Modern Technology Use at Work

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Abstract

We provide evidence from a 2025 survey of workers in Spain on workplace use of artificial intelligence (AI) and other modern technologies, including cloud services and digital collaboration tools. AI use is reported by 20% of respondents, compared with about 40% for cloud services and collaboration tools, highlighting that AI uptake is substantial but remains far from universal. Controlling for a rich set of covariates, females are significantly less likely to report AI use but more likely to report use of cloud services. Workers with a postgraduate education and workers in firms with an international scope are more likely to report AI use, while workers in larger firms are less likely to do so. The most prevalent use of AI is for text generation, and females are more likely than males to report using it for that purpose. They are less likely to report using AI, for example, to automate repetitive tasks, support decision-making, and analyze data. Workers who report AI as the most important technology in their work have significantly higher expectations of receiving a job offer within the next month, a pattern not observed for other modern technologies. Finally, although the unconditional ranking of occupation-level use of AI aligns with a skill gradient in AI use, this ranking is not invariant to accounting for the use of other technologies and within-occupation composition.

Keywords: AI, Modern Technology Use, Task Allocation, Productivity

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1 Introduction

Artificial intelligence 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, representative survey fielded in Spain in 2025 that measures workplace technology use at the individual level.

The survey covers approximately 10000 respondents. A key design feature of the survey is a conceptual separation between individual use of artificial intelligence (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. It also asks which of these technologies were introduced recently. In the AI module, we separately elicit the respondent's own AI uses, perceived impediments to effective 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 20% 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 40% of the respondents report using them at work. By contrast, the use 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 3%. About 30% of respondents report that they use none of the listed technologies in their job, underscoring that diffusion remains incomplete.

The use of these technologies varies by gender and, more significantly, by education, age, and occupation. The gender gap in AI use is modest in the descriptive tabulations, while differences are more pronounced for automation and robotics, and cloud services are slightly more common among females. Education gradients are steep, with

AI use much higher among highly educated respondents than among those with only a school-leaving certificate. Age gradients are also evident, with a higher use of AI among younger respondents and a higher reporting of "no use of these technologies" among older respondents. Occupational patterns are similarly stark, with a higher use of AI among managers, professionals, and associate professionals, and a much lower use of AI among plant and machine operators and elementary occupations.

Beyond whether AI is used, the survey documents substantial heterogeneity in how AI is used. The most common reported application is generating written content, and females report this use more frequently than males. Relative to females, males report higher use of AI for data analysis and insights, automation of repetitive tasks, and decision support, while lower use of it for multimedia content creation.

About 12% of respondents report that AI is the most significant technology in their work, while about 30% report that the most significant technology is cloud services, and another 30% report that digital collaboration tools are the most significant. These patterns suggest that, while early AI adoption was among a non-trivial share of individuals, AI was less frequently viewed as the dominant technology shaping day-to-day work than more established digital technologies. Among those who report use of AI, 42% report that it is the most significant technology in their work, while about 20% report that cloud services and another 20% report that digital collaboration tools are the most significant technologies. This indicates that AI is typically related to a broader digital technology use at the workplace, which is further confirmed with positive and significant pair-wise correlations between the reported use of these technologies.

Conditional on AI use, it is integrated into regular work routines for many users, with the majority reporting using this technology various times in a week. This reported frequency of use is remarkably similar across gender, age, education, and wage groups. In turn, among the respondents who do not use AI, a minority expects to start using AI within the next three months, a majority do not, and a large share report uncertainty, with expectations of use higher among higher-wage respondents.

These descriptive tabulations can mask important compositional differences across

groups. We therefore 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 detailed industry and occupation fixed effects. These regressions show that key patterns persist. Women remain less likely to report AI use but more likely to report cloud-services use. Higher education and the broader scope of the firm's market are strongly associated with using AI and other modern technologies. Respondents working in larger firms are more likely to report using automation and robotics technologies, collaboration tools, and big data analytics. While they are less likely to report using AI.

The use of modern technologies is positively and significantly correlated with earnings. Individuals in higher wage brackets are significantly more likely to report AI use at the workplace than those in lower wage brackets. The corresponding earnings gradients are also sizable for cloud services and collaboration tools. Taken together, these correlations suggest that early diffusion of AI and the use of other modern technologies is concentrated among higher-earning workers.

We also relate use of these technologies to the task content of jobs. We measure task content using broad categories covering abstract analytical activities, routine cognitive activities, routine and non-routine manual activities, and interactive activities with clients and coworkers. Individuals whose jobs involve a greater share of abstract and interactive tasks are significantly more likely to report using AI, cloud services, and digital collaboration tools. In contrast, individuals whose jobs are more intensive in routine manual tasks report lower AI use and higher use of robotics. These patterns are consistent with a task-based interpretation of the artificial intelligence use in the workplace.

Significant differences also remain for the different uses of AI after controlling for a rich set of covariates. For example, females are more likely than males to report using AI to generate written content, while they are less likely to report using AI to automate repetitive tasks. They are also less likely to report using AI for decision-making support, learning new skills unrelated to AI, and performing data analysis. Firm characteristics are also correlated with the composition of AI use. In particular, being in a larger firm

is associated with a lower likelihood of using AI for written content generation and for multimedia content creation. Relative to workers in firms serving primarily local markets, workers in firms operating at a broader geographic scope are substantially more likely to use AI for data analysis and insight generation.

To further assess technological complementarity at the early stage of AI diffusion, we relate the probability that AI was introduced recently to pre-existing use of other technologies, as reported by respondents. Conditional on a full set of controls, workers who report using augmented and virtual reality, big data analytics, and 3D printing are more likely to report a recent AI introduction. By contrast, the estimated association is small and statistically indistinguishable from zero for automation and robotics, cloud services, IoT, and collaboration tools, suggesting that early AI rollouts in our data are more closely linked to workplaces already engaged with frontier technologies than to workplaces that only adopted enabling digital infrastructures.

Respondents who use AI report predominantly positive effects on perceived productivity for abstract and cognitive routine tasks. For manual tasks, reported effects are smaller and more mixed, with many respondents reporting no effect. Overall, the evidence points to limited but systematic task reallocation within jobs.

In a separate module, we have elicited respondents' subjective beliefs about two very near-term labor market outcomes: receiving a job offer and being laid off in the next month. In regressions controlling for a rich set of covariates, we relate these beliefs to the technology that the respondent identifies as the most important in their job. Workers who report AI as the most important technology also report a significantly higher probability of receiving a job offer in the next month. None of the corresponding coefficients for the other technologies is statistically distinguishable from zero in the job-offer specification. By contrast, we find no robust positive association between any technology and perceived layoff risk. Overall, these results suggest that, in the early stages of AI diffusion, workers who viewed AI as central to their job were more optimistic regarding their near term job prospects.

Finally, we analyze occupation-level use of AI and how it changes once we account

for compositional differences. In the raw data, the implied ranking of occupations by the percentage of individuals reporting AI use places professionals first, followed by managers, and then associate professionals/technicians. It places clerical support workers in the middle and service and sales, craft and related trades, and skilled agricultural occupations below them. Plant and machine operators/assemblers and elementary occupations rank at the bottom. When we adjust for demographics, the exposure differences shrink and the ordering changes. In particular, managerial and professional occupations remain near the top, but several middle occupations swap positions, and the gap between high- and mid-ranked occupations narrows. When we additionally condition on the use of other workplace technologies, the ranking changes further, and the occupational differences compress further. Taken together, these patterns indicate that while the raw ranking aligns with a skill gradient in AI use, the ordering is not invariant to controls. This motivates caution in interpreting occupation-level AI use/exposure as a stand-alone shock to occupational demand when AI use is highly heterogeneous across groups and correlated with the use of other modern technologies.

The 2025 survey provides a detailed snapshot of the use of AI and other modern technologies among workers in Spain. The scheduled follow-up waves in 2026 and 2027 will generate both a panel component and repeated cross-sections. This structure will allow us to examine changes in exposure, usage, and perceived impacts over time and to assess whether differences across workers and workplace environments persist or narrow as artificial intelligence diffusion advances.

2 Related Literature (incomplete)

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. (2026) document rapid adoption in nationally oriented US surveys (Bick and Blandin, 2023) and emphasize heterogeneity by education, occupation, and earnings. 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 to infer potential productivity gains from current adoption. This survey-based evidence motivates a focus not only on whether workers interact with AI, but also on how use varies across groups and how it maps into time allocation and productivity-relevant outcomes.

Our results share several similarities with those reported by Bick et al. (2026) for the US. Consistent with their evidence, we document rapid but uneven early-stage adoption of AI, strong education and wage gradients, and a concentration of use among workers performing abstract and interactive tasks. As in their study, our evidence shows that early users integrate AI into regular workflows and perceive meaningful productivity improvements in cognitive tasks. A key difference, however, is that we observe notably lower reported rates of AI use in Spain relative to the US. Moreover, while Bick et al. (2026) emphasize worker-level gains and task reallocation, our results underscore the importance of co-use of other modern technologies and reveal substantial within-occupation heterogeneity.

There are also surveys that elicit information about AI adoption and expectations on the employer side. Bonney et al. (2024) use the US Census Bureau's Business Trends and Outlook Survey to provide high-frequency estimates of AI use by businesses and show that firm adoption was still low but rising in late 2023 and early 2024, with strong heterogeneity by sector, firm size, and firm age. They also document that non-adoption is often attributed to inapplicability and that adopters report organizational adjustments such as training and workflow changes, highlighting the role of complementary investments and organizational frictions. Related cross-country evidence from executives underscores that "adoption" and "impact" may diverge in early diffusion. Yotzov et al. (2026) survey senior executives across several advanced economies and report high rates of reported AI use alongside low weekly intensity of use by executives, limited realized impacts over recent years, and larger expected impacts over the near future, pointing to a gap between early experimentation and full organizational transformation. In a related work, Calvino et al. (2026) provide firm-level evidence across 15 OECD countries on the joint diffusion of AI, big data, IoT, robotics, and 3D printing. They document that advanced technolo-

gies tend to build on enabling digital infrastructures, such as cloud, ERP/CRM systems, and broadband, and diffusion varies strongly by sector and firm size. They also provide evidence that adopters tend to be more productive, although much of the productivity premium attenuates for AI when accounting for differences in human and technological capital, while big data and, to a lesser extent, robotics retain more robust premia. This parallel evidence reinforces our emphasis on technology co-use, and it highlights why measuring the workplace technology use and the frictions to effective use are important for interpreting adoption and productivity patterns.

A separate strand links AI investments to firm performance, innovation outcomes, and market structure using non-survey firm measures. Babina et al. (2024) propose a novel measure of firm AI investment based on AI-skilled human capital in resumes and show that firms scoring high on this measure experience higher growth in sales, employment, and market valuations. They provide evidence that effects operate primarily through product innovation and are concentrated among initially larger firms. Related macro and industry assessments, such as Chui et al. (2023) highlight potentially large global value creation from AI across industries, while emphasizing that realized gains depend on implementation and complementary investments. These results motivate our attention to workplace characteristics such as firm size and market scope when studying heterogeneity in AI use.

A related strand of work develops occupation-level measures of "AI exposure" by mapping AI capabilities to occupational task or ability content, often using U.S.-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. Svanberg et al. (2024) move beyond "exposure-as-similarity"

[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, Goos et al., 2014, Jerbashian, 2019).

by adding an explicit end-to-end cost model for computer vision automation, showing that many exposed tasks are not economically attractive to automate at firm scale even when technically feasible. Finally, Lewandowski et al. (2025) adapt the Felten et al. (2021) ability-based approach to worker task surveys (PIAAC/STEP/CULS) to obtain country-specific, task-adjusted exposure measures, emphasizing that within-occupation task variation is central for understanding cross-country differences in exposure. These measures can provide valuable proxies for where AI capabilities may matter (Bick et al., 2026), especially when measures of use of AI are not readily available.

An emerging literature links AI-related task capabilities and occupational exposure measures to realized workplace outcomes, combining task-based frameworks with evidence from field experiments. Cui et al. (2025) synthesize results from randomized field experiments in software development and document sizable productivity gains from access to an AI coding assistant, with larger adoption and larger gains among less experienced developers, highlighting the importance of task suitability and learning. Closely related evidence from a large-scale workplace deployment is provided by Brynjolfsson et al. (2025), who study the staggered rollout of a generative-AI conversational assistant in customer support and find that AI assistance increases productivity, with markedly larger gains for less experienced and lower-performing workers. They also document evidence consistent with worker learning, and they show that AI assistance improves aspects of the work experience, such as more positive customer interactions and lower attrition among newer workers.

