased	0.22	0.08	0.16
No Change	0.04	0.18	0.05	No Change	0.04	0.28	0.06
Decreased	0.02	0.02	0.08	Decreased	0.03	0.03	0.10
N. Obs.			1384	N. Obs.			1236

Manual Routine				Manual Non-Routine			
	Time				Time		
Productivity	Increased	No Change	Decreased	Productivity	Increased	No Change	Decreased
Increased	0.21	0.08	0.10	Increased	0.20	0.07	0.09
No Change	0.03	0.31	0.07	No Change	0.04	0.36	0.07
Decreased	0.04	0.04	0.12	Decreased	0.04	0.06	0.07
N. Obs.			631	N. Obs.			535

Interactive with Coworkers				Interactive with Clients			
	Time				Time		
Productivity	Increased	No Change	Decreased	Productivity	Increased	No Change	Decreased
Increased	0.20	0.07	0.07	Increased	0.22	0.08	0.07
No Change	0.03	0.49	0.05	No Change	0.05	0.39	0.07
Decreased	0.01	0.03	0.06	Decreased	0.02	0.03	0.07
N. Obs.			707	N. Obs.			1115

Note: This table reports the joint distribution of perceived changes in productivity and time allocation associated with AI use across six broad task categories. The rows indicate whether respondents report that AI increased, did not change, or decreased their productivity in the corresponding task, while the columns indicate whether the time allocated to that task increased, remained unchanged, or decreased. Each cell offers the share of AI users reporting the corresponding combination of changes out of the total included for each task. The entries are computed using calibration weights derived from the Spanish labor force survey multiplied by respondents' usual weekly working hours. The sample excludes unemployed and inactive respondents. Cells may not sum exactly to 1 because of rounding.

Table 14: Reported Probability of Job Offer and Being Unemployed Next Month

Job Offer	(1) AI	(2) Automation and Robots	(3) Cloud Services	(4) IoT	(5) AR / VR	(6) Big Data	(7) 3D Printing	(8) Collaboration Tools
	0.092***	0.001	0.004	0.027	0.064	0.060**	-0.005	0.010
	(0.020)	(0.027)	(0.012)	(0.022)	(0.064)	(0.029)	(0.060)	(0.012)
N. Obs.	6253	6253	6253	6253	6253	6253	6253	6253
R2	0.103	0.097	0.098	0.098	0.098	0.098	0.097	0.098
Unemployment	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	0.029**	0.038*	-0.017**	0.004	0.018	0.001	0.015	0.016
	(0.014)	(0.021)	(0.007)	(0.013)	(0.032)	(0.014)	(0.049)	(0.010)
N. Obs.	6253	6253	6253	6253	6253	6253	6253	6253
R2	0.057	0.057	0.056	0.055	0.055	0.055	0.055	0.056

Note: This table reports regressions relating short-horizon labor-market expectations to the technology respondents identify as the most significant in their work. The dependent variables are the respondents' reported probabilities of receiving a job offer and being unemployed within the next month, expressed on a scale from 0 to 1. All specifications include gender, age-bracket, education-level, wage-bracket, firm-size, firm-scope, 1-digit industry and occupation fixed effects, together with task controls. The regressions use calibration weights derived from the Spanish labor force survey multiplied by respondents' usual weekly working hours. The estimation sample excludes unemployed and inactive respondents and is restricted to respondents who report their wage bracket. Standard errors account for the survey design and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 15: AI Use in 1-Digit Occupations, Exposure Measures, and Ranking

Panel A. Percent of Users and Exposure Measures	Percent of Users					Exposure Measures			
			Adjusted for						
Occupation	N. Obs.	Raw Data	Tech.	Dem.	Tech. & Dem.	GPT-Human	GPT-Model	ILO GenAI	AIOE
1 Managers	717	0.24	0.20	0.23	0.20	0.44	0.48	0.37	0.88
2 Professionals	2170	0.31	0.26	0.25	0.23	0.41	0.46	0.36	0.81
3 Associate Professionals / Technicians	863	0.25	0.20	0.22	0.19	0.37	0.46	0.37	0.37
4 Clerical Support Workers	2280	0.11	0.11	0.13	0.13	0.46	0.58	0.55	0.71
5 Service and Sales Workers	866	0.08	0.12	0.10	0.13	0.29	0.26	0.29	-0.18
6 Skilled Agricultural Workers	97	0.12	0.16	0.15	0.18	0.10	0.17	0.18	-0.93
7 Craft and Related Trades Workers	483	0.09	0.13	0.11	0.14	0.09	0.14	0.17	-0.93
8 Plant and Machine Operators / Assemblers	100	0.02	0.07	0.04	0.08	0.06	0.10	0.21	-0.95
9 Elementary Occupations	510	0.05	0.11	0.09	0.13	0.05	0.05	0.13	-1.37

Panel B. Ranking								
	Adjusted for							
Occupation	Raw Data	Tech.	Dem.	Tech. & Dem.	GPT-Human	GPT-Model	ILO GenAI	AIOE
1 Managers	3	2	2	2	2	2	2	1
2 Professionals	1	1	1	1	3	4	4	2
3 Associate Professionals / Technicians	2	3	3	3	4	3	3	4
4 Clerical Support Workers	5	7	5	8	1	1	1	3
5 Service and Sales Workers	7	6	7	7	5	5	5	5
6 Skilled Agricultural Workers	4	4	4	4	6	6	7	6
7 Craft and Related Trades Workers	6	5	6	5	7	7	8	7
8 Plant and Machine Operators / Assemblers	9	9	9	9	8	8	6	8
9 Elementary Occupations	8	8	8	6	9	9	9	9

Note: Panel A reports observed workplace AI use and adjusted AI-use measures together with the number of observations in each occupation. It also reports measures of occupational AI exposure. Adjusted for Tech. accounts for the use of other workplace technologies. Adjusted for Dem. accounts for demographic and educational composition within occupations. Adjusted for Tech. & Dem. accounts for both. GPT-Human and GPT-Model are based on human and GPT-4 assessments of whether LLM-powered tools can substantially reduce task-completion time (Eloundou et al., 2024). ILO GenAI is the task-based ISCO-08 exposure index of Gmyrek et al. (2025), while AIOE is the broader AI Occupational Exposure measure of Felten et al. (2021). Panel B reports the corresponding rankings, with 1 denoting the highest observed use or exposure. The original exposure measures are at 3-digit ISCO-08. We first average them to 2-digit ISCO-08. We then aggregated them to 1-digit ISCO-08 occupations using the occupational composition observed in the survey. The sample excludes unemployed and inactive respondents. All occupation-level means are calculated using calibration weights derived from the Spanish labor force survey.

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A Appendix: Data and Variables

Table A1: Definitions and Sources of Variables

Variable Name	Definition
Technology:	
AI	Dummy variable equal to 1 if the individual reports using Artificial Intelligence technologies at work, and 0 otherwise. Artificial intelligence is a technology to simulate human intelligence in machines for performing tasks such as learning, reasoning, problem solving, perception, and decision-making (e.g., fraud detection, ChatGPT, Midjourney).
Automation and Robotics	Dummy variable equal to 1 if the individual reports using automation technologies and/or robots at work, and 0 otherwise. These technologies are tools for performing tasks or processes with minimal human intervention (e.g., chatbots, industrial robots, and autonomous vehicles).
Cloud Services	Dummy variable equal to 1 if the individual reports using cloud services at work, and 0 otherwise. These technologies deliver computing services over the Internet, allowing users to access and use cloud resources such as servers, storage, databases, networks, software, and analytics on demand (e.g., Dropbox).
IoT	Dummy variable equal to 1 if the individual reports using Internet of Things technologies at work, and 0 otherwise. These technologies form a network of physical objects or "things" embedded with sensors, software, and other technologies in order to connect and exchange data with other devices and systems over the Internet.
AR / VR	Dummy variable equal to 1 if the individual uses augmented reality and/or virtual reality technologies at work, and 0 otherwise. These technologies overlay digital content, such as images, videos, or 3D models, onto the real-world environment, improving users' perception of and interaction with their surroundings.

