BIG BROTHER AT WORK: DIGITAL MONITORING, DIGITAL SKILLS, AND WORKERS' JOB DISPLACEMENT BELIEFS IN 27 EU COUNTRIES

by

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Abstract

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Employers have two principal instruments to make workers exert full effort: paying a wage premium that raises what a worker loses if dismissed (efficiency wage), or monitoring workers more intensively so that low effort is more likely to be detected. Digital technologies, including Artificial Intelligence, are reducing the cost of monitoring, so the balance between these two instruments may be shifting in a way that strengthens employer leverage without strengthening worker bargaining position. Using Eurobarometer 101.4 data, collected in April-May 2024 across 27 EU member states, and logistic regression, this study shows that high-intensity digital monitoring and evaluation is associated with higher job displacement belief than lower and middle monitoring intensities. Moreover, reported informing about digital management tools is associated with lower job displacement belief, and the association strengthens as disclosure deepens. While self-assessed digital skill sufficiency is not associated with lower job displacement belief in the simple linear form. These findings suggest that regulatory attention may be most warranted for high-intensity monitoring, and that meaningful rather than purely formal disclosure of digital management tools may be a relevant policy lever.

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AI USE DECLARATION

During the preparation of this thesis, Generative AI (ChatGPT, Claude and Gemini) was used solely as a supplementary tool to support grammar correction, improvement of sentence clarity, brainstorming and refinement of research ideas and thesis structure, and coding support for selected technical tasks. Any suggestions produced by the AI tool were critically evaluated, independently verified, and substantially modified by the author before being incorporated into the thesis.

The tool was not used to generate research findings, produce literature summaries used directly in the thesis, create citations. All research questions, theoretical framing, methodology, analysis, interpretation of results, and conclusions were developed independently by the author. The author takes full responsibility for the originality, validity, and academic integrity of the work presented in this thesis.

LIST OF ABBREVIATIONS

AI. Artificial intelligence.

AM. Algorithmic management.

AME. Average marginal effect.

AUC. Area under the receiver operating characteristic curve.

CI. Confidence interval.

DFBETA. Difference in beta coefficient after deleting an observation.

DM. Digital management.

EU. European Union.

FE. Fixed effects.

ICT. Information and communication technology.

ILO. International Labour Organization.

ISCED. International Standard Classification of Education.

ISCO-08. International Standard Classification of Occupations, 2008.

N/A. Not applicable.

SE. Standard error.

VIF. Variance inflation factor.

Chapter 1

INTRODUCTION

Digital technologies have become substantially more capable and less costly over the past two decades, and the latest generation of Artificial Intelligence has accelerated this trend. Most existing research on worker displacement concerns measures which workers face the greatest technical risk of being substituted by these technologies, using occupational exposure indices. However, these indices are useful for characterising potential labour-market transformations, but they do not capture how digital technologies are actually being deployed inside workplaces.

This distinction matters because digital technologies are not only a means of substituting for particular tasks but can also be used by employers as tools of workplace governance to monitor workers, evaluate performance, allocate tasks, impose sanctions, and attribute rewards. Bowles (1985) argues that employers must elicit effort from workers, and that they can do so either by raising the cost of job loss through higher wages or by monitoring workers more intensively. As digital technologies reduce the cost of monitoring, employers may rely more heavily on oversight and less on wage-based incentives, so that technological change may strengthen employer leverage without strengthening worker bargaining position.

Evidence from the algorithmic management (AM) literature supports this broader framing. Digital management tools are increasingly used to monitor and evaluate workers, allocate tasks, assess performance, and structure managerial decisions, while these applications may constrain worker voice and increase the perceived salience of replacement threats, thereby weakening workers' position (Kellogg, Valentine, and Christin, 2020). AM have diffused beyond platform

work into conventional employment settings such as warehouses, retail, manufacturing, and office work (Wood, 2021).