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 disciplined upper bounds on aggregate effects, concluding that the medium-run macroeconomic gains from current AI advances are likely to be positive but modest. He also emphasizes that even when AI raises productivity in some tasks, the distributional implications need not be equalizing. Aggregate wage gains may be limited, the capital share may rise, and inequality can increase even when

low-skill workers benefit in specific tasks. Filippucci et al. (2024) develop a micro-to-macro framework that combines evidence on exposure, adoption, and micro performance with sectoral linkages and project positive but moderate aggregate productivity gains, emphasizing that uneven diffusion and frictions can materially dampen aggregate effects. On the worker side, 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, with heterogeneous wage effects by skill.

Our survey contributes to this literature by providing direct, individual-level measures of workplace use of AI and other modern technologies in a representative sample for Spain. The survey further documents heterogeneity in the purposes of AI use, perceived impediments to its effective use, and perceived impacts on productivity and time allocation across broad task categories. The survey also documents firm characteristics, near-term labor-market expectations, and remote work arrangements. Our findings underscore that, at this stage of diffusion, AI use varies systematically across demographic groups, education and wage brackets, firm size and scope, as well as across occupations and industries. There is also substantial variation in the use of AI across the demographic groups within occupations. In addition, reported use across AI and other modern technologies is highly correlated, consistent with complementary use of these technologies.[2] Our findings indicate that the unconditional ranking of occupations in terms of the percentage of individuals reporting use of AI aligns well with a skill gradient. However, this ranking is not invariant to accounting for the use of other modern technologies and within-occupation composition. Looking ahead, the planned 2026 and 2027 follow-up waves will add both a panel component and repeated cross-sections, enabling within-person analyses of changes in workplace technology use, AI applications, perceived impediments, and perceived impacts over time.

[2] Jerbashian (2025) provides estimates of the elasticity of substitution between information and communication technologies (ICT) and intellectual property (IP) capital, which includes software and databases. He finds that these types of modern technologies are gross complements in production.

3 Data Sources and Measurement

Our empirical analysis is based on a unique, nationally oriented 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. Approximately 2500 completed interviews in February 2025 and approximately 7500 completed interviews in April 2025, yielding about 10000 completed interviews in total.

The sample is designed to be nationally representative for Spain and is constructed using quota-based stratification by territory and major demographic groups. The achieved distributions are close to the target quotas along these key dimensions.

Netquest operates a closed, invitation-based panel, with documented recruitment sources, explicit consent procedures, and standardized panel management protocols consistent with ISO norms for online access panels. In particular, ISO 26362 emphasizes transparent recruitment, active-panel definitions, auditable sampling procedures, and multi-criterion fraud detection (e.g., speed checks and consistency checks), all of which inform Netquest's panel operations and data-validation practices. In addition, Netquest's panel documentation describes extensive profiling and the use of panelist management systems to minimize unnecessary invitations and support efficient sampling. The questionnaire is fully documented and available in the Questionnaire Appendix.

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 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.

For the relevant job, the survey measures usual weekly hours and 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. 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, with responses bounded between zero and one hundred, and an adding-up constraint that reported shares do not exceed one hundred in total. These task measures are intended to capture broad differences in job content rather than precise time allocation. Responses are provided as percentages bounded between zero and one hundred. This is currently a limitation in the survey because of the variables are not mutually exclusive. We treat these categories as ordinal scale variables in the analysis. In waves from 2026 and 2027, we will ask a question with frequency: e.g., how important are analytical tasks at work, a lot, a little, etc. Despite these limitations, the task measures are well correlated with occupations.

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 systems 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 use of it by the respondent using an ordered scale ranging from daily use to less-than-monthly use.

3.3 AI-Specific Measurement

The survey contains a dedicated module focused on different uses of AI. Among respondents who report that AI is used at their job, the survey records the purposes for which they have used AI on the job. The response format allows multiple selections. Respondents are asked whether they have used AI to generate written content such as reports, articles, or emails. They are asked whether they have used AI to perform data analysis and generate insights. They are asked whether they have used AI to automate repetitive tasks such as programming or data entry. They are asked whether they have used AI

to improve interactions with customers, including through tools such as chatbots or virtual assistants. They are asked whether they have used AI to support decision-making processes. They are asked whether they have used AI for the design and creation of multimedia content. They are asked whether they have used AI to learn new skills that are not directly related to AI itself.

The module measures the frequency with which respondents use AI at work using an ordered scale that ranges from daily use to less-than-monthly use. For respondents who do not report AI use at the workplace, the survey elicits expectations about whether they will use AI at work in the next three months.

Perceived impediments to effective AI use are captured 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.

3.4 Measurement of Impacts on Work

The survey measures perceived impacts of technology, eliciting information regarding its impact on perceived 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, decreased, or did not change. The survey treats tasks that are not performed as not applicable and is designed to ask these questions only when the respondent reports positive time spent in the corresponding task category. When AI is used at the workplace but is not selected as the most significant technology, the survey repeats the same productivity and time-allocation questions specifically for AI.

3.5 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.

4 Results

We begin by documenting the sample. According to Table 1, the survey yields a near-even gender split, and it covers a wide education distribution with substantial mass in the undergrad and professional-training category and sizable groups at both the school-leaving certificate and master's/PhD levels. The distribution across labor-market statuses is also sensible, with full-time employees forming the largest group, followed by part-time employees and the self-employed. Industry and occupation coverage in the survey is broad, as shown in Table 2 and Table 3. The occupational task profiles also look coherent. According to Table 3, managers and professionals report higher shares of abstract and cognitive tasks, while plant and machine operators report much higher manual routine intensity and relatively low interaction shares, and service and sales workers report comparatively high interaction intensity with clients and coworkers. Finally, average hours and wage brackets across groups align relatively well with standard labor-market patterns according to Table 4.

We then document the overall prevalence of modern technologies used at work. Workplace use of modern technologies is widespread but uneven across technology types. According to Table 5, about 20% 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 40% of the respondents report using them at work. By contrast, the

use 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 3%. About 30% of respondents report that they use none of the listed technologies in their job, underscoring that diffusion remains incomplete.

The descriptive tabulations in Table 6 show that the use of these technologies varies significantly by gender, education, age, and occupation. The gender gap in the use of AI in the workplace is modest in these tabulations. Males report using automation and robotics technologies more than females, 11% versus 6%, while the use of cloud services is slightly higher among females, 45% versus 40%. The education gradient is especially pronounced for AI, cloud services, and collaboration tools. Among respondents with school-leaving certificate, reported AI use is 8%, compared with 37% among those with a master's or doctorate. The corresponding figures are 23% versus 60% percent for cloud services and 24% versus 62% percent for collaboration tools. Reported AI use is 30% among respondents up to 35 years old and falls to 18% and below among those above age 45, while the share reporting use of "none of these technologies" rises from 24% to 35% across the same age range. Occupational patterns are similarly stark. Managers, professionals, and associate professionals report the highest use of AI and other modern technologies, whereas elementary occupations and plant and machine operators report much lower use of AI and a much higher incidence of use of none of these technologies.

Table 7 summarizes the joint contribution of broad covariate blocks to explaining variation in reported AI. The ANOVA results show that demographics, education and wage brackets, firm characteristics, and industry and occupation fixed effects are jointly significant predictors of AI use. They also indicate that the reported use of other modern technologies is a statistically significant correlate of reported AI use. Table 8 shows that these results about the explanatory contribution of demographic variables, education and wage brackets, and firm characteristics are robust to including more detailed 2-digit occupation fixed effects.

There is a substantial heterogeneity in the purposes for which workers use AI according to Table 9. The most commonly reported application is generating written content,

reported by 56% of men and 62% of women. Males are more likely to report using AI for data analysis and insights, at 39% versus 28% for females, and for automating repetitive tasks, at 44% versus 33%. Males are also more likely to report using AI for decision support, at 28% versus 19%, whereas females are more likely to report using AI for multimedia content creation, at 37% versus 31%.

About 12% of respondents report that AI is the most significant technology in their work, while about 30% report that the most significant technology is cloud services, and another 30% report that digital collaboration tools are the most significant, as reported in Table 10. These patterns suggest that, while early AI adoption was among a non-trivial share of individuals, AI was less frequently viewed as the dominant technology shaping day-to-day work than more established digital technologies. Among those who report use of AI, 42% report that it is the most significant technology in their work, while about 20% report that cloud services and another 20% report that digital collaboration tools are the most significant technologies as reported in Figure 5 and column 2 of Table 10. This indicates that AI is typically related to a broader digital technology use at the workplace, which is further confirmed with positive and significant pair-wise correlations between the reported use of these technologies reported in Table 11.

Conditional on reporting AI use at work, the intensity of use is remarkably similar across gender, age, education, and wage groups. According to Table 12, roughly one quarter of AI users report daily use and about two-fifths report using AI various times in a week across essentially all groups. In addition, 52% of employees report that they have suggested using AI at their job, while 45% report that the firm has suggested that (Table 13). Among those who did not use AI at the moment of the survey, 12% expected to use it during the next 3 months, 53% did not expect to do so, and another 35% could not say, reflecting the novelty and uncertainty surrounding these technologies (Table 14). There is considerable heterogeneity in these expectations across age, education, and wage groups, with higher expectations for use among younger, more educated, and higher-wage individuals.

These descriptive tabulations can mask important compositional differences across

groups. We therefore 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 detailed industry and occupation fixed effects. Table 15 reports the results. Females remain significantly less likely than males to report use of AI and automation/robotics at the workplace. The estimated female differential is -3.9 percentage points for AI and -3.1 percentage points for automation/robotics. They are more likely to report use of cloud services and Internet of Things (IoT) than males. The estimated female differential is 4.3 percentage points for cloud services and 3.8 percentage points for IoT.

Educational gradients across technologies persist and are pronounced in these regressions. Relative to holding a school-leaving certificate, holding a postgraduate and PhD degree is associated with a 9.6 percentage point increase in the likelihood of use. The corresponding increases are even larger for cloud services, 6.3 and 14.2 percentage points, and collaboration tools, 6.4 and 14.7 percentage points.

Firm characteristics are also strongly correlated with the reported use of these technologies at the workplace. Conditional on the full set of controls, as compared to small firms, being employed in a firm with fifty or more employees is associated with a 3.6 percentage point decline in the likelihood of using AI. It is also associated with an increase of 4.4 percentage points in the use of automation and robotics, 6.6 percentage points in the use of collaboration tools, and 4.5 percentage points in the use of big data analytics. Compared to firms serving primarily local markets, national scope is associated with a 5.7 percentage points higher reported use of AI. It is also associated with about an 8 percentage points increase in the use of cloud services and digital collaboration tools, and an increase of 4.4 percentage points in the use of big data and analytics. International scope is associated with substantially larger differences. This includes a 14 percentage points higher use of AI, 18.1 percentage points higher use of cloud services, 11 percentage points higher use of big data and analytics, and 17.6 percentage points higher use of collaboration tools.

AI use is positively and significantly correlated with earnings. Individuals in higher

wage brackets are significantly more likely to report artificial intelligence use at the workplace than those in lower wage brackets. The corresponding earnings gradients are also sizable for cloud services and collaboration tools, consistent with the broader pattern that advanced digital workplace environments are more prevalent among higher-earning workers. Taken together, these correlations suggest that early diffusion of AI and related digital technologies is concentrated among higher-earning workers. These results reflect a correlation. Investigating, for example, the causal relationship between use of AI and earnings would be important, as it could reveal whether early AI adoption reinforces existing earnings disparities, at least in the short run.

We also relate workplace technology exposure to the task content of jobs. We measure task content using broad categories covering abstract analytical activities, routine cognitive activities, routine and non-routine manual activities, and interactive activities with clients and coworkers. Individuals whose jobs involve a greater share of abstract and interactive tasks are significantly more likely to report using artificial intelligence, cloud services, and digital collaboration tools. In contrast, individuals whose jobs are more intensive in routine manual tasks report lower artificial intelligence use and higher use of robotics. Regression results show robust correlations between artificial intelligence use and the intensity of abstract cognitive tasks and interactive tasks with coworkers and clients, and negative correlations with routine manual work. These patterns are consistent with a task-based interpretation of the artificial intelligence use in the workplace.