Table A1 – (Continued)

Variable Name	Definition
Big Data	Dummy variable equal to 1 if the individual reports using big data technologies and tools at work, and 0 otherwise. These technologies allow the users to analyze large and complex datasets to discover insights, patterns, trends, and relationships that can inform decision-making, optimize processes, and improve business outcomes.
3D Printing	Dummy variable equal to 1 if the individual reports using 3D printing technologies at work, and 0 otherwise. These technologies constitute a manufacturing process that creates three-dimensional objects by building layers of material, generally layer by layer, based on a digital 3D model.
Collaboration Tools	Dummy variable equal to 1 if the individual reports using digital collaboration tools at work, and 0 otherwise. These tools are software applications and platforms designed to facilitate communication, coordination, and teamwork among individuals or groups (e.g., Zoom).
Tasks:	
Abstract	Percentage of working time devoted to abstract (analytical/cognitive non-routine) tasks in a regular week. These tasks involve analyzing and interpreting data/information, thinking creatively, and interpreting information for others. The variable is based on respondents' self-reported percentage of time devoted to the task.
Cognitive Routine	Percentage of working time devoted to cognitive routine tasks in a regular week. These tasks involve using mental abilities for repetitive tasks, structured work following instructions. The variable is based on respondents' self-reported percentage of time devoted to the task.
Manual Routine	Percentage of working time devoted to manual routine tasks in a regular week. These tasks involve controlling machines and processes, spending time doing repetitive movements. The variable is based on respondents' self-reported percentage of time devoted to the task.

Table A1 – (Continued)

Variable Name	Definition
Manual Non-Routine	Percentage of working time devoted to manual tasks in a regular week. These tasks involve operating vehicles, devices, or mechanized equipment; using hands to handle, control, or feel objects, tools, or controls. The variable is based on respondents' self-reported percentage of time devoted to the task.
Inter. with Clients	Percentage of working time devoted to interactions with clients, customers, or users in a regular week. These tasks involve establishing and maintaining personal relationships with clients or suppliers. The variable is based on respondents' self-reported percentage of time devoted to the task.
Inter. with Coworkers	Percentage of working time devoted to interactions with coworkers or colleagues in a regular week. These tasks involve establishing and maintaining personal relationships with other workers; guiding, directing, and motivating subordinates; training/developing others. The variable is based on respondents' self-reported percentage of time devoted to the task.
Additional variables on AI:	
Purpose of AI use at work	Set of binary indicators describing AI use at work. The options are (1) generating written content (shorter names here), (2) performing data analysis and generating insights (shorter names here), (3) automating repetitive tasks, (4) improving customer interactions (shorter names here), (5) supporting decision-making, (6) designing/creating multimedia content, (7) learning new skills unrelated to AI, and (8) other.
Number of AI uses	The sum of the seven purpose-specific indicators: (1) generating written content, (2) performing data analysis and generating insights, (3) automating repetitive tasks, (4) improving customer interactions, (5) supporting decision-making, (6) designing/creating multimedia content, and (7) learning new skills unrelated to AI.
Frequency of AI use at work	Categorical variable indicating the frequency of AI use at work. The options are (1) daily, (2) several times a week, (3) once per week, (4) several times a month, (5) once per month, and (6) less than once per month.
Suggestion of AI use at work	Categorical variable indicating who suggested the use of AI at work. The categories are: the employee, the employer, and others.

Table A1 – (Continued)

Variable Name	Definition
Expected use of AI in the next 3 months	Categorical variable indicating the expected use of AI at work within the next 3 months among respondents who do not currently use AI at work. Categories are: Yes, No, I don't know.
Impediments to AI use at work	Individuals using AI are asked, if any, which impediments they find to effectively use AI. The options are: (1) lack of training or knowledge, (2) difficulty integrating AI with existing systems, (3) privacy and security concerns, (4) high cost, (5) resistance to change among colleagues, and (6) fear of job loss.
Impact of AI on productivity change for each task	AI users are asked about the impact of AI use on productivity in each task (Abstract, Cognitive Routine, Manual Routine, Manual Non-routine, Interaction with coworkers, Interaction with clients). The options available are: it has increased, it has decreased, it did not change, and it does not apply.
Impact of AI on total time allocated to each task	AI users are asked about the impact of AI use on total time allocation to each task (Abstract, Cognitive Routine, Manual Routine, Manual Non-routine, Interaction with coworkers, Interaction with clients). The options available are: it has increased, it has decreased, it did not change, and it does not apply.
Training	A dummy variable attaining value 1 if the respondent reports having received any training on the use of AI technologies in the workplace, and 0 otherwise.
GPT-Human	Occupational exposure to LLMs based on human assessments of whether LLMs or LLM-powered tools can substantially reduce completion time of tasks (Eloundou et al., 2024). The measure is an unweighted mean across 3-digit ISCO-08 occupations, aggregated to 2-digit ISCO-08. Higher values indicate greater exposure.
GPT-Model	Occupational exposure to LLMs based on GPT-4 assessments of whether LLMs or LLM-powered tools can substantially reduce completion time of tasks (Eloundou et al., 2024). The measure is an unweighted mean across 3-digit ISCO-08 occupations, aggregated to 2-digit ISCO-08. Higher values indicate greater exposure.

Table A1 – (Continued)

Variable Name	Definition
ILO GenAI	Task-based occupational exposure to generative AI, constructed by evaluating the potential for GenAI to automate or transform tasks (Gmyrek et al., 2025). The measure is an unweighted mean across 3-digit ISCO-08 occupations, aggregated to 2-digit ISCO-08. Higher values indicate greater exposure.
AIOE	Occupational exposure to AI, constructed by linking advances in AI applications to the abilities required in each occupation (Felten et al., 2021). The measure is an unweighted mean across 3-digit ISCO-08 occupations, aggregated to 2-digit ISCO-08. Higher values indicate greater exposure.
Individual and job characteristics:	
Female	Dummy variable equal to 1 for female respondents and 0 for male respondents.
Education Level	Categorical variable capturing the respondent's highest completed education level: at most high school leaving certificate, university undergraduate degree or professional training, Master or PhD.
Age bracket	Age measured in brackets: 18-34, 35-49, 50 or more.
Firm size	Categorical variable capturing the number of employees in the firm in brackets: at most 10 people, from 11 to 49, and 50 or more people.
Firm scope	The territorial scope of operations of the firm/workplace: local, regional, national, international.
Wage bracket	Net monthly wage measured in brackets: less than 1500 euros, 1500-2500 euros, and more than 2500 euros.
Industry	Respondent's industry of work following 1-digit NACE Rev. 2 classification. It is derived from the respondents' selected industry from a list of 19 1-digit NACE Rev. 2 industries that best describes the job/firm of the respondent.
Occupation 1D	Respondent's occupation following 1-digit ISCO-08 classification. It is derived from the respondent's selected occupation from a list of 39 2-digit ISCO-08 occupations that best describes the job of the respondent.
Job offer	Reported probability of receiving a job offer during the next month, on scale 0 to 1.

Table A1 – (Continued)

Variable Name	Definition
Unemployment	Reported probability of being unemployed during the next month, on scale 0 to 1.

B Appendix: Elasticity of Substitution Between Abstract Tasks and AI

This appendix illustrates one way of using the survey to discipline a task-based production framework. In particular, for a given value of the elasticity of substitution between routine cognitive tasks and AI, we calibrate the elasticity of substitution between abstract (cognitive analytical) tasks and AI and the productive AI weights in abstract and routine cognitive tasks. We focus on these two task categories because respondents report the largest and least mixed perceived productivity effects of AI for them. For the calibration, we construct within respondent and task-specific variation in AI-use intensity from the reported purposes and frequency of AI use. We combine this information with perceived changes in productivity and time allocation by task.