Belloc et al. (2023) develop a two-stage, partial-equilibrium, labour-discipline model in which one of the effects is disciplinary: the spread of digital monitoring allows employers to detect underperformance more reliably and to use the threat of dismissal as a more effective instrument for eliciting effort. This mechanism is taken as the analytical starting point in this study. The association between digital monitoring and evaluation and job displacement belief is examined in a general population of conventional employees, in contrast to existing AM research, which has often focused on platform work or qualitative evidence. Moreover, previous research has examined occupational exposure to AI or worker concerns about automation, while a separate literature has studied digital monitoring and algorithmic management. In this thesis, the AI exposure channel is added to broad occupational categories and is included as a control. The paper also expands this logic further, according to Manning (2003) workers with stronger outside options face weaker employer power and may therefore be less likely to hold job displacement beliefs. Digital skills are the most theoretically plausible source of outside-option heterogeneity, since workers with portable digital competencies can more credibly threaten exit. So the research question is "How are employers' digital monitoring and evaluation and workers' digital skills associated with job displacement beliefs?" Then the hypotheses are:

H1: Greater digital monitoring and evaluation are associated with stronger job displacement belief among employees.

H2: Greater digital skills are associated with lower job displacement belief among employees.

Data from Eurobarometer 101.4 / Special Eurobarometer 554, collected in April-May 2024 across 27 European countries, is used in this thesis. The survey contains self-reported measures of workplace digital monitoring and evaluation, informing about digital management tools, technology attitudes, a proxy for job-related digital skills, and broad indicator for job displacement belief, along with standard demographic and workplace characteristics. Survey-weighted logistic regression with country fixed effects is used in the empirical strategy, reporting average marginal effects in the main results.

The study shows that digital monitoring and evaluation is not positively associated with job displacement belief across all specifications, but the association becomes positive in the more conditional models and is more clearly concentrated at higher levels of monitoring intensity. However, using the available self-assessed job-related proxy, greater digital skills are not associated with lower job displacement belief in a simple linear way. The analysis also shows that workers with more negative attitudes toward robots and AI in the workplace are more likely to hold job displacement beliefs. While workers who report some form of disclosure about digital management tools are less likely to hold such beliefs, and this likelihood decreases as the level of disclosure becomes more detailed. Finally, occupational AI exposure (at group level) is negatively associated with job displacement belief in the main models, reinforcing the distinction between technical task exposure and workers' perceived employment threat.

The remainder of the thesis is organised as follows. Chapter 2 reviews the relevant literature. Chapter 3 sets out the hypotheses and empirical strategy. Chapter 4 describes the data and key variables. Chapter 5 reports the estimation results and acknowledges limitations. Chapter 6 draws together the findings, discusses their implications for theory and policy.

Chapter 2

LITERATURE REVIEW

2.1 Worker displacement concerns

Worker concerns about AI-driven job loss are widespread and shaped by factors that extend beyond the technical substitutability of occupational tasks. Survey evidence across several advanced economies suggests that displacement concerns remain salient even where AI's aggregate employment effects are ambiguous. Lane, Williams and Broecke (2023) report worker awareness of AI-related job loss alongside broader patterns of job reallocation within firms, and document that AI is already used in workplace governance, including performance assessment. These findings suggest that worker concerns may be associated not only with task substitution, but also with broader changes in how work is organised under AI.

Dekker, Salomons and van der Waal (2017) provide systematic cross-national evidence on the social structuring of these concern, using multilevel regressions on Eurobarometer 2012 data across 20 European countries. They show that fear of robots is socially structured and partly rooted in economic self-interest: lower-educated respondents, manual workers, and those in weaker labour-market positions report higher fear than managers and professionals. While country-level fear tends to be higher where unemployment is greater and lower where trade union density is stronger. The overall pattern is consistent with workers perceiving displacement risk through the lens of their labour-market position, and is reinforced by more recent evidence: Kozak et al. (2020), analysing Eurobarometer data across 28 EU countries, find that automation insecurity is more common among lower-educated and manual workers and is higher in countries with greater automation risk, a pattern they interpret as

reflecting workers' vulnerability and exposure to objective automation risk rather than simply an irrational fear of new technologies. Włoch, Śledziewska and Rożynek (2025) add a further dimension: fear of automation rises not only with routine task intensity but also with workers' direct experience of technology in the workplace, sector-level technological exposure, and perceived lack of control over life. Taken together, these results suggest that fear of automation reflects broader workplace and social conditions, but not only occupational task structure.