Significant differences also remain for the different uses of AI after controlling for a rich set of covariates according to the regression results reported in Table 16. For example, women are 8 percentage points more likely than men to report using AI to generate written content, while they are 9 percentage points less likely to report using AI to automate repetitive tasks. They are also 8 percentage points less likely to report using AI for decision-making support, and about 6 percentage points less likely to report using AI for analysis and insights, and learning new skills unrelated to AI. Firm characteristics are also correlated with the composition of AI use. In particular, being in a workplace with fifty or more employees is associated with an 11.8 percentage point lower probability

of using AI for written content generation and an 18.3 percentage point lower probability of using AI for multimedia content creation. Relative to workers in firms serving primarily local markets, workers in firms operating at a broader geographic scope are substantially more likely to use AI for data analysis and insight generation. In particular, workers in firms operating in regional, national, and international markets are 10, 12, and 17 percentage points more likely, respectively, to report using AI for analysis and insights.

To further assess technological complementarity at the early stage of AI diffusion, we relate the probability that AI was introduced recently to pre-existing use of other technologies, as reported by respondents. Table 17 reports the results from regressions that include a full set of controls. Workers who report using augmented and virtual reality are 13.0 percentage points more likely to report a recent AI introduction, those using big data analytics are 8.9 percentage points more likely, and those using 3D printing are 12.4 percentage points more likely. By contrast, the estimated association is small and statistically indistinguishable from zero for automation and robotics, cloud services, IoT, and collaboration tools, suggesting that early AI rollouts in our data are more closely linked to workplaces already engaged with frontier technologies than to workplaces that only adopted enabling digital infrastructures. Demographic and workplace correlates also exhibit systematic heterogeneity. Women are about 3.4 to 3.9 percentage points less likely to report a recent AI introduction, older workers report substantially lower probabilities of recent introduction, and larger firms are about 5 to 6 percentage points less likely to report a recent introduction. In contrast, international scope and being in the top wage bracket are each associated with roughly 4 to 5 percentage points higher probabilities of reporting a recent AI introduction.

We also examine perceived impediments to effective AI use using regressions reported in Table 18, which condition on the same rich set of covariates. The most salient demographic pattern is a gender difference in integration concerns. The coefficient in the female row of Table 18 for "integration difficulty" is negative and statistically significant, indicating that females are less likely than males to report integration with existing systems as a barrier. The coefficient in the row for the oldest age group in Table 18 is positive

and statistically significant for the "training" impediment, consistent with older workers being more likely to cite lack of training or knowledge as a barrier. Finally, the coefficient on the international scope of the firm Table 18 is positive and statistically significant for "privacy/security," implying that workers in firms with international markets are more likely to cite privacy and security concerns as impediments to AI use.

Respondents who use AI report predominantly positive effects on perceived productivity for abstract and cognitive routine tasks according to Table 19. For manual tasks, reported effects are smaller and more mixed, with many respondents reporting no effect. More specifically, for abstract tasks, about 50% of responses indicate increased productivity, compared with about 10% indicating decreases and about 20% indicating no effect. For routine cognitive tasks, about 36% report increases, 10% report decreases, and 30% report no effect. For manual tasks, the share reporting productivity gains is lower, and "no effect" is more common as compared to cognitive tasks. In interactive tasks, the use of AI is more often associated with reported productivity gains than losses. Particularly for coworker interactions, about 26% report productivity gains versus 8% report losses, and 36% report no effect. In turn, reported effects on time allocation are muted except for abstract and interactive tasks and when the respondent identifies AI as the most significant technology at work. In this case, for abstract tasks, roughly 39% report spending more time because of using AI, and 30% report spending less time. For interactive tasks, roughly 18% report spending more time because of using AI, and more than 55% report spending less time. Overall, the evidence points to limited but systematic task reallocation within jobs. These findings are based on self-reported perceptions, but not on direct measures of productivity.

In a separate module, we have elicited respondents' subjective beliefs about two very near-term labor market outcomes: receiving a job offer and being laid off in the next month. In regressions controlling for a rich set of covariates, we relate these beliefs to the technology that the respondent identifies as the most important technology in their work. Table 20 reports the results. Workers who report AI as the most important technology also report a 4.4 percentage point higher probability of receiving a job offer

in the next month. None of the corresponding coefficients for the other technologies is statistically distinguishable from zero in the job-offer specification. By contrast, in the layoff-expectations specification, we find no robust positive association between any technology and perceived layoff risk. Overall, these results suggest that, in the early stages of AI diffusion, workers who viewed AI as central to their work were more optimistic regarding their job prospects in the very near term.

Finally, we examine occupational exposure to AI and how the relative ranking of occupations changes once we account for the use of other modern technologies and for compositional differences in demographics and education within occupations. Conditioning on the use of other technologies is particularly relevant, as technology uses tend to be correlated and often complementary.[3] In this sense, a raw ranking based solely on the share of workers using AI represents one conceptual extreme: it abstracts from complementarities across technologies and from correlated shocks to their adoption. At the opposite extreme lies a ranking that fully conditions on the use of other modern technologies, thereby purging AI exposure of correlations with the broader technological environment. The true exposure of occupations likely lies between these two benchmarks.

Table 22 presents the results for 1-digit ISCO-08 occupations. In the raw data, professionals exhibit the highest reported AI use, followed by managers and then associate professionals and technicians. Clerical support workers fall in the middle of the distribution, while service and sales workers, craft and related trades workers, and skilled agricultural workers appear below them. Plant and machine operators/assemblers and elementary occupations record the lowest levels of AI use.

Adjusting for the use of other modern technologies compresses the variance across occupations and alters the ordering. Managerial and professional occupations remain among the most exposed, but several mid-ranked occupations shift positions, and the gap between the upper and middle tiers narrows noticeably. A similar pattern emerges when adjusting solely for demographic composition. When we jointly adjust for both the use of other technologies and demographic composition, the dispersion in exposure

[3]For example, Jerbashian (2025) estimates the elasticity of substitution between ICT and intellectual property (IP) capital and finds that these technologies are gross complements.

declines further, and the resulting ranking remains closer to—but still distinct from—the raw ordering. Comparable patterns appear at the 2-digit level in Table 23. In that case, the ranking deviates more substantially from the raw ordering, especially among occupations that exhibited low raw exposure.

Taken together, these findings indicate that although the raw occupational ranking aligns with a clear skill gradient in AI use, this gradient is not invariant to compositional differences or to the correlated adoption of other workplace technologies. The evidence, therefore, cautions against interpreting the raw occupation-level distribution of AI use as a stand-alone shock to occupational demand at this early stage of AI adoption, when it remains uneven and sensitive to within-occupation heterogeneity.

5 Conclusions

This paper provides new evidence on workplace use of modern technologies among individuals in Spain using a bespoke, representative survey fielded in 2025. In particular, the survey measures workplace use of artificial intelligence (AI), automation and robotics, cloud services, the Internet of Things, big data analytics, augmented and virtual reality, 3D printing, and digital collaboration tools. It also records which technology respondents view as most significant for their work. In a separate module for AI, the survey further measures the purposes of its use, perceived impediments to effective AI use, and perceived impacts of AI on productivity and time allocation across broad task categories.

AI use is already substantial but far from universal, according to our data. In our data, 20% of respondents report using AI at work, compared with roughly 40% reporting use of cloud services and digital collaboration tools, while about 30% report using none of the listed technologies. Reported use across technologies is positively correlated. Moreover, regressions relating recent AI introduction to pre-existing technology use suggest that early AI use is more tightly linked to the use of other frontier technologies. Together, these patterns support an interpretation in which early AI use and adoption are bundled with complementary technologies.

AI use is highly heterogeneous across workers, jobs, and firms, and this heterogeneity extends beyond whether AI is used to how it is used. In descriptive tabulations, adoption varies systematically with education, age, earnings, and occupation, with managers, professionals, and associate professionals reporting substantially higher AI use than more manual and elementary occupations. Conditional on adoption, the reported frequency of AI use is relatively similar across demographic and wage groups, consistent with AI being integrated into regular work routines for many users. The most prevalent reported AI application is text generation, and the composition of AI use differs by gender, with women more likely to report text generation and less likely to report uses such as automation of repetitive tasks, decision support, and data analysis. Regression results confirm that these patterns persist after conditioning on a rich set of covariates, including detailed industry and occupation fixed effects, and they highlight additional workplace correlates such as firm scope and firm size.

Perceived impacts of AI indicate meaningful, but nuanced, early-stage effects. Respondents who use AI report predominantly positive perceived productivity effects for abstract and routine cognitive tasks, while effects for manual tasks are smaller and more mixed, and reported time-allocation effects suggest limited but systematic within-job task reallocation, especially when AI is identified as the most significant technology at work.

In the near-term expectations module, workers who identify AI as the most important technology in their work report higher expectations of receiving a job offer within the next month, while there is no robust positive association with the other modern technologies, as well as the perceived layoff risk. Among non-users, expectations of adopting AI within the next three months exhibit substantial uncertainty. These patterns suggest that workers who use AI and view it as central to their job perceive themselves as well-positioned in the near-term labor market. At the same time, the substantial uncertainty among non-users highlights that expectations about future AI integration remain fluid and weakly anchored, reflecting both limited information and uneven adoption across jobs. Together, these findings suggest that early AI diffusion can temporarily widen perceived opportunity gaps, even before measurable labor-market outcomes diverge.

In the raw data, the ranking of occupations by AI use aligns well with a skill gradient, though the ordering is sensitive to accounting for the use of other modern technologies and compositional differences within occupations. This evidence suggests that occupation-level AI use is intertwined with the use of other modern technologies. Taken together, these patterns could motivate a cautious interpretation of the raw occupation-level distribution of AI use as a stand-alone shock to occupational demand, at least in the early stages of AI adoption.

Looking ahead, the planned follow-up waves in 2026 and 2027 will add both a panel component and repeated cross-sections. This structure will allow within-person analyses of changes in workplace technology use, AI applications, training and impediments, and perceived impacts over time, and it will enable a sharper assessment of whether heterogeneity across workers and firms persists or narrows as adoption advances.

6 Tables

Table 1: Sample Composition

	N. Obs.		N. Obs.
Sex		Education Level	
Male	4571	School Certificate	2032
Female	4724	Undergrad & Prof. Training	5444
		Master's & PhD	1819
Age Bracket		Labor Status	
[18,24]	548	Full-time Employee	6266
[25,34]	1410	Part-Time Employee	1036
[35,44]	2002	Unemployed	563
[45,54]	2362	Self-Employed	787
>55	2684	Inactive	638
Firm Scope		Firm Size	
Local	2567	1 to 10 People	2116
Regional	1863	11 to 49 People	1640
National	2244	50 People or More	5163
International	1672		
Wage Bracket			
< 1500	2630		
[1500,2500]	2658		
>2500	2128		

Note: This table reports basic sample composition by sex, education level, age bracket, labor-market status, firm scope, firm size, and net monthly wage bracket. The sample consists of respondents in Spain interviewed in 2025. Wage brackets are reported in monthly net euros. Firm scope is self-reported on an ordered scale from local to international, and firm size is reported in employment bins.

Table 2: Sample Composition: Industries

Industry 1D	N. Obs.
Agriculture, Forestry and Fishing	206
Manufacturing, Mining and Quarrying	430
Utilities	145
Construction	375
Wholesale and Retail trade	302
Transportation and Storage	376
Accommodation and Food Service Activities	369
Information and Communication	387
Financial, Insurance, and Real Estate Activities	407
Professional, Scientific and Technical Activities	601
Administrative and Support Service Activities	380
Public Administration	761
Education	914
Human Health and Social Work Activities	835
Arts, Entertainment and Recreation	229
Other Service Activities	1629

Notes: This table reports the distribution of respondents across 1-digit NACE Rev.2 industries for the relevant job (current job for employed respondents and last significant job otherwise).