B.A Technology and Effective AI Intensity

We use $i \in \{A, C\}$ to denote abstract and routine cognitive tasks. Output of respondent n in task i is

$$y_{ni} = \left[(1-\omega_i)L_{ni}^{(\varepsilon_i-1)/\varepsilon_i} + \omega_i A_{ni}^{(\varepsilon_i-1)/\varepsilon_i}\right]^{\varepsilon_i/(\varepsilon_i-1)}, \tag{1}$$

where L_{ni} is labor time, A_{ni} is effective AI services, ε_i is their elasticity of substitution, and $\omega_i \in (0,1)$ is an effective CES distribution weight. We calibrate the values of ε_A and ω_i for $i \in \{A, C\}$ given a value of ε_C.

We use $i \in \{A, C\}$ to denote abstract and routine cognitive tasks. Output of respon-

dent n in task i is

$$y_{ni} = \left[(1-\omega_i)L_{ni}^{(\varepsilon_i-1)/\varepsilon_i} + \omega_i A_{ni}^{(\varepsilon_i-1)/\varepsilon_i}\right]^{\varepsilon_i/(\varepsilon_i-1)}, \tag{2}$$

where L_{ni} is labor time, A_{ni} is productive AI services, ε_i is the elasticity of substitution between labor and AI, and $\omega_i \in (0,1)$ is a weight. For a given value of ε_C, we calibrate ε_A and ω_i for $i \in \{A, C\}$.

B.A.1 Task-Specific AI Use Indices

We construct task-specific measures of AI-use intensity from the seven reported purposes and six frequency categories of AI use. First, we summarize the seven purposes using the first 3 components from a weighted principal-components analysis. These components account for slightly more than 50% of the standardized variation in the reported purposes of AI use. We then allow the relevance of the components to differ across tasks by estimating

$$s_{ni} = \alpha_i + \sum_{j=1}^{3} \beta_{ij} PC_{nj} + u_{ni}, \tag{3}$$

where s_{ni} is the fraction of the respondent's regular workweek allocated to task i, and PC_{nj} is respondent n's score on principal component j.

We construct the raw task-specific AI-use index as

$$m_{ni}^{\text{raw}} = \sum_{j=1}^{3} \widehat{\beta}_{ij} PC_{nj}. \tag{4}$$

Since these indices can be negative, we rescale each index to the unit interval while preserving its ranking and relative spacing:

$$m_{ni} = \frac{m_{ni}^{\text{raw}} - \min_n m_{ni}^{\text{raw}}}{\max_n m_{ni}^{\text{raw}} - \min_n m_{ni}^{\text{raw}}}. \tag{5}$$

We next combine the resulting task-specific index with the reported frequency of AI

use. Raw effective AI intensity is defined as

$$q_{ni} = \frac{1 + m_{ni}}{f_n}, \tag{6}$$

where $f_n \in \{1, \ldots, 6\}$ denotes AI-use frequency, ordered from daily to less than monthly use. Thus, lower values of f_n imply more intensive AI use. The addition of one ensures strictly positive AI-intensity measure for all AI users.

Using a normalization common to both tasks, we define

$$a_{ni} = \frac{q_{ni}}{\bar{q}}, \tag{7}$$

where

$$\bar{q} = \frac{1}{2}\left[\frac{\sum_n w_n q_{nA}}{\sum_n w_n} + \frac{\sum_n w_n q_{nC}}{\sum_n w_n}\right], \tag{8}$$

and w_n is the respondent-level analysis weight, constructed from the Spanish labor force survey calibration weight multiplied by the respondent's usual weekly working hours. The common normalization preserves differences in the level of effective AI intensity across the two tasks.

Finally, the change in effective respondent- and task-specific AI services is defined as

$$\Delta \ln A_{ni} = \delta a_{ni}, \tag{9}$$

where δ is common across tasks and respondents.

B.B Objective Function and Calibration Routine

The perceived productivity and time-allocation responses are coded as $R_{ni}, T_{ni} \in \{-1, 0, 1\}$ for a decrease, no change, and an increase, respectively. Because the survey does not measure the magnitudes of these changes, we normalize one response-category movement to $\kappa = 0.10$ log points:

$$\Delta \ln P_{ni} = \kappa R_{ni}, \tag{10}$$

and

$$\Delta \ln L_{ni} = \kappa T_{ni}. \tag{11}$$

We treat these cardinal changes as normalization-dependent representations of the ordinal responses.

We further normalize baseline labor and AI inputs to 1. For $\varepsilon_i \neq 1$, model-predicted labor-productivity growth is

$$g_{ni}(\varepsilon_i, \omega_i, \delta) = \frac{\varepsilon_i}{\varepsilon_i - 1} \ln \left[(1-\omega_i) e^{[(\varepsilon_i - 1)/\varepsilon_i]\kappa T_{ni}} + \omega_i e^{[(\varepsilon_i - 1)/\varepsilon_i]\delta a_{ni}} \right] - \kappa T_{ni}. \tag{12}$$

At $\varepsilon_i = 1$, the Cobb–Douglas limit is

$$g_{ni}(1, \omega_i, \delta) = \omega_i \left(\delta a_{ni} - \kappa T_{ni} \right). \tag{13}$$

The survey data cannot separately distinguish both task elasticities ε_i, both CES weights ω_i, and the scale of effective AI services δ from the ordinal reports. We therefore impose the baseline value $\varepsilon_C = 1.5$. This choice reflects the automation hypothesis that computer-based technologies substitute relatively readily for labor in routine cognitive tasks (e.g., Autor et al., 2003, Autor and Dorn, 2013, Jerbashian, 2019). For a given ε_C, we calibrate the vector of parameters

$$\theta = (\varepsilon_A, \omega_A, \omega_C, \delta). \tag{14}$$

Let $\mathcal{S}_i$ denote the set of respondents with valid task-specific information on perceived productivity, time allocation, task shares, and AI-use intensity. Task shares enter the calibration as observation weights. Reports concerning tasks that occupy a larger fraction of the respondent's workweek therefore receive greater weight.

The weighted task-level component of the calibration criterion is

$$\mathcal{L}_L(\theta) = \frac{\sum_{i \in \{A,C\}} \sum_{n \in \mathcal{S}_i} w_n s_{ni} \left[\kappa R_{ni} - g_{ni}(\theta) \right]^2}{\sum_{i \in \{A,C\}} \sum_{n \in \mathcal{S}_i} w_n s_{ni}}. \tag{15}$$

This term includes both observations when a respondent reports valid outcomes for both tasks, but treats them as separate task observations.

We additionally exploit the paired structure of the survey. Let $\mathcal{S}_{AC}$ contain respondents with valid reports for both abstract and routine cognitive tasks, and let

$$\bar{s}_n = \frac{s_{nA} + s_{nC}}{2}. \tag{16}$$

The within-person calibration criterion is

$$\mathcal{L}_W(\theta) = \frac{\sum_{n \in \mathcal{S}_{AC}} w_n \bar{s}_n \left[\kappa(R_{nA} - R_{nC}) - \{g_{nA}(\theta) - g_{nC}(\theta)\}\right]^2}{\sum_{n \in \mathcal{S}_{AC}} w_n \bar{s}_n}. \tag{17}$$

This term requires the model to reproduce the difference between abstract- and routine-cognitive-task outcomes reported by the same respondent. It therefore gives additional weight to the relative task pattern while partially removing respondent-specific reporting tendencies that are common across the two tasks.

The full calibration criterion is

$$\mathcal{L}(\theta) = \mathcal{L}_L(\theta) + \gamma \mathcal{L}_W(\theta) + \chi \sum_{i \in \{A,C\}} \left[\overline{\kappa R}_{i,w} - \overline{g_i(\theta)}_{i,w}\right]^2. \tag{18}$$

The final term penalizes discrepancies between observed and predicted weighted mean productivity changes.