Acemoglu and Johnson (2023) argue that the effects of technology are not automatic, but depend on the choices that shape the direction of innovation and who benefits from it, what offers a theoretical grounding for the empirical pattern: if technology outcomes depend on deployment decisions rather than technical capability alone, then worker concerns may respond not only to task exposure, but also to how digital technologies are used in workplaces, including for monitoring and performance assessment, rather than to task substitution risk alone.

2.2 Occupational AI exposure

While the intellectual roots of this literature lie in earlier task-based analyses of technological change, especially Autor, Levy and Murnane (2003), Frey and Osborne (2017) represented an important step in the development of occupation-based automation research by operationalising automation exposure as an occupation-level probability of computerisation. Building on this tradition, Gmyrek et al. (2025) develop a refined task-based global index of occupational exposure to generative AI by combining nearly 30,000 tasks with worker scoring, expert review, and AI-assisted prediction to generate ISCO-08-compatible exposure scores. Their results suggest that generative AI is more

likely to transform the content of jobs than to automate most occupations fully, with only a small share of global employment falling into the highest exposure category.

AI exposure indicators should be interpreted as measures of the technical susceptibility of tasks and occupations to AI, not as forecasts of actual job loss. The ILO brief notes that results vary substantially across methods: older computerisation and automation measures tended to emphasise lower-paid routine manual and routine cognitive work whereas newer AI- and GenAI-focused measures more often identify higher exposure in professional occupations. More fundamentally, these measures rest on static task descriptions, often draw heavily on U.S. data, and do not capture profitability, firm strategy or institutional context — factors that shape whether technical substitutability translates into actual employment change, so exposure measures are therefore best treated as early-warning indicators of possible job transformation rather than predictions of displacement (ILO, 2026). In particular, they do not capture workplace use of digital technologies for monitoring and performance assessment, including AI-enabled tools, which may shape workers' job displacement beliefs independently of task substitution risk.

2.3 Employer power and labour discipline

Labour market frictions and imperfect information create the structural conditions under which employer power is sustained, and the dismissal threat becomes an effective disciplinary instrument. Manning (2003) contends that labour markets are more plausibly characterised by monopsony than by perfect competition, because labour market frictions prevent workers from moving freely and instantaneously between employers. These frictions arise from

imperfect information and mobility costs, which limit worker responsiveness to wage differences across firms, and as a result, the labour supply facing an individual employer is not perfectly elastic but upward sloping, giving firms a degree of wage-setting power. Crucially, this also means that job loss is costly for workers: because outside options are constrained by frictions, dismissal imposes a genuine penalty rather than a trivial inconvenience.

Given that workers face real exit costs, employers can use the threat of dismissal as a disciplinary instrument, but only in case if that threat is credible. Shapiro and Stiglitz (1984) show that under full employment, dismissal loses its disciplinary force because workers can be immediately rehired, removing the penalty associated with job loss and thereby undermining the incentive to exert effort. So to restore this incentive, firms pay wages above the market-clearing level, creating a rent that workers stand to lose upon dismissal. Bowles (1985) deepens this analysis by introducing monitoring intensity as a second disciplinary instrument alongside the wage premium: the cost of job loss and the probability of detecting shirking each operate as levers of labour discipline, with effort rising with both surveillance intensity and the wage premium over outside options. Because both monitoring and wage premia are costly, firms choose an optimal combination of the two, so that the equilibrium level of effort elicited depends on the relative cost of each instrument.