Table 3: Sample Composition: Occupations

Occupation 1D	N. Obs.	(1) Abstract	(2) Cognitive Routine	(3) Manual Routine	(4) Manual Non-Routine	(5) Interaction with Coworkers	(6) Interaction with Clients	(7) Wage	(8) Hours
1 Managers	736	21.53	16.10	7.30	7.30	26.00	22.37	2.29	41.28
2 Professionals	2205	25.41	19.71	6.74	6.74	19.57	22.34	2.10	38.02
3 Associate Professionals / Technicians	880	27.76	20.38	7.31	7.31	20.13	19.06	2.00	38.70
4 Clerical Support Workers	2350	18.64	23.64	9.18	9.18	24.53	17.35	1.59	37.61
5 Service and Sales Workers	910	11.96	17.83	9.93	9.93	32.62	18.28	1.59	38.28
6 Skilled Agricultural Workers	108	12.17	23.11	18.66	18.66	10.33	21.86	1.43	41.55
7 Craft and Related Trades Workers	505	12.89	18.74	23.11	23.11	9.76	16.31	1.74	39.98
8 Plant and Machine Operators / Assemblers	104	8.72	22.56	32.51	32.51	6.57	10.67	1.69	40.27
9 Elementary Occupations	547	8.77	26.29	20.10	20.10	10.76	16.73	1.43	36.86

Notes: This table reports the distribution of respondents across 1-digit ISCO-08 occupations and summarizes average reported task content by occupation. Task measures are based on respondents' self-reported time shares allocated to abstract analytical tasks, routine cognitive tasks, routine and non-routine manual tasks, and interactions with coworkers and clients. The table also reports the average wage bracket and usual weekly hours by occupation.

Table 4: Wage Bracket by Group

	Wage	Hours		Wage	Hours
Sex			Labor Situation		
Male	1.99	39.76	Full-Time Employee	1.88	39.16
Female	1.65	37.02	Part-Time Employee	1.17	26.91
			Self-Employed	2.13	42.33
Age Bracket			Firm Scope		
[18,24]	1.44	35.69	Local	1.63	36.97
[25,34]	1.71	38.08	Regional	1.88	38.47
[35,44]	1.81	38.24	National	1.87	38.78
[45,54]	1.83	38.65	International	1.99	39.95
>55	2.00	38.99			
Education Level			Firm Size		
School Certificate	1.58	38.23	1 to 10 People	1.70	38.94
Undergrad & Prof. Training	1.80	38.39	11 to 49 People	1.74	38.17
Master's & PhD	2.14	38.80	50 People or More	1.90	38.35

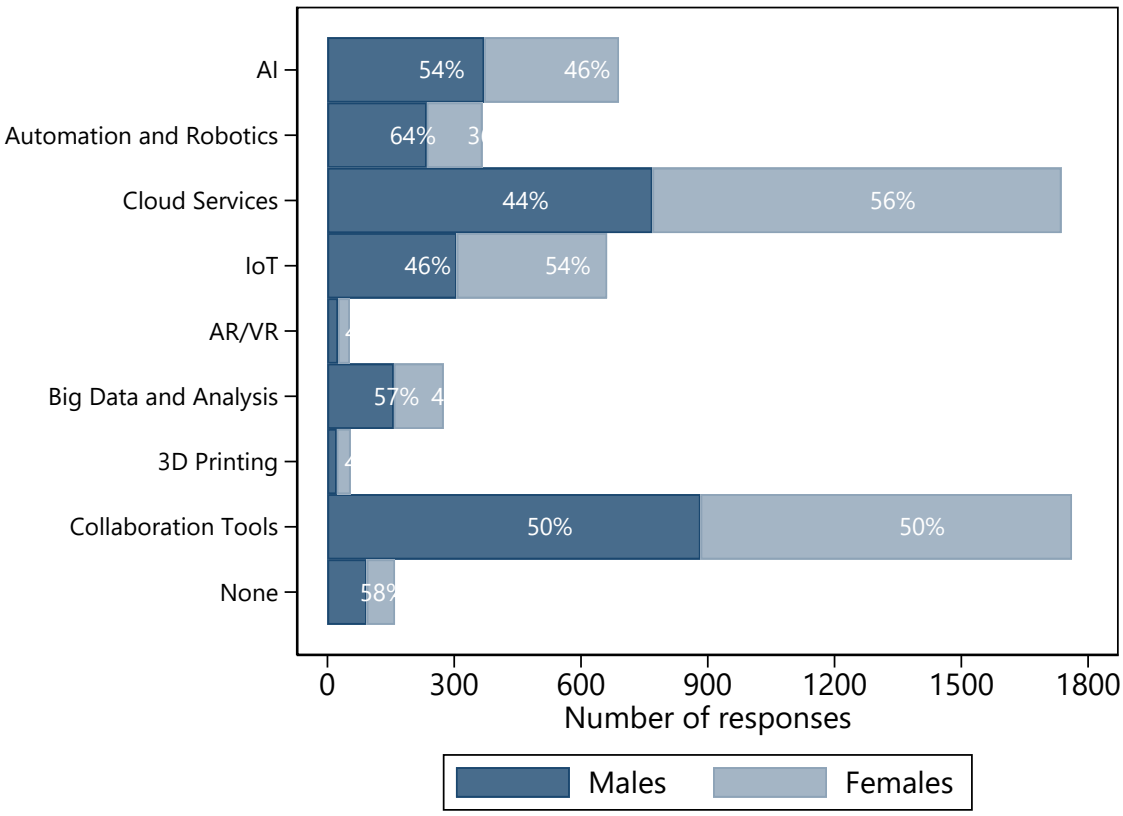
Note: This table reports mean wage bracket (coded as 1 for <1500, 2 for [1500,2500], and 3 for >2500 euros) and usual weekly hours across key demographic and job groups. Wage and hours refer to the respondent's relevant job (current job for employed respondents and last significant job otherwise).

Table 5: Technology Use at the Workplace

N. Obs.	8338	Introduced Last 3 Months
	Frequency	Frequency
1. AI	0.20	0.51
2. Automation and Robotics	0.09	0.27
3. Cloud Services	0.42	0.16
4. IoT	0.20	0.17
5. AR / VR	0.03	0.31
6. Big Data	0.11	0.15
7. 3D Printing	0.03	0.24
8. Collaboration Tools	0.43	0.15
9. None	0.30	0.31

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.

Figure 1: Most Significant Technology Used at the Workplace



Notes: 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. Technologies correspond to the categories in the technology-use module (AI, automation and robotics, cloud services, IoT, AR/VR, big data and analysis, 3D printing, and digital collaboration tools), with an additional category for respondents reporting that none of the listed technologies are used. Responses refer to the respondent's relevant job (current job for employed respondents and last significant job otherwise).

Table 6: Technology Use at the Workplace by Groups

	1. AI	2. Automation and Robotics	3. Cloud Services	4. IoT	5. AR / VR	6. Big Data and Analysis	7. 3D Printing	8. Collaboration Tools	9. None
Sex									
Male	0.21	0.11	0.40	0.19	0.03	0.13	0.04	0.44	0.30
Female	0.19	0.06	0.45	0.21	0.02	0.10	0.02	0.43	0.30
Education Level									
School Certificate	0.08	0.07	0.23	0.18	0.01	0.05	0.01	0.24	0.49
Undergrad & Prof. Training	0.18	0.09	0.42	0.20	0.02	0.11	0.03	0.43	0.30
Master's & PhD	0.37	0.09	0.60	0.22	0.05	0.19	0.04	0.62	0.14
Age Bracket									
[18,24]	0.29	0.19	0.41	0.21	0.04	0.17	0.06	0.33	0.23
[25,34]	0.28	0.09	0.50	0.20	0.03	0.16	0.03	0.49	0.22
[35,44]	0.24	0.11	0.47	0.21	0.03	0.14	0.03	0.47	0.27
[45,54]	0.18	0.07	0.39	0.19	0.02	0.10	0.03	0.42	0.32
>55	0.13	0.06	0.38	0.20	0.02	0.07	0.02	0.40	0.35
Occupation 1D									
1 Managers	0.29	0.11	0.54	0.23	0.03	0.17	0.04	0.51	0.18
2 Professionals	0.32	0.09	0.54	0.22	0.04	0.15	0.04	0.55	0.19
3 Associate Professionals / Technicians	0.27	0.08	0.57	0.22	0.02	0.18	0.02	0.60	0.17
4 Clerical Support Workers	0.14	0.05	0.43	0.19	0.02	0.09	0.01	0.42	0.29
5 Service and Sales Workers	0.09	0.04	0.23	0.18	0.01	0.07	0.01	0.26	0.48
6 Skilled Agricultural Workers	0.06	0.17	0.16	0.14	0.00	0.09	0.00	0.17	0.55
7 Craft and Related Trades Workers	0.13	0.19	0.20	0.20	0.02	0.05	0.06	0.27	0.44
8 Plant and Machine Operators / Assemblers	0.03	0.20	0.15	0.14	0.02	0.03	0.03	0.15	0.52
9 Elementary Occupations	0.05	0.11	0.11	0.12	0.02	0.02	0.02	0.12	0.64

Note: This table reports the share of respondents reporting use of each modern technology category in the respondent's job. 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. The table reports subgroup means by sex, education, age, and occupation.

Table 7: ANOVA for AI Use

Source	Partial SS	df	MS	F	P-stat
Model	218.894	44	4.975	38.670	0.000
Sex	1.126	1	1.126	8.750	0.003
Education Level	2.678	2	1.339	10.410	0.000
Age Bracket	8.517	4	2.129	16.550	0.000
Firm Size	2.082	2	1.041	8.090	0.000
Firm Scope	6.821	3	2.274	17.670	0.000
Wage Bracket	4.591	2	2.296	17.840	0.000
Occupation 1D	4.173	8	0.522	4.050	0.000
Industry 1D	31.382	15	2.092	16.260	0.000
Automation and Robotics	1.356	1	1.356	10.540	0.001
Cloud Services	9.750	1	9.750	75.780	0.000
IoT	0.068	1	0.068	0.530	0.468
AR / VR	3.122	1	3.122	24.260	0.000
Big Data	11.031	1	11.031	85.740	0.000
3D Printing	2.924	1	2.924	22.730	0.000
Collaboration Tools	4.133	1	4.133	32.120	0.000
Residual	772.084	6001	0.129		
Total	990.978	6045	0.164		

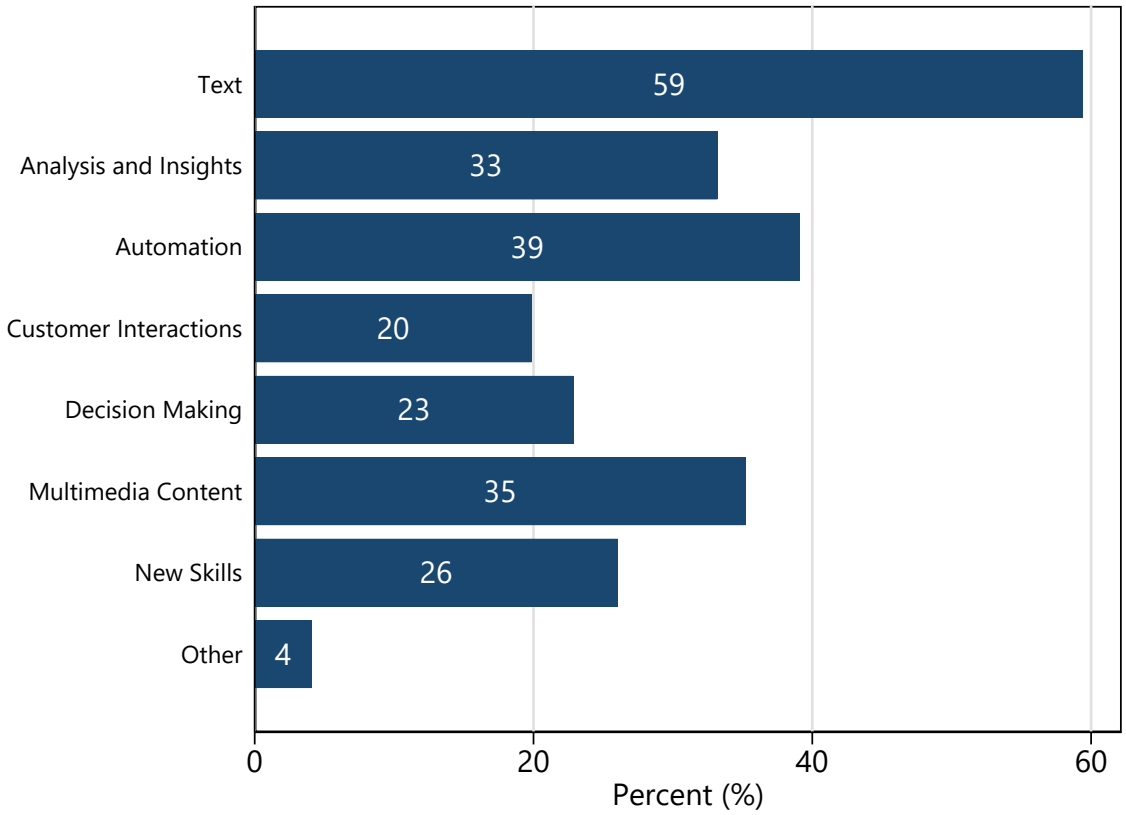
Note: This table reports the results from an ANOVA exercise for AI use variable. The number of observations is 6046 and R-squared is 0.22.