We set $\gamma = 1$ and $\chi = 5$. These values are calibration choices rather than estimated technological parameters. The calibrated parameter vector solves

$$\widehat{\theta} = \arg\min_{\theta} \mathcal{L}(\theta). \tag{19}$$

We implement bounded multistart optimization, using several initial parameter values to reduce dependence on a particular starting point.

B.C Results

The task-level calibration samples contain 1,384 abstract-task and 1,236 routine-cognitive-task reports, 1,158 respondents provide valid reports for both tasks. Table B2 reports the results for the baseline $\varepsilon_C = 1.5$ and alternative values $\varepsilon_C = 1.1$ and $\varepsilon_C = 5$.

Table B2: Calibration Results

	Baseline $\varepsilon_C = 1.5$	$\varepsilon_C = 1.1$	$\varepsilon_C = 5$
Abstract-task elasticity, ε_A	0.561	0.591	0.453
Abstract-task weight, ω_A	0.064	0.051	0.093
Routine-cognitive weight, ω_C	0.016	0.014	0.017
AI-input scale, δ	1.279	1.855	0.925
Task-level loss	0.00482	0.00477	0.00489
Within-person loss	0.00514	0.00510	0.00525
Total objective	0.00996	0.00986	0.01014

Notes: The baseline uses $\varepsilon_C = 1.5$. Each column imposes the indicated routine-cognitive elasticity and recalibrates ε_A, ω_A, ω_C, and δ. All calibrated parameters are interior to their numerical bounds.

The calibrated abstract-task elasticity is below one in all specifications, ranging from 0.453 to 0.591 among the values reported in Table B2. Within this framework, labor and effective AI services therefore behave as complements in abstract (cognitive analytical) tasks. The effective AI weight is also consistently larger in abstract than in routine cognitive tasks.

Admittedly, this exercise has limitations. The values of ω_i and δ need to be interpreted jointly because the calibration criterion disciplines their combined contribution more strongly than either parameter separately. The relatively small differences in the minimized objective across the imposed values of ε_C also indicate that the survey does not allow us to identify the routine-cognitive elasticity. We therefore treat $\varepsilon_C = 1.5$ as a baseline based on earlier work and use the remaining values as sensitivity checks. At the same time, the calibrated parameters may not be interpreted as causal estimates. Task content and the purposes of AI use may be jointly determined. The AI-intensity measure provides a convenient empirical scale rather than structural unit. The mapping of ordinal responses into log changes, the mean-fit penalty, γ, and the imposed values of

ε_C are also calibration choices. Stronger identification would require cardinal measures of task-level productivity and time changes, direct measures and prices of productive AI services, task-specific factor payments, or exogenous variation in AI adoption and intensity.

C Appendix: Additional Survey Details

The survey was administered by Netquest, which operates an invitation-based, closed, online access panel. Its documented recruitment procedures use identifiable recruitment sources, require active consent, and include measures intended to prevent duplicate or unverifiable registrations. Netquest also maintains extensive panelist profiles, records participation, and uses these data to improve sample targeting and reduce unnecessary invitations.

Panel recruitment, management, and validation follow standardized procedures consistent with the quality principles originally codified in ISO 26362 for online access panels. Data validation combines checks implemented during panel recruitment and management with survey-specific quality controls. Netquest describes a multilayered fraud-prevention approach covering onboarding, registration, survey participation, panelist support, and incentive redemption. The survey-specific cleaning procedures additionally identify implausibly short or long completion times and inconsistent responses. We additionally remove observations with interviews lasting more than four hours, as well as interviews lasting less than five minutes among respondents who were neither unemployed nor inactive.

The sample was selected using quotas defined by territory and major demographic characteristics. The achieved sample distributions closely match the corresponding quota targets. To further align the sample with the Spanish adult population, we construct calibration weights using the 2024 Spanish labor force survey. These weights adjust for differences in gender, age, and education groups between the survey sample and the reference population. The harmonized categories are reported in Table C1.

Table C1: Variables Used to Construct the Baseline Calibration Weights

Calibration variable	Harmonized categories
Sex	Male; Female
Age	18–34; 35–49; 50+
Education	School certificate; Undergraduate and professional training; Master's and PhD

Note: The baseline weights calibrate the survey to the corresponding population distributions in the Spanish labor force survey by sex, age, and educational attainment. Variables are harmonized across the two datasets before calibration. The weights are normalized over the relevant estimation sample.

C.A Individual, Job, Employment, and Firm Characteristics

The survey directly elicits standard individual characteristics, including sex, age, educational attainment, and marital status. It also directly inquires about current labor-market status, distinguishing full-time employment, part-time employment, unemployment, self-employment, and non-participation. For respondents who are not employed at the time of interview, it records whether the respondent held a significant job during the previous twelve months, and subsequent questions refer to the current job for employed respondents and to the most recent significant job otherwise. We use exclusively the job information of those currently employed throughout the analysis.

For the relevant job, the survey inquires about usual weekly hours and net wage/labor income in brackets. It records employer size in broad employment bins and measures the scope of workplace operations on an ordered scale from local to international reach.

The survey records occupation using the 2-digit ISCO-08 occupational classification and industry using the 1-digit NACE Rev.2 classification. Respondents select, respectively, the occupation from a list of 39 categories and the industry from a list of 19 categories that best describe their job and employer.

The survey measures job task content using broad categories that cover abstract analytical activities, routine cognitive activities, routine and non-routine manual activities, and interactive activities with clients and coworkers. Respondents are provided with standardized descriptions of the task categories and report the share of their working time allocated to each category in a typical workweek. Table A1 presents the corresponding

task definitions.

C.B AI-Specific Measurement

The survey records perceived impediments to effective AI use through a checklist. The checklist includes lack of training or knowledge, difficulty integrating AI with existing systems, privacy and security concerns, high cost, resistance to change among colleagues, and fear of job loss. Table F3 reports the prevalence of these perceived impediments across worker and firm characteristics.

C.C Other Modern Technology-Specific Measurement

Similar to AI, the survey records perceived changes in productivity and time allocation associated with other modern workplace technologies. For the technology identified as most significant in the respondent's work, respondents indicate whether productivity and time allocated to each applicable task increased, remained unchanged, or decreased.

Table F4 groups the technologies into Data (cloud services and big data), Collaboration Tools, and Automation (automation and robotics, IoT, AR/VR, and 3D printing). It also aggregates the six task categories into four groups: abstract, routine, non-routine manual, and interactive tasks. Across technology groups, no change in either productivity or time is particularly common for non-routine manual tasks, reaching 54% for Data and 55% for Collaboration Tools. Increases in both productivity and time are most prevalent in abstract tasks for Data and Automation Technologies, at 31% and 30%, respectively, and in interactive tasks for Collaboration Tools, at 35%. None of the these technology groups matches the prevalence of perceived productivity gains because of AI in abstract tasks as reported in Table 13. All these descriptive associations reflect respondents' perceptions.

C.D Regions

The survey features extensive regional coverage. As reported in Table F6, there are meaningful regional differences in the use of AI and other modern technologies, with

especially high use of AI, cloud services, and collaboration tools observed in larger cities.

C.E Additional Modules

The survey includes additional modules that provide household and contextual covariates. It records household composition and housing conditions, including the number of household members, the presence of children, and the number of rooms. It measures access to digital devices and connectivity that can facilitate remote work. It records household income in brackets.

The survey includes a detailed module on remote work arrangements for employed respondents. It measures whether respondents work from home, actual and desired remote-work hours, constraints that prevent achieving desired intensity, and investments made by employees and inputs provided by employers to support remote work. The instrument further includes short-horizon expectations about labor-market outcomes and housing payments, including rent and mortgage amounts and expectations when applicable.