In settings with limited direct observability, effort is only imperfectly observed, creating a classic moral hazard problem, while information about underlying ability is revealed gradually through performance over time (Holmström, 1979; Farber and Gibbons, 1996). This informational constraint is the binding limit on the disciplining mechanism: if employers cannot observe effort with sufficient precision, the dismissal threat loses credibility and the efficiency-wage premium must bear a greater share of the disciplinary burden, that's why any reduction in monitoring costs or increase in monitoring precision should

therefore shift the equilibrium toward more effective discipline at lower wage cost, by making the dismissal threat more credible.

2.4 Digital monitoring and AM as workplace discipline

Algorithmic management emerged as a distinct organisational phenomenon in platform-based labour markets, where the structural features of gig work created particularly strong incentives for employer-side information accumulation and control. As platform workers are classified as independent contractors rather than employees, traditional hierarchical supervision is unavailable, and the need to build client trust pushes platforms beyond simple matching toward greater control over workers, so power may lie largely with the platform, while ongoing electronic performance tracking and algorithmic decisions over opportunities, pay, and removal from the platform can reduce worker autonomy (Kuhn and Maleki, 2017). Duggan et al. (2020) document that the gig economy has pioneered algorithmic techniques of worker control that deepen employer advantage through monitoring, discipline, and behavioral steering with limited worker recourse, thereby weakening worker voice. Kellogg, Valentine, and Christin (2020) provide a systematic framework for these practices, identifying six mechanisms through which employers use algorithmic systems to direct, evaluate, and discipline workers. Their review suggests that algorithmic management can weaken workers' position by increasing precarity, restricting worker voice, and heightening the threat of replacement. They also note that algorithmic systems may limit communication among workers, making managerial decisions harder for workers to understand or collectively contest.

These power asymmetries are not incidental features of platform work but reflect structural choices about job design and governance that employers make

strategically. Belloc et al. (2022) argue that automation risk is not purely technologically determined but is shaped by workplace governance and job design: in their theoretical framework, the absence of employee representation can make more routine, automation-prone job designs more attractive to employers because such jobs are easier to monitor and can strengthen labour discipline. Using European worker-level data, they document a negative association between employee representation and automation risk. This strategic logic extends to the informational dimension of algorithmic governance. Rosenblat and Stark (2016) illustrate this in practice: despite presenting drivers as independent workers, Uber retains significant indirect control through opaque algorithmic systems, and workers' attempts to navigate or contest these arrangements remain limited and individualised, underscoring the structural asymmetry between platform and worker.

Algorithmic management has since diffused beyond platform work into conventional employment relationships. Wood (2021) argues that algorithmic management in platform work more closely approximates high automation, because platforms such as Uber, UberEATS, Deliveroo, and Foodora use algorithms to allocate work, evaluate workers, and restrict access to future work. This can create insecurity, since ratings, rankings, and platform decisions shape continued access to work. By contrast, in conventional employment such as warehouses, retail, and manufacturing, algorithmic management is more often conditional: algorithms structure workflow and monitor performance, but human managers remain part of the managerial circuit; insecurity remains present in conventional settings, though more often mediated through monitoring, metrics, and managerial use of algorithmic outputs. This distinction is analytically important, standard employees may face digital monitoring and algorithmic management within institutional employment relationships.

The descriptive evidence from platform research motivates a more precise question: through what economic mechanism might digital monitoring strengthen employer oversight, and can this logic extend to standard employment? Belloc et al. (2023) frame digital monitoring within a labour-discipline model in which monitoring improves work transparency and thus strengthens the disciplining channel. In their framework, greater transparency makes low effort easier to detect, increases the credibility of dismissal threats, and thereby facilitates effort extraction. At the same time, this disciplining effect is not unconstrained, as employee representation can limit the use of monitoring data for sanctions and thus moderate the extent to which digital monitoring translates into employer discipline.

Experimental evidence from economics journals supports key parts of this monitoring-discipline logic and the moderating role of worker institutions. Using laboratory experiments to test whether dismissal threats remain effective when managers have only limited information about workers, Brandts et al. (2021) find that even relatively weak forms of supervision can substantially increase performance: when supervisors observe only overall organizational output, worker output rises by around 70 per cent relative to salary-only contracts, while observing time spent working leads to an approximately twofold increase. This provides direct experimental support for the theoretical prediction that monitoring access is the binding constraint on dismissal threat credibility. Grund, Sliwka, and Titz (2024) provide observational evidence from linked German employer-employee data showing that the positive association between performance appraisals and job satisfaction is concentrated in firms with works councils, consistent with the prediction that institutional worker representation moderates how monitoring practices translate into worker outcomes.