Table 8: ANOVA for AI Use with 2-Digit Occupations

Source	Partial SS	df	MS	F	P-stat
Model	235.788	77	3.062	24.200	0.000
Sex	1.100	1	1.100	8.700	0.003
Education Level	4.988	5	0.998	7.880	0.000
Age Bracket	8.138	4	2.034	16.080	0.000
Firm Size	1.856	2	0.928	7.330	0.001
Firm Scope	5.615	3	1.872	14.790	0.000
Wage Bracket	3.752	2	1.876	14.830	0.000
Occupation 2D	18.428	38	0.485	3.830	0.000
Industry 1D	9.594	15	0.640	5.050	0.000
Automation and Robotics	1.662	1	1.662	13.140	0.000
Cloud Services	7.525	1	7.525	59.470	0.000
IoT	0.053	1	0.053	0.420	0.519
AR / VR	3.362	1	3.362	26.570	0.000
Big Data	10.799	1	10.799	85.340	0.000
3D Printing	2.882	1	2.882	22.770	0.000
Collaboration Tools	2.982	1	2.982	23.560	0.000
Residual	755.190	5968	0.127		
Total	990.978	6045	0.164		

Note: Note: This table reports the results from an ANOVA exercise for AI use variable. The number of observations is 6046 and R-squared is 0.23.

Figure 2: The Purpose of AI Use at the Workplace



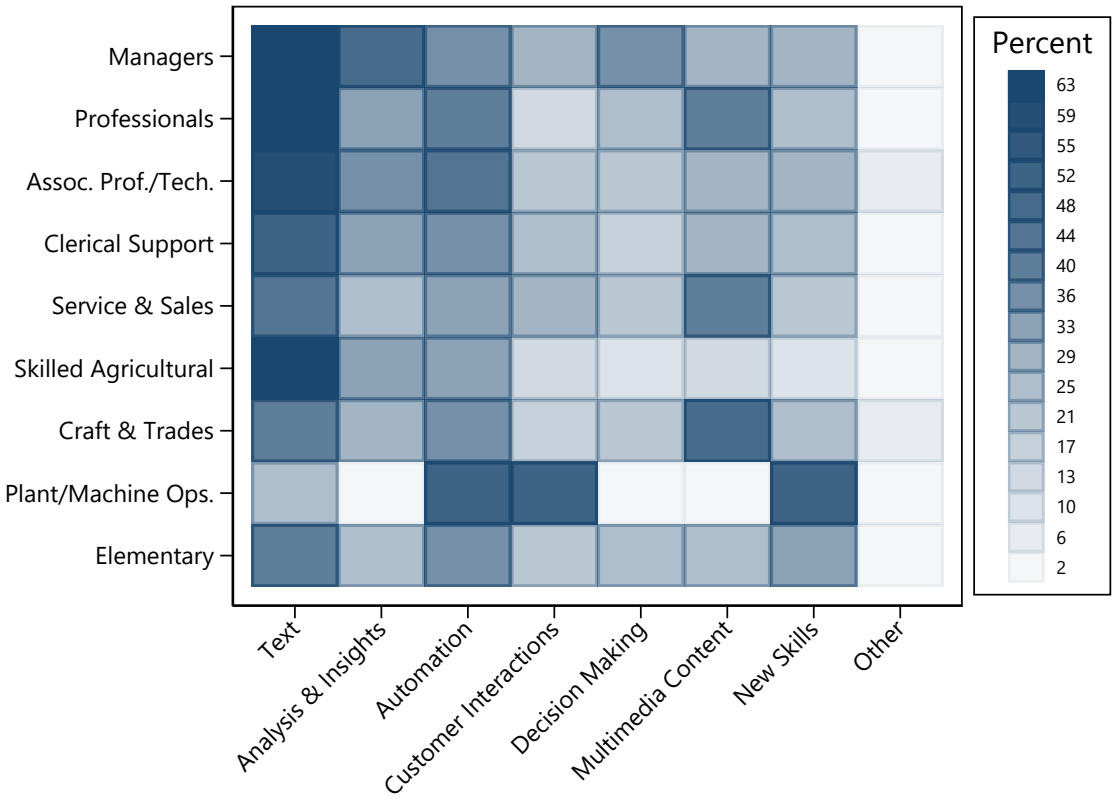
Notes: This figure reports the distribution of reported purposes of AI use in the respondent's job. Categories correspond to the multiple-response AI-purpose question (generating written content; performing data analysis and generating insights; automating repetitive tasks; improving customer interactions; supporting decision-making; designing/creating multimedia content; learning new skills unrelated to AI; and other). Because responses are multiple-choice, category shares need not sum to one. Responses refer to AI use in the respondent's relevant job.

Table 9: The Purpose of AI Use at the Workplace by Groups

	1. Generate written content	2. Perform data analysis and generate insights	3. Automate repetitive tasks	4. Improve customer interactions	5. Support decision-making processes	6. Design and create multimedia content	7. Learn new skills unrelated to AI	8. Other
Sex								
Male	0.57	0.39	0.45	0.20	0.28	0.32	0.29	0.04
Female	0.63	0.29	0.33	0.20	0.19	0.37	0.23	0.05
Education Level								
School Certificate	0.46	0.30	0.38	0.25	0.17	0.33	0.30	0.03
Undergrad & Prof. Training	0.59	0.32	0.38	0.21	0.22	0.32	0.28	0.05
Master's & PhD	0.63	0.39	0.42	0.18	0.27	0.38	0.23	0.04
Age Bracket								
[18,24]	0.44	0.30	0.42	0.22	0.23	0.30	0.39	0.04
[25,34]	0.59	0.33	0.38	0.20	0.22	0.38	0.23	0.03
[35,44]	0.60	0.33	0.43	0.21	0.22	0.33	0.26	0.05
[45,54]	0.62	0.36	0.37	0.20	0.22	0.34	0.26	0.04
>55	0.63	0.39	0.39	0.20	0.31	0.35	0.26	0.04
Occupation 1D								
1 Managers	0.66	0.47	0.36	0.26	0.35	0.30	0.30	0.01
2 Professionals	0.65	0.32	0.42	0.15	0.24	0.40	0.26	0.05
3 Associate Professionals / Technicians	0.61	0.36	0.44	0.21	0.21	0.26	0.29	0.06
4 Clerical Support Workers	0.54	0.33	0.37	0.26	0.19	0.28	0.25	0.05
5 Service and Sales Workers	0.43	0.23	0.31	0.29	0.21	0.35	0.20	0.00
6 Skilled Agricultural Workers	0.69	0.13	0.42	0.06	0.03	0.23	0.04	0.00
7 Craft and Related Trades Workers	0.37	0.32	0.37	0.19	0.17	0.48	0.23	0.07
8 Plant and Machine Operators / Assemblers	0.32	0.00	0.37	0.63	0.00	0.00	0.38	0.00
9 Elementary Occupations	0.48	0.28	0.40	0.15	0.24	0.27	0.27	0.00

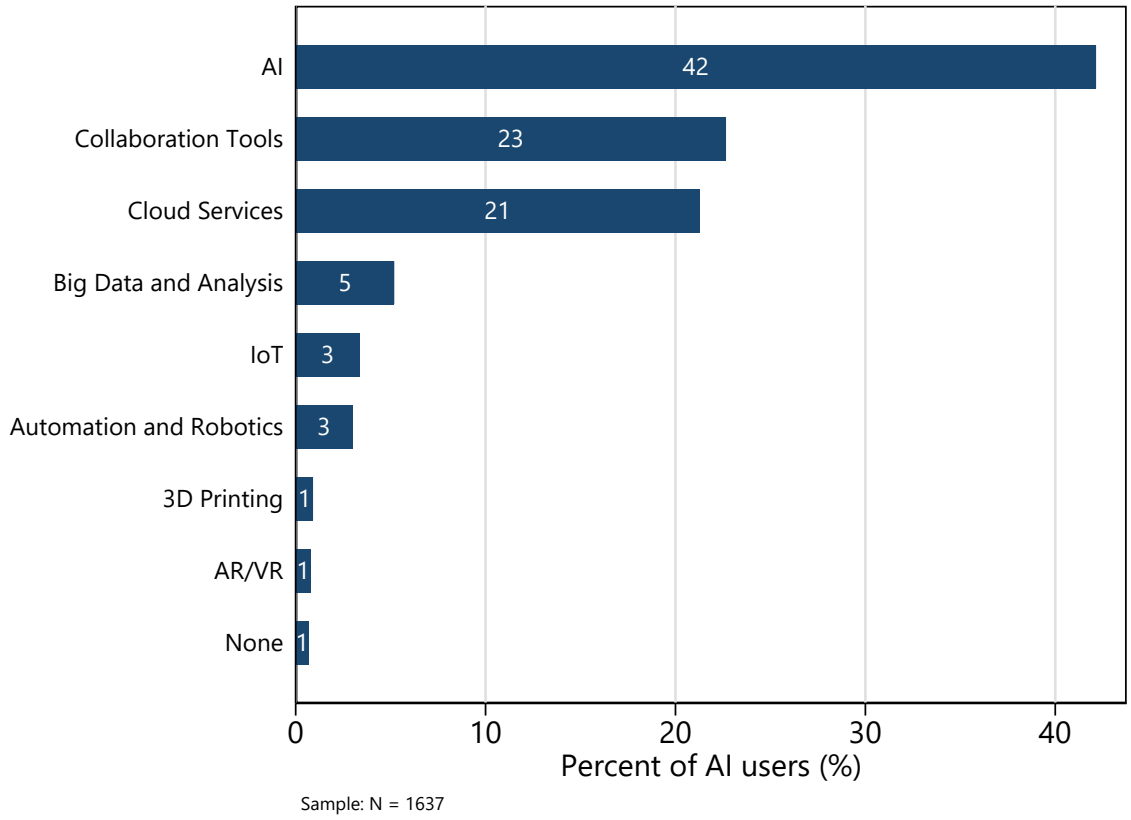
Note: This table reports the distribution of reported purposes of AI use among respondents in their job (at work). Each column is a separate AI-use purpose, and responses are multiple-choice. The table reports subgroup means by sex, education, age, and occupation.

Figure 3: 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.

Figure 4: The Most Significant Technology Among AI Users



Notes: This figure reports the distribution of the technology that respondents, who use AI in their job, identify as the most significant for their work.