D Appendix: Discussion of Limitations

D.A Task Module

Table 13 shows that simultaneous increases in productivity and time are concentrated in abstract and somewhat less in routine cognitive tasks, while no-change responses are especially prevalent for interactive tasks. This pattern may partly reflect a measurement limitation, as respondents may not always distinguish changes in task efficiency from changes in the amount or importance of the task performed. Although this limitation is important, several observations suggest that it may not be very consequential. First, for example, respondents who use AI for customer interaction are more likely to report simultaneous increases in productivity and time allocation in tasks related to interaction with clients, 35% compared with 22% in Table 13. The responses also vary systematically across tasks and technologies, as shown in Table F4. This suggests that responses are not driven solely by a common response pattern for productivity and time. In turn, the two

dimensions are positively but moderately correlated, with same-task correlations ranging from 0.22 for abstract tasks to 0.42 for interactive tasks. Moreover, a two-factor specification separating productivity and time allocation fits the data substantially better than a common-factor specification and yields a latent-factor correlation of approximately 0.49. Allowing for task-specific residual correlations further improves model fit, particularly for interactive tasks. These results suggest against respondents mechanically treating productivity and time allocation as the same concept. Nevertheless, the joint responses do not always permit a clear distinction between changes in task efficiency, task volume, and task importance. We therefore interpret the joint responses as descriptive evidence of perceived task adjustment, with simultaneous increases providing the clearest evidence of productive task expansion and productivity increases combined with time reductions indicating labor-saving efficiency gains.

D.B Number of Observations in Cells

Reported use of some of technologies, including AI, is close to zero in several 1- and 2-digit ISCO-08 occupations. In turn, AR/VR and 3D printing have low prevalence more generally. Accordingly, extreme estimates, including zero shares, may require cautious interpretation. This is especially relevant for some of the values reported in Tables 7, 8, F2, F5, Figure 1, and Figure 5.

E Appendix: Composition Adjusted AI Use by Occupation

To assess whether differences in AI use across occupations reflect differences in worker or technology use composition, we construct measures of raw and composition-adjusted AI use for each occupation. The raw measure is the weighted share of workers in each occupation who report using AI at work, using calibration weights from the Spanish labor force survey. Occupations are ranked according to this weighted share, with higher ranks indicating greater workplace AI use.

The adjusted measures are obtained from weighted linear probability models in which AI use is regressed on occupation dummies and alternative sets of compositional controls. We estimate 3 such specifications. The first controls for the use of other modern workplace technologies. The second controls for worker demographics, including sex, education group, and age group. The third jointly controls for other technology use and worker demographics. All specifications use calibration weights derived from the Spanish labor force survey.

For each specification, we use the estimated model to predict AI use for every occupation while averaging over the same empirical distribution of the included compositional controls. The resulting predictive margins can be interpreted as occupation-specific AI-use rates standardized to a common technology use composition, demographic composition, or both. We opt for this parametric procedure since it avoids constructing highly disaggregated composition cells, many of which would contain few or no observations within particular occupations.

F Appendix: Additional Results

Table F1: Occupations: Task Shares and Ranking, Wage Brackets, and Hours

Occupation	(1) Abstract	(2) Cognitive Routine	(3) Manual Routine	(4) Manual Non-Routine	(5) Interaction with Coworkers	(6) Interaction with Clients	(7) Wage Bracket	(8) Hours
1 Managers	0.20	0.16	0.08	0.08	0.26	0.23	2.16	36.16
2 Professionals	0.24	0.19	0.07	0.07	0.20	0.23	2.00	34.98
3 Associate Professionals / Technicians	0.27	0.20	0.07	0.06	0.22	0.18	1.93	36.24
4 Clerical Support Workers	0.17	0.23	0.10	0.08	0.25	0.17	1.52	34.63
5 Service and Sales Workers	0.11	0.18	0.10	0.09	0.33	0.19	1.52	34.34
6 Skilled Agricultural Workers	0.12	0.24	0.21	0.14	0.10	0.19	1.45	31.59
7 Craft and Related Trades Workers	0.12	0.19	0.23	0.21	0.10	0.16	1.63	36.58
8 Plant and Machine Operators / Assemblers	0.06	0.23	0.32	0.22	0.06	0.12	1.64	39.20
9 Elementary Occupations	0.09	0.24	0.19	0.20	0.11	0.17	1.38	31.29

Occupation	(9) Abstract	(10) Cognitive Routine	(11) Manual Routine	(12) Ranking Manual Non-Routine	(13) Interaction with Coworkers	(14) Interaction with Clients
1 Managers	3.22	3.25	3.13	2.41	4.45	4.53
2 Professionals	3.62	3.52	2.97	2.22	4.10	4.58
3 Associate Professionals / Technicians	3.78	3.60	2.97	2.05	4.20	4.40
4 Clerical Support Workers	2.91	3.82	3.26	2.31	4.34	4.36
5 Service and Sales Workers	2.35	3.33	3.47	2.80	4.65	4.40
6 Skilled Agricultural Workers	2.32	3.56	4.08	2.88	3.65	4.51
7 Craft and Related Trades Workers	2.37	3.31	4.08	3.65	3.39	4.20
8 Plant and Machine Operators / Assemblers	1.76	3.74	4.58	3.92	2.89	4.11
9 Elementary Occupations	1.92	3.65	3.95	3.39	3.66	4.43

Note: This table reports the average reported shares of working time spent in each task in 1-digit occupations and the average monthly net wages and usual weekly hours within occupations. It also reports the ranking of occupations within each task. For each respondent, tasks are ranked by their reported time shares, and these ranks are then averaged within occupations. All entries are computed using calibration weights derived from the Spanish labor force survey. The sample excludes unemployed and inactive respondents. It is also restricted to respondents who report their wage bracket in columns 7 and 8.

Table F2: Shapley Decomposition of Explained Variation in AI Use for 2-Digit ISCO-08 and Non-Overlapping Technologies and AI Uses

Blocks	(1) Baseline	(2) Frequencies and Number of Uses	(3) W/t Overlapping Technologies	(4) AI Uses
Sex	0.00	0.01	0.01	0.00
Education Level	0.08	0.06	0.09	0.08
Age Bracket	0.05	0.02	0.07	0.05
Firm Size	0.00	0.01	0.00	0.01
Firm Scope	0.05	0.07	0.07	0.01
Wage Bracket	0.05	0.05	0.06	0.02
Occupation 1D			0.10	0.10
Occupation 2D	0.22	0.19		
Industry 1D	0.15	0.10	0.22	0.36
Technologies	0.33	0.44	0.21	0.23
Tasks	0.06	0.05	0.07	0.06
Exposure Measures			0.10	0.08
R2	0.24	0.18	0.20	0.11
N. Obs.	6253	6253	6253	5431

Note: In columns 1 and 2, this table reports Shorrocks-Shapley decompositions of the R^2 for observed workplace AI use across blocks for sex, education, age, firm size, firm scope, wages, 2-digit occupation, 1-digit industry, other technologies, task content, and occupational AI exposure. Column (1) presents the full specification, and column (2) additionally uses weights to account for AI-use frequency and the number of reported AI uses. Specifically, the weight multiplies the AI-use indicator by the number of reported AI uses and a frequency measure ranging from 1 for daily use to 1/6 for use less than once a month and 0 for non-use. Other technologies include automation and robotics, cloud services, IoT, AR/VR, big data, 3D printing, and collaboration tools. The sample excludes unemployed and inactive respondents and is restricted to respondents who report their wage bracket. The Exposure Measures block is omitted due to collinearity with 2-digit occupation fixed effects. Column 3 and 4 use 1-digit occupation. Column 3 excludes technologies which have the greatest potential for conceptual overlap with AI from the other technologies block, keeping only IoT, AR/VR, 3D printing, and collaboration tools. Column 4 in contrast drops from the sample those who report using AI for automation, data analysis and insights, and customer interaction. The values are each block's average incremental contribution to R^2 across all possible orderings and sum to 100% of explained variation.