Table 10: 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	9. None from the List
1. AI	0.12	0.42	0.12	0.11	0.09	0.20	0.15	0.16	0.10	0.00
2. Automation and Robotics	0.06	0.03	0.53	0.03	0.05	0.06	0.05	0.09	0.03	0.01
3. Cloud Services	0.30	0.21	0.12	0.51	0.20	0.19	0.19	0.16	0.24	0.03
4. IoT	0.11	0.03	0.05	0.05	0.40	0.05	0.05	0.09	0.05	0.01
5. AR / VR	0.01	0.01	0.01	0.01	0.01	0.26	0.00	0.05	0.00	0.00
6. Big Data	0.05	0.05	0.05	0.05	0.04	0.03	0.31	0.06	0.05	0.02
7. 3D Printing	0.01	0.01	0.00	0.01	0.01	0.04	0.01	0.23	0.00	0.00
8. Collaboration Tools	0.31	0.23	0.12	0.24	0.20	0.17	0.23	0.15	0.51	0.04
9. None from the List	0.03	0.01	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.90
N. Obs.	5761	1636	692	3410	1652	206	874	235	3469	178

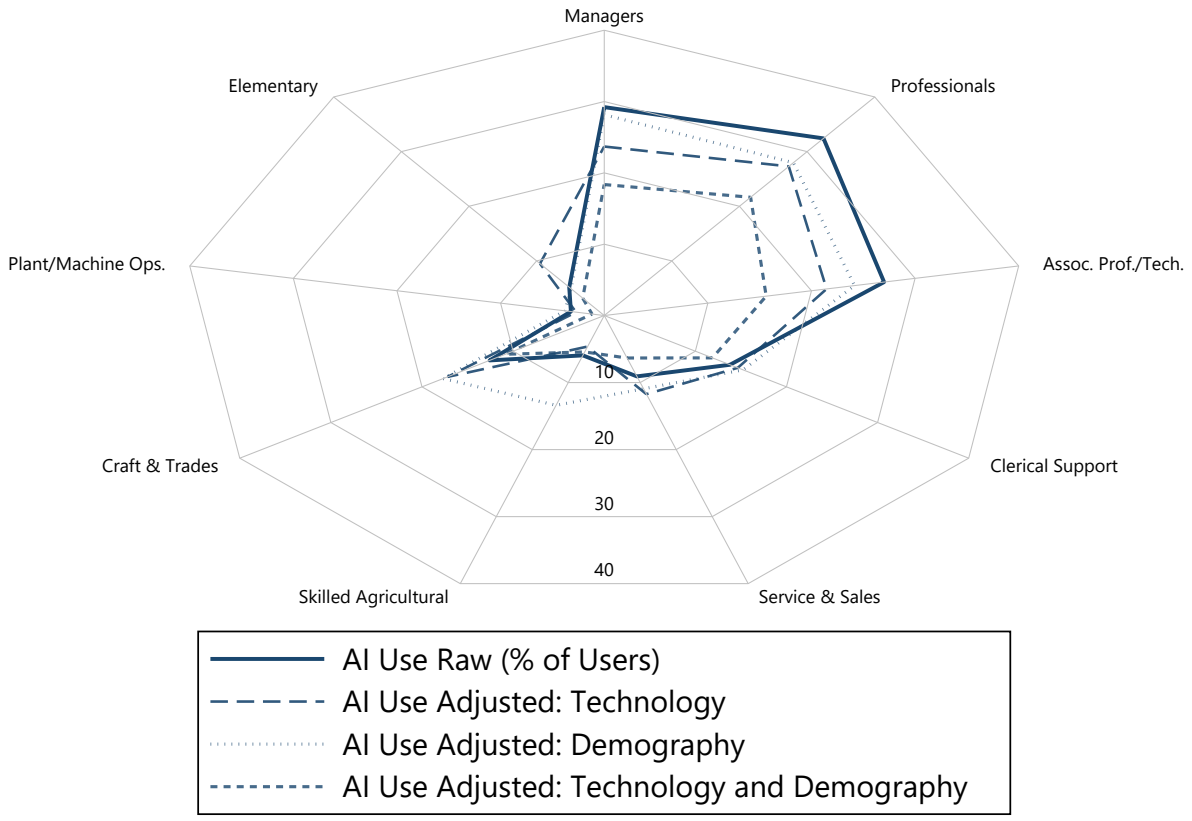
Note: This table reports the distribution of the technology that respondents identify as the most significant for their work. The first column reports the share of respondents selecting each technology as most significant. The remaining columns report, for each technology-use group (e.g., AI users, cloud-services 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.

Table 11: Correlations Between Used Technologies at the Workplace

	1.00	2.00	3.00	4.00	5.00	6.00	7.00
1. AI							
2. Automation and Robotics	0.0955*						
3. Cloud Services	0.2788*	0.0486*					
4. IoT	0.0696*	0.1166*	0.1490*				
5. AR / VR	0.1334*	0.1090*	0.0640*	0.0915*			
6. Big Data and Analysis	0.2282*	0.1412*	0.2433*	0.1383*	0.0969*		
7. 3D Printing	0.1330*	0.1458*	0.0765*	0.1026*	0.2390*	0.0766*	
8. Collaboration Tools	0.2533*	0.0283*	0.3926*	0.1353*	0.0522*	0.2386*	0.0503*

Note: This table reports pairwise correlations between technology use indicators, including the use of AI, automation and robotics, cloud services, IoT, AR/VR, big data and analysis, 3D printing, and collaboration tools. All correlations are sinsignificant at least 5% significance level.

Figure 5: AI Use in 1-Digit Occupations: Raw and Adjusted



Notes: 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.

Table 12: Frequency of AI Use

		Sex		Age Bracket					Education Level			Wage		
		Male	Female	[18,24]	[25,34]	[35,44]	[45,54]	>55	School Certificate	Undergrad & Prof. Training	Master's & PhD	< 1500	[1500,2500]	>2500
Daily	0.25	0.27	0.23	0.30	0.23	0.25	0.26	0.24	0.22	0.27	0.24	0.25	0.25	0.27
Various Times in a Week	0.39	0.40	0.37	0.36	0.38	0.40	0.36	0.42	0.36	0.38	0.41	0.36	0.37	0.44
Once per Week	0.12	0.11	0.14	0.15	0.15	0.12	0.12	0.10	0.10	0.11	0.15	0.15	0.15	0.07
Various Times in a Month	0.13	0.13	0.13	0.13	0.12	0.12	0.13	0.14	0.19	0.12	0.12	0.13	0.13	0.13
Once per Month	0.04	0.04	0.05	0.03	0.05	0.04	0.04	0.04	0.01	0.06	0.03	0.03	0.04	0.05
Less than Once a Month	0.07	0.05	0.09	0.03	0.07	0.07	0.09	0.05	0.11	0.07	0.06	0.08	0.07	0.04
N. Obs.	1636	860	776	118	365	450	399	266	134	867	635	336	572	389

Note: This table reports the share of reported frequency of AI use at the job among respondents who report AI use. Frequency categories range from daily use to less-than-monthly use. The table also reports frequency distributions by sex, age bracket, education level, and wage bracket.

Table 13: Initiation of AI Use at the Workplace (Employee vs. Employer)

Employee	0.52
Employeer	0.45
Others	0.03
N. Obs.	1438

Note: This table reports who suggested the use of AI at the workplace among AI users. Categories indicate whether AI use was suggested by the employee, the employer, or others.

Table 14: Expected Use of IA in the Next 3 Months

	N. Obs.	Yes	No	I Don't Know
	6473	0.12	0.53	0.35
Sex				
Male	3165	0.13	0.53	0.34
Female	3308	0.11	0.53	0.36
Age Bracket				
[18,24]	279	0.19	0.52	0.28
[25,34]	919	0.14	0.55	0.31
[35,44]	1444	0.12	0.55	0.33
[45,54]	1847	0.11	0.53	0.37
>55	1747	0.12	0.50	0.38
Education Level				
School Certificate	1411	0.08	0.58	0.34
Undergrad & Prof. Training	3980	0.13	0.53	0.35
Master's & PhD	1082	0.17	0.46	0.37
Wage				
< 1500	2152	0.10	0.59	0.32
[1500,2500]	2048	0.14	0.51	0.35
>2500	779	0.21	0.44	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. Response categories are "yes," "no," and "don't know." The table also reports expectations by sex, age bracket, education level, and wage bracket.

Table 15: The Use of Technologies at the Workplace

	(1) AI	(2) Automation and Robots	(3) Cloud Services	(4) IoT	(5) AR / VR	(6) Big Data	(7) 3D Printing	(8) Collaboration Tools
Female	-0.039***	-0.031***	0.043**	0.038**	-0.002	-0.017	-0.010*	-0.004
	(0.011)	(0.008)	(0.014)	(0.012)	(0.005)	(0.010)	(0.005)	(0.014)
Education Level								
Undergrad & Prof. Tr.	0.022	0.005	0.063***	0.007	0.002	0.014	0.016**	0.064***
	(0.012)	(0.010)	(0.017)	(0.015)	(0.005)	(0.009)	(0.005)	(0.017)
Master's & PhD	0.096***	-0.003	0.142***	0.008	0.015	0.053***	0.017*	0.147***
	(0.018)	(0.014)	(0.022)	(0.020)	(0.009)	(0.016)	(0.008)	(0.022)
Age Bracket								
[25,34]	-0.063*	-0.125***	0.004	0.000	-0.019	-0.035	-0.053**	0.062
	(0.030)	(0.026)	(0.033)	(0.029)	(0.014)	(0.026)	(0.017)	(0.032)
[35,44]	-0.100***	-0.105***	-0.016	0.013	-0.013	-0.062*	-0.048**	0.063*
	(0.029)	(0.026)	(0.032)	(0.028)	(0.013)	(0.025)	(0.017)	(0.031)
[45,54]	-0.139***	-0.145***	-0.047	-0.011	-0.021	-0.092***	-0.052**	0.043
	(0.028)	(0.025)	(0.031)	(0.027)	(0.013)	(0.024)	(0.017)	(0.030)
>55	-0.202***	-0.157***	-0.065*	-0.009	-0.032*	-0.121***	-0.060***	0.020
	(0.028)	(0.026)	(0.032)	(0.028)	(0.013)	(0.024)	(0.017)	(0.031)
Firm Size								
11 to 49 people	-0.014	0.014	0.023	0.030	-0.009	0.036**	-0.004	0.043*
	(0.016)	(0.011)	(0.020)	(0.018)	(0.007)	(0.012)	(0.008)	(0.020)
50 people or more	-0.036**	0.038***	-0.005	-0.005	-0.009	0.048***	-0.007	0.065***
	(0.014)	(0.009)	(0.017)	(0.015)	(0.007)	(0.011)	(0.006)	(0.017)
Firm Scope								
Regional	-0.006	0.014	0.035*	0.016	-0.001	0.027**	0.008	0.054**
	(0.013)	(0.009)	(0.018)	(0.015)	(0.006)	(0.010)	(0.006)	(0.018)
National	0.062***	0.027**	0.088***	0.040**	0.013*	0.049***	0.017**	0.093***
	(0.014)	(0.010)	(0.018)	(0.015)	(0.006)	(0.011)	(0.006)	(0.018)
International	0.134***	0.064***	0.177***	0.026	0.011	0.107***	0.020**	0.174***
	(0.017)	(0.013)	(0.020)	(0.018)	(0.008)	(0.014)	(0.007)	(0.020)
Wage Bracket								
[1500,2500]	0.036**	0.017	0.090***	0.052***	0.004	0.022*	0.008	0.082***
	(0.011)	(0.009)	(0.015)	(0.013)	(0.005)	(0.009)	(0.005)	(0.015)
>2500	0.116***	0.037**	0.130***	0.064***	0.023**	0.083***	0.022**	0.106***
	(0.018)	(0.013)	(0.020)	(0.018)	(0.008)	(0.015)	(0.008)	(0.021)
Tasks								
Abstract	0.183***	-0.113***	0.331***	0.043	-0.038**	0.110***	-0.013	0.336***
	(0.034)	(0.032)	(0.044)	(0.037)	(0.014)	(0.031)	(0.015)	(0.046)
Cognitive Routine	0.024	-0.134***	0.165***	0.026	-0.042**	-0.008	-0.000	0.138**
	(0.030)	(0.032)	(0.040)	(0.036)	(0.013)	(0.027)	(0.015)	(0.043)
Manual Non-Routine	0.046	-0.099**	0.088	0.075	0.036	0.006	0.020	-0.035
	(0.035)	(0.037)	(0.050)	(0.044)	(0.019)	(0.030)	(0.016)	(0.052)
Inter. with Clients	0.060*	-0.152***	0.182***	0.058	-0.021	0.029	-0.006	0.199***
	(0.029)	(0.029)	(0.040)	(0.035)	(0.013)	(0.026)	(0.013)	(0.042)
Inter. with Coworkers	0.132***	-0.114***	0.192***	0.015	-0.029	0.024	-0.005	0.241***
	(0.032)	(0.032)	(0.042)	(0.036)	(0.015)	(0.028)	(0.015)	(0.045)
Location Type								
Big City	0.024*	-0.001	0.034*	0.003	0.002	0.028**	-0.006	0.021
	(0.011)	(0.008)	(0.013)	(0.012)	(0.005)	(0.009)	(0.005)	(0.013)
Industry 1D FE	YES	YES	YES	YES	YES	YES	YES	YES
Occupation 1D FE	YES	YES	YES	YES	YES	YES	YES	YES
N. Obs.	6046	6046	6046	6046	6046	6046	6046	6046
R2	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178

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: artificial intelligence (AI), automation and robotics, cloud services, Internet of Things (IoT), augmented/virtual reality (AR/VR), big data and analytics, 3D printing, and digital collaboration tools. Regressors include demographic characteristics, wage brackets, firm size and firm scope indicators, task-content controls, and location type, and all specifications include 1-digit industry and occupation fixed effects as indicated. Coefficients can be interpreted as changes in probability. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 16: 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
Female	0.080**	-0.065*	-0.090**	0.002	-0.080**	0.050	-0.061*
	(0.031)	(0.029)	(0.030)	(0.026)	(0.026)	(0.029)	(0.028)
Education Level							
Undergrad & Prof. Tr.	0.089	-0.010	-0.021	-0.047	0.018	0.022	-0.054
	(0.057)	(0.055)	(0.057)	(0.051)	(0.048)	(0.054)	(0.055)
Master's & PhD	0.097	0.037	-0.033	-0.052	0.058	0.047	-0.103
	(0.061)	(0.060)	(0.062)	(0.054)	(0.053)	(0.058)	(0.059)
Age Bracket							
[25,34]	0.097	-0.002	-0.054	0.030	-0.039	0.040	-0.138*
	(0.060)	(0.057)	(0.061)	(0.052)	(0.054)	(0.060)	(0.061)
[35,44]	0.135*	-0.057	-0.007	0.025	-0.087	-0.008	-0.144*
	(0.060)	(0.057)	(0.061)	(0.051)	(0.053)	(0.060)	(0.061)
[45,54]	0.122*	0.010	-0.035	0.018	-0.081	-0.005	-0.138*
	(0.060)	(0.057)	(0.062)	(0.053)	(0.053)	(0.061)	(0.062)
>55	0.139*	-0.021	-0.043	0.026	-0.029	0.019	-0.145*
	(0.067)	(0.063)	(0.067)	(0.059)	(0.060)	(0.067)	(0.066)
Firm Size							
11 to 49 people	0.012	-0.089	-0.004	0.036	-0.095*	-0.121*	-0.001
	(0.047)	(0.046)	(0.046)	(0.043)	(0.041)	(0.048)	(0.044)
50 people or more	-0.118**	-0.058	0.032	-0.002	-0.037	-0.183***	0.045
	(0.041)	(0.040)	(0.040)	(0.037)	(0.037)	(0.041)	(0.037)
Firm Scope							
Regional	0.069	0.104*	-0.008	0.029	0.024	0.025	0.003
	(0.046)	(0.041)	(0.045)	(0.038)	(0.039)	(0.047)	(0.042)
National	0.044	0.124**	0.037	0.014	0.012	-0.057	-0.001
	(0.043)	(0.039)	(0.042)	(0.035)	(0.037)	(0.042)	(0.040)
International	0.071	0.171***	0.048	0.043	0.008	-0.096*	-0.006
	(0.045)	(0.042)	(0.045)	(0.039)	(0.039)	(0.043)	(0.041)
Wage Bracket							
[1500,2500]	0.044	0.071	-0.009	0.008	-0.001	0.020	0.007
	(0.039)	(0.036)	(0.037)	(0.032)	(0.032)	(0.037)	(0.034)
>2500	-0.035	0.074	-0.011	0.017	0.082*	0.037	0.041
	(0.045)	(0.043)	(0.044)	(0.039)	(0.039)	(0.043)	(0.042)
Tasks							
Abstract	0.257	0.130	0.089	-0.147	0.188	-0.157	-0.083
	(0.144)	(0.123)	(0.149)	(0.115)	(0.107)	(0.142)	(0.137)
Cognitive Routine	0.475**	-0.064	-0.005	-0.134	0.121	-0.027	-0.128
	(0.158)	(0.129)	(0.160)	(0.126)	(0.115)	(0.157)	(0.152)
Manual Non-Routine	-0.075	-0.030	0.104	0.070	0.093	-0.055	-0.222
	(0.220)	(0.184)	(0.212)	(0.168)	(0.150)	(0.213)	(0.187)
Inter. with Clients	0.427**	0.065	-0.117	0.022	0.199	-0.239	-0.146
	(0.146)	(0.126)	(0.151)	(0.121)	(0.110)	(0.147)	(0.136)
Inter. with Coworkers	0.297*	-0.084	0.010	-0.099	0.092	0.010	-0.135
	(0.150)	(0.127)	(0.154)	(0.124)	(0.107)	(0.150)	(0.145)
Location Type							
Big City	-0.021	0.023	0.016	0.012	0.046	-0.070*	0.013
	(0.029)	(0.027)	(0.028)	(0.024)	(0.025)	(0.028)	(0.027)
Industry 1D FE	YES	YES	YES	YES	YES	YES	YES
Occupation 1D FE	YES	YES	YES	YES	YES	YES	YES
Freq. Use FE	YES	YES	YES	YES	YES	YES	YES
N. Obs.	1249	1249	1249	1249	1249	1249	1249
R2	0.114	0.165	0.137	0.078	0.123	0.125	0.077

Note: This table reports regression results for the purposes of AI use among AI users. Each column corresponds to a separate binary dependent variable indicating whether the respondent reports using AI for the listed purpose: generating written content, performing data analysis and generating insights, automating repetitive tasks, improving customer interactions, supporting decision-making, designing/creating multimedia content, and learning new skills unrelated to AI. Regressors include demographic characteristics, wage brackets, firm size and firm scope indicators, task-content controls, and location type. They also include 1-digit industry and occupation fixed effects and AI-use frequency fixed effects. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 17: Recent Introduction of AI at the Job and the Earlier Use of Other Technologies

	(2) Automation and Robots	(3) Cloud Services	(4) IoT	(5) AR / VR	(6) Big Data	(7) 3D Printing	(8) Collaboration Tools
Technology	0.040	-0.004	0.016	0.130**	0.089***	0.124**	-0.002
	(0.022)	(0.012)	(0.013)	(0.044)	(0.019)	(0.042)	(0.013)
Gender							
Female	-0.037**	-0.032*	-0.039**	-0.036**	-0.034**	-0.038**	-0.034*
	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)
Education Level							
Undergrad & Prof. Tr.	0.021	0.013	0.022	0.018	0.015	0.017	0.017
	(0.015)	(0.016)	(0.016)	(0.015)	(0.015)	(0.015)	(0.016)
Master's & PhD	0.042*	0.040	0.045*	0.039	0.034	0.037	0.037
	(0.020)	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)	(0.021)
Age Bracket							
[25,34]	-0.052	-0.051	-0.053	-0.053	-0.059	-0.045	-0.044
	(0.032)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
[35,44]	-0.076*	-0.057	-0.070*	-0.072*	-0.073*	-0.062*	-0.065*
	(0.031)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
[45,54]	-0.096**	-0.078**	-0.096**	-0.094**	-0.094**	-0.087**	-0.080**
	(0.031)	(0.030)	(0.030)	(0.029)	(0.030)	(0.029)	(0.030)
>55	-0.112***	-0.093**	-0.112***	-0.109***	-0.110***	-0.104***	-0.102***
	(0.031)	(0.030)	(0.030)	(0.030)	(0.031)	(0.030)	(0.030)
Firm Size							
11 to 49 people	-0.024	-0.022	-0.026	-0.017	-0.018	-0.022	-0.029
	(0.020)	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)	(0.021)
50 people or more	-0.057***	-0.055**	-0.054**	-0.051**	-0.053**	-0.056***	-0.057**
	(0.017)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)
Firm Scope							
Regional	-0.017	-0.017	-0.017	-0.016	-0.027	-0.019	-0.017
	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)	(0.016)	(0.016)
National	0.027	0.012	0.023	0.024	0.014	0.022	0.026
	(0.016)	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)	(0.017)
International	0.044*	0.038	0.043*	0.048*	0.032	0.045*	0.050*
	(0.019)	(0.020)	(0.020)	(0.019)	(0.019)	(0.019)	(0.020)
Wage Bracket							
[1500,2500]	0.006	-0.002	0.007	0.004	0.001	0.005	0.001
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)
>2500	0.045*	0.049*	0.050**	0.048*	0.049*	0.050**	0.053**
	(0.019)	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)
Tasks							
Abstract	0.073	0.068	0.061	0.067	0.040	0.067	0.048
	(0.042)	(0.042)	(0.042)	(0.040)	(0.041)	(0.041)	(0.044)
Cognitive Routine	-0.028	-0.011	-0.029	-0.026	-0.041	-0.032	-0.053
	(0.040)	(0.040)	(0.041)	(0.039)	(0.039)	(0.039)	(0.042)
Manual Non-Routine	0.031	0.023	0.008	0.014	-0.004	0.009	0.002
	(0.053)	(0.053)	(0.053)	(0.052)	(0.051)	(0.051)	(0.055)
Inter. with Clients	0.027	0.013	0.001	0.012	-0.001	0.009	-0.014
	(0.039)	(0.039)	(0.039)	(0.037)	(0.038)	(0.037)	(0.040)
Inter. with Coworkers	0.124**	0.113**	0.113**	0.109**	0.094*	0.112**	0.107*
	(0.043)	(0.043)	(0.044)	(0.042)	(0.042)	(0.042)	(0.046)
Location Type							
Big City	0.023	0.026*	0.019	0.019	0.014	0.021	0.020
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)
Industry 1D FE	YES	YES	YES	YES	YES	YES	YES
Occupation 1D FE	YES	YES	YES	YES	YES	YES	YES
N. Obs.	4161	3883	4081	4241	4191	4253	3888
R2	0.069	0.064	0.065	0.068	0.074	0.070	0.064

Note: This table reports regressions relating reported recent introduction of AI at the job to pre-existing use of other technologies. "Recent" refers to the previous three months. The dependent variable is a binary indicator equal to one if the respondent reports that AI was introduced in the workplace during the previous three months. Each column includes a different technology-use indicator as the main regressor of interest. All specifications include the demographic, wage, firm, task-content, and location controls listed in the table and include 1-digit industry and occupation fixed effects. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 18: The Impediments to AI Use at the Workplace

	(1) Training	(2) Integration	(3) Privacy / Security	(4) Cost	(5) Resistance	(6) Fear
Female	0.041	-0.072*	-0.003	0.007	-0.044	-0.021
	(0.032)	(0.029)	(0.031)	(0.027)	(0.026)	(0.023)
Education Level						
Undergrad & Prof. Tr	0.057	-0.011	-0.089	-0.012	-0.021	-0.035
	(0.060)	(0.052)	(0.060)	(0.050)	(0.051)	(0.052)
Master's & PhD	0.032	0.060	-0.005	0.015	0.028	-0.014
	(0.065)	(0.057)	(0.064)	(0.055)	(0.055)	(0.054)
Age Bracket						
[25,34]	0.053	0.030	0.050	-0.034	-0.031	-0.071
	(0.063)	(0.055)	(0.059)	(0.053)	(0.048)	(0.056)
[35,44]	0.060	0.028	0.144*	-0.039	-0.044	-0.095
	(0.062)	(0.055)	(0.059)	(0.053)	(0.047)	(0.056)
[45,54]	0.134*	0.069	0.031	-0.019	0.029	-0.109*
	(0.063)	(0.055)	(0.060)	(0.053)	(0.048)	(0.055)
>55	0.184**	0.070	0.091	-0.027	0.056	-0.113
	(0.069)	(0.061)	(0.066)	(0.059)	(0.055)	(0.059)
Firm Size						
11 to 49 people	0.021	0.057	0.016	-0.037	0.041	-0.039
	(0.050)	(0.047)	(0.048)	(0.044)	(0.041)	(0.038)
50 people or more	0.018	0.015	0.059	-0.041	0.040	-0.017
	(0.043)	(0.039)	(0.042)	(0.037)	(0.035)	(0.035)
Firm Scope						
Regional	0.036	0.076	0.013	0.018	0.010	0.003
	(0.049)	(0.044)	(0.047)	(0.040)	(0.039)	(0.034)
National	-0.012	0.013	0.024	-0.009	0.053	0.037
	(0.046)	(0.040)	(0.045)	(0.038)	(0.038)	(0.033)
International	0.023	0.062	0.128**	0.022	0.003	0.023
	(0.048)	(0.043)	(0.048)	(0.042)	(0.039)	(0.035)
Wage Bracket						
[1500,2500]	0.057	-0.011	-0.089	-0.012	-0.021	-0.035
	(0.060)	(0.052)	(0.060)	(0.050)	(0.051)	(0.052)
>2500	0.032	0.060	-0.005	0.015	0.028	-0.014
	(0.065)	(0.057)	(0.064)	(0.055)	(0.055)	(0.054)
Tasks						
Abstract	0.063	-0.168	0.265	-0.005	0.080	-0.289*
	(0.146)	(0.143)	(0.140)	(0.127)	(0.116)	(0.130)
Cognitive Routine	0.291	-0.176	-0.002	-0.043	0.095	-0.296*
	(0.164)	(0.155)	(0.153)	(0.140)	(0.131)	(0.142)
Manual Non-Routine	0.122	-0.322	0.044	0.104	0.003	-0.135
	(0.221)	(0.199)	(0.202)	(0.193)	(0.173)	(0.197)
Inter. with Clients	0.099	-0.227	0.306*	-0.046	-0.085	-0.287*
	(0.151)	(0.147)	(0.146)	(0.130)	(0.118)	(0.130)
Inter. with Coworkers	0.269	-0.156	0.178	0.033	0.084	-0.212
	(0.156)	(0.147)	(0.148)	(0.136)	(0.123)	(0.138)
Industry 1D FE	YES	YES	YES	YES	YES	YES
Occupation 1D FE	YES	YES	YES	YES	YES	YES
N. Obs.	1249	1249	1249	1249	1249	1249
R2	0.040	0.054	0.068	0.035	0.066	0.067