Table F3: The Impediments to AI Use at the Workplace

Sex	(1) Training	(2) Integration	(3) Privacy & Security	(4) Cost	(5) Resistance	(6) Fear
Male	0.44	0.33	0.41	0.20	0.25	0.16
Female	0.43	0.24	0.39	0.20	0.17	0.15
Education Level						
School Certificate	0.36	0.24	0.35	0.21	0.21	0.20
Undergrad & Prof. Tr.	0.46	0.28	0.37	0.19	0.19	0.15
Master's & PhD	0.45	0.32	0.46	0.20	0.23	0.14
Age Bracket						
18-34	0.37	0.26	0.35	0.20	0.20	0.20
35-49	0.44	0.26	0.44	0.20	0.19	0.14
50+	0.49	0.34	0.40	0.21	0.24	0.14
Firm Size						
1 to 10 people	0.41	0.23	0.34	0.21	0.14	0.16
11 to 49 people	0.39	0.27	0.35	0.20	0.25	0.17
50 people or more	0.45	0.31	0.44	0.20	0.22	0.16
Firm Scope						
Local	0.42	0.22	0.38	0.17	0.18	0.11
Regional	0.46	0.34	0.34	0.21	0.22	0.13
National	0.41	0.26	0.35	0.20	0.24	0.19
International	0.44	0.33	0.49	0.22	0.20	0.17

Note: This table offers the share of AI users reporting each perceived impediment to effective AI use. The impediments are: lack of training or knowledge, difficulty integrating AI with existing systems, privacy and security concerns, high cost, resistance to change among colleagues, and fear of job loss. The sample excludes unemployed and inactive respondents. All the reported results are computed using the calibration weights derived from the Spanish labor force survey.

Table F4: The Perceived Effect of Technologies on Productivity and Reported Effect on Time Allocation

Panel A. Data: Cloud Services and Big Data

Abstract				Routine				Manual Non-Routine				Interactive			
	Time				Time				Time				Time		
Productivity	Increased	No Change	Decreased	Productivity	Increased	No Change	Decreased	Productivity	Increased	No Change	Decreased	Productivity	Increased	No Change	Decreased
Increased	0.31	0.11	0.09	Increased	0.20	0.09	0.07	Increased	0.17	0.05	0.03	Increased	0.27	0.11	0.05
No Change	0.06	0.34	0.04	No Change	0.06	0.40	0.06	No Change	0.05	0.54	0.05	No Change	0.07	0.41	0.03
Decreased	0.01	0.01	0.03	Decreased	0.02	0.03	0.05	Decreased	0.02	0.04	0.05	Decreased	0.02	0.02	0.04
N. Obs.			1584	N. Obs.			2318	N. Obs.			587	N. Obs.			2961

Panel B. Collaboration Tools

Abstract				Routine				Manual Non-Routine				Interactive			
	Time				Time				Time				Time		
Productivity	Increased	No Change	Decreased	Productivity	Increased	No Change	Decreased	Productivity	Increased	No Change	Decreased	Productivity	Increased	No Change	Decreased
Increased	0.25	0.11	0.06	Increased	0.16	0.08	0.05	Increased	0.18	0.07	0.03	Increased	0.35	0.11	0.05
No Change	0.06	0.41	0.04	No Change	0.04	0.50	0.05	No Change	0.02	0.55	0.05	No Change	0.04	0.35	0.03
Decreased	0.01	0.02	0.03	Decreased	0.02	0.03	0.07	Decreased	0.01	0.03	0.05	Decreased	0.01	0.02	0.04
N. Obs.			1308	N. Obs.			1945	N. Obs.			562	N. Obs.			2707

Panel C. Automation: Automation and Robotics, IoT, AR/VR, 3D Printing

Abstract				Routine				Manual Non-Routine				Interactive			
	Time				Time				Time				Time		
Productivity	Increased	No Change	Decreased	Productivity	Increased	No Change	Decreased	Productivity	Increased	No Change	Decreased	Productivity	Increased	No Change	Decreased
Increased	0.30	0.12	0.08	Increased	0.25	0.09	0.06	Increased	0.21	0.07	0.06	Increased	0.24	0.06	0.03
No Change	0.05	0.22	0.06	No Change	0.06	0.26	0.08	No Change	0.06	0.34	0.08	No Change	0.05	0.36	0.07
Decreased	0.03	0.02	0.11	Decreased	0.05	0.04	0.10	Decreased	0.03	0.06	0.09	Decreased	0.03	0.05	0.09
N. Obs.			789	N. Obs.			1519	N. Obs.			583	N. Obs.			1583

Note: This table reports the joint distribution of perceived changes in productivity and time allocation associated with the technology identified as most significant in the respondent's work. Panel A groups cloud services and big data and analytics as Data. Panel B reports the results for digital collaboration tools. Panel C groups automation and robotics, IoT, AR/VR, and 3D printing as Automation. The original task categories are aggregated into abstract, routine, non-routine manual, and interactive tasks. Rows indicate whether perceived productivity increased, remained unchanged, or decreased, while columns report the corresponding change in time allocation. Each cell reports the weighted share of valid responses within the relevant technology-task group, and the cells within each distribution sum to one. The bottom row reports the number of valid respondent-task observations. Shares are calculated using calibration weights derived from the Spanish labor force survey multiplied by respondents' usual weekly working hours. The sample excludes unemployed and inactive respondents. Cells may not sum exactly to one because of rounding.

Table F5: AI Use in 2-Digit Occupations and Exposure Measures

Occupation	N. Obs.	Raw Data	Adjusted for Tech.	Adjusted for Dem.	Adjusted for Tech. & Dem.	Exposure Measures GPT-Human	GPT-Model	ILO GenAI	AIOE
11 Chief executives & senior officials	134	0.29	0.26	0.25	0.23	0.42	0.48	0.35	1.00
12 Admin & commercial managers	292	0.29	0.25	0.28	0.26	0.48	0.49	0.39	1.16
13 Production & services managers	166	0.30	0.23	0.28	0.22	0.41	0.45	0.35	0.69
14 Hospitality, retail & other services mgrs	125	0.05	0.07	0.08	0.09	0.40	0.48	0.38	0.54
21 Science & engineering professionals	334	0.35	0.26	0.27	0.21	0.50	0.55	0.41	1.02
22 Health professionals	597	0.12	0.11	0.07	0.08	0.27	0.33	0.25	0.35
23 Teaching professionals	665	0.43	0.39	0.36	0.35	0.37	0.37	0.32	0.86
24 Business & admin professionals	151	0.23	0.19	0.20	0.17	0.57	0.54	0.50	1.29
25 ICT professionals	282	0.51	0.41	0.48	0.40	0.56	0.77	0.54	1.12
26 Legal, social & cultural professionals	138	0.26	0.21	0.21	0.18	0.46	0.50	0.42	0.90
31 Science & engineering assoc. pros	130	0.35	0.30	0.29	0.26	0.27	0.36	0.29	-0.05
32 Health assoc. professionals	110	0.11	0.12	0.10	0.11	0.22	0.29	0.21	-0.13
33 Business & admin assoc. pros	211	0.22	0.17	0.20	0.17	0.50	0.58	0.47	0.95
34 Legal, social & cultural assoc. pros	168	0.18	0.15	0.14	0.13	0.30	0.34	0.30	0.04
35 ICT technicians	244	0.34	0.27	0.32	0.27	0.41	0.55	0.43	0.48
41 General & keyboard clerks	980	0.17	0.15	0.18	0.17	0.51	0.69	0.62	0.93
42 Customer services clerks	797	0.06	0.09	0.08	0.10	0.45	0.52	0.51	0.73
43 Numerical & material recording clerks	191	0.13	0.10	0.13	0.11	0.46	0.59	0.53	0.65
44 Other clerical support workers	313	0.09	0.09	0.11	0.10	0.38	0.49	0.51	0.00
51 Personal services workers	142	0.11	0.16	0.13	0.16	0.18	0.20	0.22	-0.49
52 Sales workers	474	0.09	0.12	0.10	0.12	0.33	0.28	0.36	-0.02
53 Personal care workers	102	0.05	0.11	0.09	0.13	0.22	0.24	0.20	-0.19
54 Protective services workers	148	0.04	0.07	0.07	0.09	0.28	0.30	0.17	-0.41
61 Market$_o rientedskilledagriculturalworkers$	78	0.14	0.18	0.17	0.19	0.10	0.18	0.19	-0.88
62 Market$_o rientedskilledforestry\&fisheryworkers$	14	0.04	0.09	0.05	0.08	0.09	0.14	0.14	-1.02
63 Subsistence farmers, fishers, hunters, gatherers	5	0.00	0.04	0.02	0.05	0.06	0.09	0.13	-1.37
71 Building & related trades workers	83	0.04	0.09	0.07	0.11	0.05	0.07	0.12	-1.33
72 Metal, machinery & related trades workers	148	0.02	0.04	0.04	0.05	0.07	0.10	0.16	-1.04
73 Handicraft & printing workers	79	0.23	0.22	0.23	0.22	0.15	0.26	0.23	-0.41
74 Electrical & electronic trades workers	85	0.20	0.21	0.20	0.21	0.14	0.21	0.21	-0.68
75 Food processing, woodworking, garment & related trades	88	0.10	0.15	0.13	0.16	0.11	0.15	0.18	-0.87
81 Stationary plant & machine operators	82	0.02	0.07	0.05	0.08	0.06	0.10	0.20	-0.98
82 Assemblers	18	0.00	0.04	0.02	0.06	0.04	0.11	0.29	-0.69
91 Cleaners & helpers	235	0.04	0.10	0.08	0.13	0.03	0.04	0.12	-1.54
92 Agricultural, forestry & fishery labourers	18	0.09	0.13	0.12	0.15	0.05	0.06	0.11	-1.42
93 Labourers in mining, construction, manufacturing, transport	114	0.02	0.07	0.04	0.08	0.09	0.12	0.14	-1.31
94 Food preparation assistants	118	0.09	0.13	0.11	0.14	0.01	0.01	0.16	-1.24
95 Street sales & related service workers	10	0.09	0.07	0.08	0.06	0.32	0.15	0.19	1.11
96 Refuse workers & pest controllers	15	0.00	0.03	0.05	0.06	0.23	0.22	0.18	-0.70