Note: This table reports regressions for perceived impediments to effective AI use among AI users. Each column corresponds to a separate binary dependent variable indicating whether the respondent reports the listed impediment: 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. Specifications include demographic, wage, firm, task-content, and location controls and include 1-digit industry and occupation fixed effects. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 19: The Perceived Effect of AI on Productivity and Reported Effect on Time Allocation

					IF AI is Most Significant Technology			
Percieved productivity	Increased	Decreased	Did not Affect	Does not Apply	Increased	Decreased	Did not Affect	Does not Apply
Abstract	0.52	0.10	0.23	0.14	0.54	0.09	0.22	0.15
Cognitive Routine	0.36	0.11	0.29	0.23	0.36	0.13	0.28	0.23
Manual Routine	0.15	0.08	0.17	0.60	0.18	0.09	0.19	0.54
Manual Non-Routine	0.12	0.06	0.16	0.66	0.13	0.08	0.18	0.61
Interaction with Coworkers	0.26	0.08	0.36	0.31	0.26	0.09	0.35	0.30
Interaction with Clients	0.25	0.07	0.44	0.24	.	.	.	.

				IF AI is Most Significant Technology		
Time Allocation	Increased	Decreased	Did not Affect	Increased	Decreased	Did not Affect
Abstract	0.34	0.32	0.34	0.39	0.30	0.31
Cognitive Routine	0.26	0.28	0.46	0.33	0.26	0.41
Manual Routine	0.19	0.19	0.62	0.22	0.21	0.56
Manual Non-Routine	0.17	0.15	0.68	0.18	0.20	0.62
Interaction with Coworkers	0.24	0.16	0.59	0.18	0.55	0.27
Interaction with Clients	0.24	0.15	0.62	0.17	0.58	0.26

Note: This table reports self-reported effects of AI on productivity and time allocation across task categories. Entries are shares of responses indicating increased, decreased, or no effect, and "does not apply" denotes respondents who report not performing the corresponding task category. The table distinguishes cases where AI is identified as the most significant technology in the respondent's work from the remaining cases.

Table 20: Reported Probability of Job Offer and Layoff 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
	0.061***	0.016	0.010	0.010	0.051	0.025	-0.001	0.005
	(0.016)	(0.021)	(0.010)	(0.017)	(0.054)	(0.023)	(0.067)	(0.010)
N. Obs.	6046	6046	6046	6046	6046	6046	6046	6046
R2	0.090	0.088	0.088	0.088	0.088	0.088	0.088	0.088
Layoff								
	0.015	0.021	-0.011	0.009	0.039	0.009	0.006	0.005
	(0.010)	(0.015)	(0.006)	(0.010)	(0.032)	(0.015)	(0.043)	(0.006)
N. Obs.	6046	6046	6046	6046	6046	6046	6046	6046
R2	0.048	0.048	0.048	0.048	0.048	0.048	0.048	0.048
Gender FE	YES	YES	YES	YES	YES	YES	YES	YES
Age Bracket FE	YES	YES	YES	YES	YES	YES	YES	YES
Education-Level FE	YES	YES	YES	YES	YES	YES	YES	YES
Wage Bracket FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm Size FE	YES	YES	YES	YES	YES	YES	YES	YES
Big City FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm Scope FE	YES	YES	YES	YES	YES	YES	YES	YES
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

Note: This table reports regressions relating short-horizon labor-market expectations to the technology identified as most significant at work. The dependent variables are the respondent's reported probabilities of receiving a job offer and of being laid off during the next month. Each column includes an indicator for a different "most significant technology" category as the main regressor of interest, with the omitted category given by the remaining options. Specifications include demographic, wage, firm, location, 1-digit industry and occupation, and technology-use frequency fixed effects. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 21: Ranking of AI Use in 1-Digit Occupations

	Raw Data		Adjusted for Technology		Adjusted for Demography		Adjusted for Technology and Demography	
Occupation	% of Users	Ranking	% of Users	Ranking	% of Users	Ranking	% of Users	Ranking
1 Managers	0.29	2	0.24	2	0.28	1	0.18	2
2 Professionals	0.32	1	0.27	1	0.28	2	0.22	1
3 Associate Professionals / Technicians	0.27	3	0.21	3	0.24	3	0.16	3
4 Clerical Support Workers	0.14	4	0.15	5	0.15	5	0.12	4
5 Service and Sales Workers	0.09	6	0.12	6	0.11	7	0.06	6
6 Skilled Agricultural Workers	0.06	7	0.05	8	0.13	6	0.05	7
7 Craft and Related Trades Workers	0.13	5	0.17	4	0.18	4	0.11	5
8 Plant and Machine Operators / Assemblers	0.03	9	0.03	9	0.04	9	0.01	9
9 Elementary Occupations	0.05	8	0.09	7	0.05	8	0.03	8

Note: This table reports occupation-level rankings of AI use. "Average" is the raw occupation-level share of respondents reporting AI use. "Adjusted to demography" reports occupation ranking when controlling for demographic composition, and "Adjusted to demography and technology" further controls for the use of other workplace technologies, so that differences reflect residual occupation-level variation after accounting for these factors. The table also reports the distribution of reported AI-use purposes among AI users by occupation.

Table 22: Ranking of AI Use in 1-Digit Occupations

	Raw Data		Adjusted for Technology		Adjusted for Demography		Adjusted for Technology and Demography	
Occupation	% of Users	Ranking	% of Users	Ranking	% of Users	Ranking	% of Users	Ranking
1 Managers	0.29	2	0.24	2	0.28	1	0.18	2
2 Professionals	0.32	1	0.27	1	0.28	2	0.22	1
3 Associate Professionals / Technicians	0.27	3	0.21	3	0.24	3	0.16	3
4 Clerical Support Workers	0.14	4	0.15	5	0.15	5	0.12	4
5 Service and Sales Workers	0.09	6	0.12	6	0.11	7	0.06	6
6 Skilled Agricultural Workers	0.06	7	0.05	8	0.13	6	0.05	7
7 Craft and Related Trades Workers	0.13	5	0.17	4	0.18	4	0.11	5
8 Plant and Machine Operators / Assemblers	0.03	9	0.03	9	0.04	9	0.01	9
9 Elementary Occupations	0.05	8	0.09	7	0.05	8	0.03	8

Note: This table reports occupation-level rankings of AI use. "Average" is the raw occupation-level share of respondents reporting AI use. "Adjusted to demography" reports occupation ranking when controlling for demographic composition, and "Adjusted to demography and technology" further controls for the use of other workplace technologies, so that differences reflect residual occupation-level variation after accounting for these factors. The table also reports the distribution of reported AI-use purposes among AI users by occupation.

Table 23: Ranking of AI Use in 2-Digit Occupations

Occupation	Raw Data		Adjusted for Technology		Adjusted for Demography		Adjusted for Technology and Demography	
	% of Users	Ranking	% of Users	Ranking	% of Users	Ranking	% of Users	Ranking
11 Chief executives & senior officials	0.32	8	0.27	5	0.28	7	0.12	7
12 Admin & commercial managers	0.33	7	0.23	8	0.32	6	0.13	5
13 Production & services managers	0.37	5	0.28	4	0.33	5	0.18	3
14 Hospitality, retail & other services mgrs	0.08	27	0.06	25	0.08	25	0.03	25
21 Science & engineering professionals	0.33	6	0.22	10	0.24	8	0.11	8
22 Health professionals	0.13	19	0.14	16	0.09	24	0.07	16
23 Teaching professionals	0.47	2	0.39	1	0.41	2	0.24	1
24 Business & admin professionals	0.24	12	0.17	13	0.23	11	0.08	13
25 ICT professionals	0.52	1	0.37	2	0.43	1	0.19	2
26 Legal, social & cultural professionals	0.25	10	0.19	11	0.16	14	0.08	14
31 Science & engineering assoc. pros	0.29	9	0.23	9	0.24	10	0.09	11
32 Health assoc. professionals	0.13	18	0.12	20	0.09	22	0.04	21
33 Business & admin assoc. pros	0.25	11	0.18	12	0.24	9	0.10	10
34 Legal, social & cultural assoc. pros	0.20	13	0.16	15	0.17	13	0.09	12
35 ICT technicians	0.38	3	0.26	6	0.34	4	0.16	4
41 General & keyboard clerks	0.18	14	0.17	14	0.20	12	0.12	6
42 Customer services clerks	0.09	25	0.10	23	0.11	21	0.07	15
43 Numerical & material recording clerks	0.14	16	0.12	21	0.12	20	0.05	19
44 Other clerical support workers	0.13	17	0.12	18	0.13	18	0.06	18
51 Personal services workers	0.12	20	0.10	24	0.14	17	0.03	23
52 Sales workers	0.10	21	0.11	22	0.12	19	0.05	20
53 Personal care workers	0.07	29	0.14	17	0.08	27	0.01	30
54 Protective services workers	0.05	32	0.05	27	0.07	28	0.03	24
61 Market-oriented skilled agricultural workers	0.06	30	0.05	28	0.15	16	0.06	17
62 Market-oriented skilled forestry & fishery workers	0.07	28	0.04	30	0.04	33	0.01	34
63 Subsistence farmers, fishers, hunters, gatherers	0.00	37	0.00	37	0.00	37	0.00	37
71 Building & related trades workers	0.05	31	0.05	29	0.08	26	0.01	31
72 Metal, machinery & related trades workers	0.05	34	0.02	35	0.07	29	0.01	33
73 Handicraft & printing workers	0.38	4	0.29	3	0.37	3	0.10	9
74 Electrical & electronic trades workers	0.15	15	0.12	19	0.16	15	0.04	22
75 Food processing, woodworking, garment & related trades	0.10	22	0.05	26	0.09	23	0.02	27
81 Stationary plant & machine operators	0.04	35	0.03	33	0.05	32	0.01	29
82 Assemblers	0.00	37	0.00	37	0.00	37	0.00	37
91 Cleaners & helpers	0.05	33	0.03	32	0.05	31	0.02	28
92 Agricultural, forestry & fishery labourers	0.10	23	0.03	31	0.00	36	0.00	35
93 Labourers in mining, construction, manufacturing, transport	0.03	36	0.02	34	0.04	34	0.01	32
94 Food preparation assistants	0.08	26	0.23	7	0.05	30	0.02	26
95 Street sales & related service workers	0.09	24	0.00	36	0.02	35	0.00	36
96 Refuse workers & pest controllers	0.00	37	0.00	37	0.00	37	0.00	37

Note: This table reports occupation-level rankings of AI use. "Average" is the raw occupation-level share of respondents reporting AI use. "Adjusted to demography" reports occupation ranking when controlling for demographic composition, and "Adjusted to demography and technology" further controls for the use of other workplace technologies, so that differences reflect residual occupation-level variation after accounting for these factors. The table also reports the distribution of reported AI-use purposes among AI users by occupation.

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