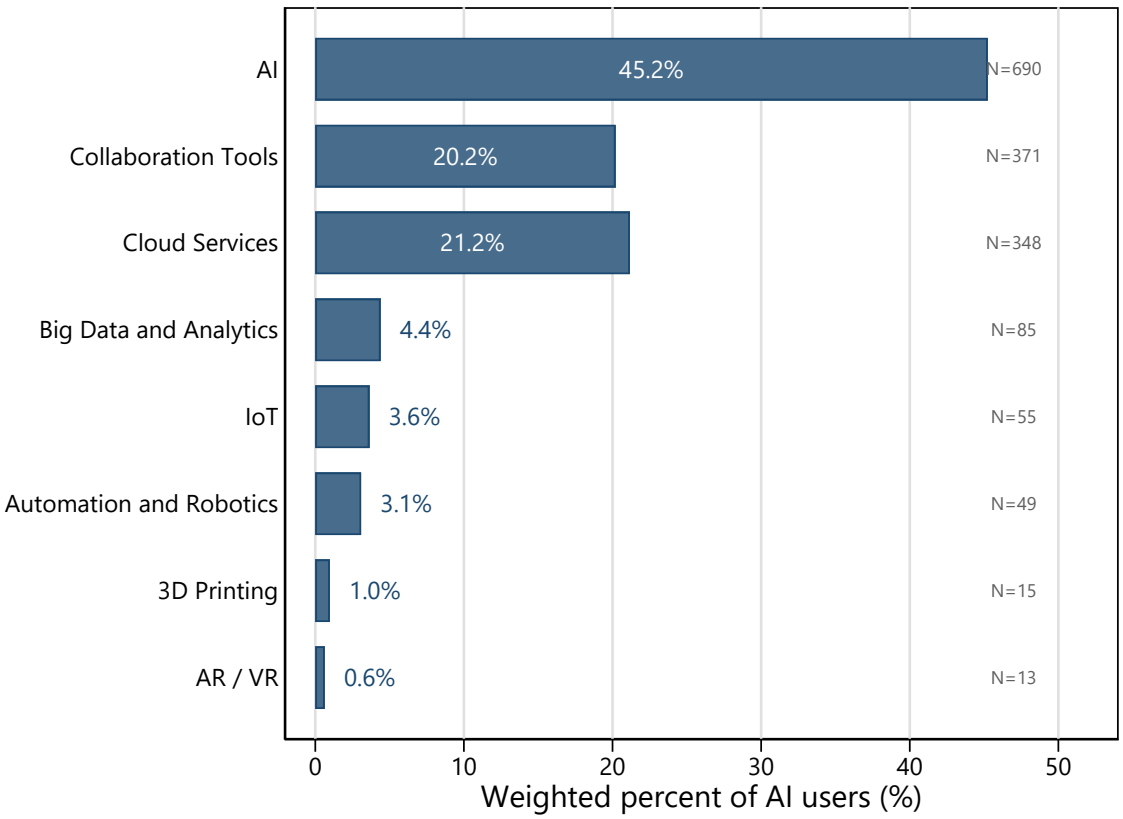
Note: This table reports observed workplace AI use and adjusted AI-use measures together with the number of observations in each 2-digit ISCO-08 occupation. It also reports measures of occupational AI exposure. Adjusted for Tech. accounts for the use of other workplace technologies. Adjusted for Dem. accounts for demographic composition within occupations. Adjusted for Tech. & Dem. accounts for both. GPT-Human and GPT-Model are based on human and GPT-4 assessments of whether LLM-powered tools can substantially reduce task-completion time (Eloundou et al., 2024). ILO GenAI is the task-based ISCO-08 exposure index of Gmyrek et al. (2025), while AIOE is the broader AI Occupational Exposure measure of Felten et al. (2021). The original exposure measures are at 3-digit ISCO-08. We average them to 2-digit ISCO-08. The sample excludes unemployed and inactive respondents. All entries are calculated using calibration weights derived from the Spanish labor force survey.

Table F6: Technology Use at the Workplace in Regions and Large Cities

Autonomous Community	(1) AI	(2) Automation and Robotics	(3) Cloud Services	(4) IoT	(5) AR / VR	(6) Big Data	(7) 3D Printing	(8) Collaboration Tools
Andalusia	0.14	0.07	0.30	0.18	0.02	0.06	0.03	0.29
Aragon	0.16	0.10	0.33	0.20	0.03	0.09	0.03	0.37
Principality of Asturias	0.11	0.07	0.30	0.15	0.01	0.05	0.01	0.31
Balearic Islands	0.11	0.05	0.26	0.16	0.01	0.08	0.01	0.36
Canary Islands	0.15	0.06	0.30	0.20	0.03	0.07	0.03	0.34
Cantabria	0.16	0.12	0.36	0.21	0.04	0.07	0.03	0.41
Castile and León	0.12	0.10	0.31	0.18	0.03	0.07	0.02	0.28
Castile-La Mancha	0.13	0.09	0.28	0.19	0.01	0.06	0.02	0.31
Catalonia	0.19	0.08	0.42	0.20	0.02	0.11	0.02	0.41
Valencian Community	0.17	0.09	0.36	0.19	0.03	0.09	0.02	0.34
Extremadura	0.12	0.06	0.28	0.11	0.03	0.05	0.02	0.31
Galicia	0.15	0.06	0.36	0.21	0.02	0.08	0.01	0.37
Madrid	0.19	0.08	0.43	0.19	0.02	0.11	0.02	0.44
Region of Murcia	0.16	0.08	0.34	0.23	0.02	0.08	0.02	0.42
Navarre	0.10	0.03	0.33	0.15	0.02	0.06	0.08	0.24
Basque Country	0.14	0.05	0.31	0.15	0.01	0.05	0.03	0.28
La Rioja	0.12	0.08	0.27	0.15	0.01	0.06	0.01	0.25
Large Cities								
Barcelona	0.23	0.04	0.47	0.20	0.02	0.12	0.01	0.47
Madrid	0.20	0.06	0.44	0.20	0.02	0.12	0.02	0.45
Malaga	0.19	0.06	0.32	0.21	0.01	0.09	0.03	0.37
Seville	0.12	0.09	0.37	0.17	0.02	0.05	0.03	0.29
Valencia	0.24	0.10	0.50	0.21	0.02	0.12	0.03	0.46
Zaragoza	0.18	0.09	0.33	0.21	0.04	0.10	0.03	0.35

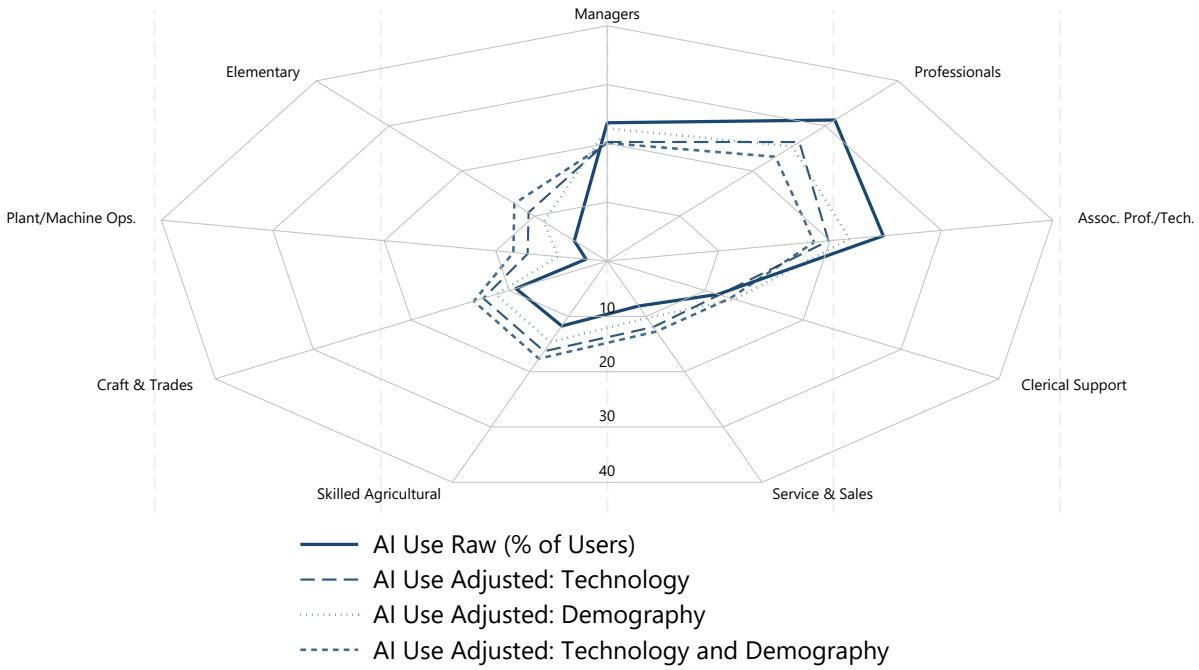
Note: This table offers the share of respondents reporting use of each modern technology category in the respondent's job. Technology-use indicators are derived from a multiple-response question covering artificial intelligence, automation and robotics, cloud services, the Internet of Things, augmented and virtual reality, big data and analytics, 3D printing, and digital collaboration tools. The upper panel reports estimates by autonomous community, and the lower panel reports estimates for cities with more than 500,000 inhabitants. The sample excludes unemployed and inactive respondents. All the reported results are computed using the calibration weights derived from the Spanish labor force survey.

Figure 3: The Most Significant Technology Among AI Users



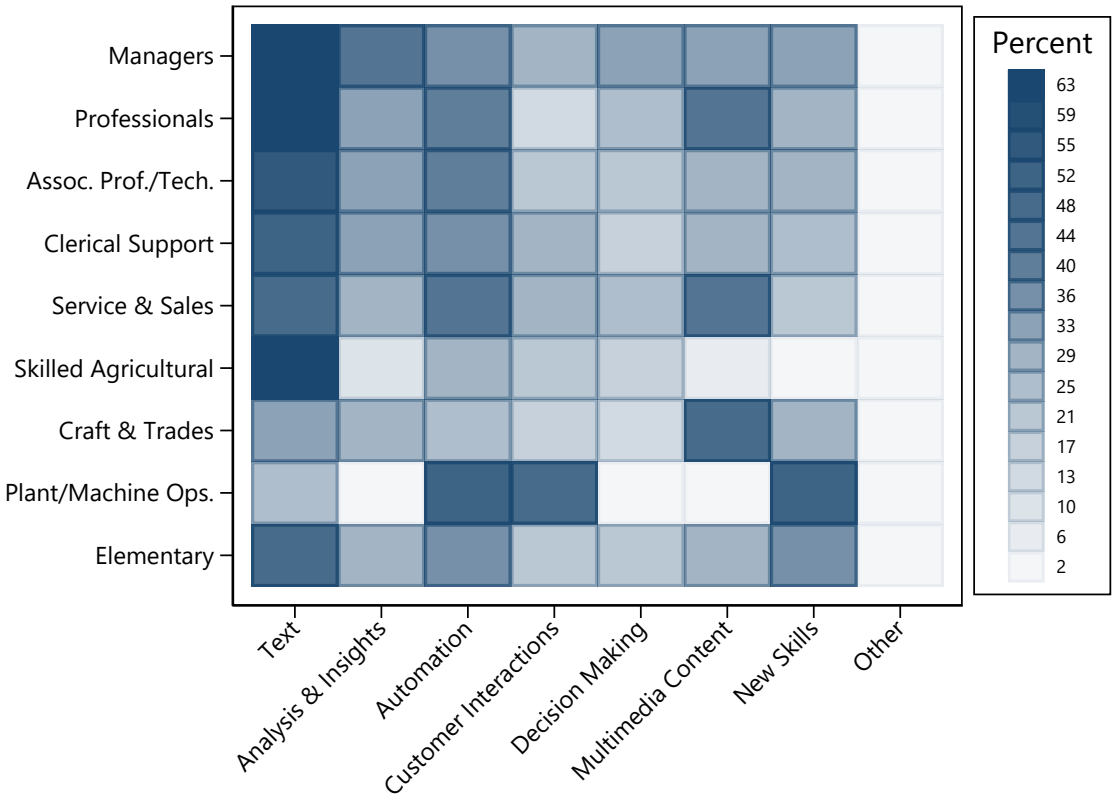
Note: This figure reports the distribution of the technology that respondents, who use AI in their job, identify as the most significant for their work. All the reported results are computed using the calibration weights derived from the Spanish labor force survey.

Figure 4: AI Use in 1-Digit Occupations: Raw and Adjusted



Note: This figure reports occupation-level AI use. Raw corresponds to the share of respondents reporting AI use within an occupation. It also reports the share of respondents reporting AI use when controlling for use of other modern technologies, demographic composition, and both. All the reported results are computed using the calibration weights derived from the Spanish labor force survey.

Figure 5: The Purpose of AI Use at the Workplace by Occupation



Note: This heatmap reports the distribution of reported purposes of AI use among respondents in their job (at work) by occupation. All the reported results are computed using the calibration weights derived from the Spanish labor force survey. Skilled agricultural workers, plant and machine operators, and elementary occupations have particularly small AI use rates. The interpretation of results for them can require a degree of caution.