2.5 Digital skills and outside options

Returning to the monopsony framework developed by Manning (2003), employer market power is weaker when workers have stronger outside options, since greater mobility and better alternative employment opportunities reduce the firm's wage-setting latitude and may also weaken the disciplining force of job loss. The strength of workers' outside options may shape job displacement beliefs, and digital skills are a plausible source of outside-option heterogeneity in an AI-transformed labour market. Whether workers can translate their skills into strong outside options depends less on the abstract generality of individual skills than on how transferable their accumulated skill bundle is across alternative firms and occupations (Lazear, 2009; Gathmann and Schönberg, 2010). Workers whose skills are portable across employers face a more competitive market for their labour, limiting the employer's power to impose terms.

Empirical evidence supports the claim that digital and ICT skills improve outside options in European labour markets. Akerman et al. (2015) show that broadband internet adoption was skill-complementary: it improved labour-market outcomes for skilled workers while worsening them for unskilled workers, consistent with a task-based pattern in which broadband complements non-routine abstract work and substitutes for routine tasks. Falck, Heimisch-Roecker and Wiederhold (2021) document substantial wage returns to ICT skills in a multi-country sample that includes several European economies, indicating that strong digital competencies are valued across labour markets. Brynjolfsson, Li, and Raymond (2025) find that within-firm productivity gains from generative AI are concentrated among lower-skilled workers, although they stress that these findings are limited to short- and medium-run effects within a single firm and do not speak to long-run labour market outcomes. Taken together, this evidence suggests that digital skills are associated with

stronger labour market positions and wider outside options, implying lower monopsony exposure for workers at higher skill levels.

Bharti, Balducci, and Zappalà (2026), using Eurobarometer ZA8844 — the same dataset used in this thesis — argue that favorable views of AI's supportive role in work and concerns about AI-related job loss should be treated as separate attitudinal dimensions rather than as opposite poles of a single scale. Their analysis shows that stronger digital skills predict the complementarity-oriented dimension more strongly than the displacement-concern dimension, with the latter pathway present but substantially weaker.

2.6 Research gap and contribution

Existing research has not directly examined whether employer digital monitoring and evaluation is associated with worker job displacement beliefs in a cross-national sample of employees. Research on algorithmic management and digital monitoring suggests that workplace governance practices are associated with job insecurity and related worker outcomes, but the evidence remains concentrated in platform settings, qualitative studies, and single-country analyses. Research on job displacement beliefs and occupational AI exposure, by contrast, focuses mainly on task-substitution risk or broader social correlates of automation concern, while typically lacking any direct measure of employer digital monitoring and evaluation. This thesis addresses that gap by examining that association across 27 EU member states, while controlling for occupational AI exposure at the group level. It also examines whether digital skills are associated with lower job displacement belief, consistent with the outside-options mechanism discussed in the literature.

Chapter 3

METHODOLOGY

3.1 Research question and hypotheses

The research question: How are employers' digital monitoring and evaluation and workers' digital skills associated with job displacement beliefs?

The first hypothesis is motivated by the labour-discipline framework developed by Bowles (1985) and extended to the disciplinary effect by Belloc et al. (2023). If digital monitoring increases the credibility of employer oversight and dismissal threats, workers in more intensively monitored workplaces may experience higher levels of perceived job insecurity. But as the survey does not measure own-job insecurity directly, H1 is tested using broad indicator for job displacement belief as an imperfect proxy.

H1: Greater digital monitoring and evaluation is associated with stronger job displacement belief among employees.

The second hypothesis is motivated by the outside-options framework associated with Manning (2003). If stronger digital skills improve workers' outside options and reduce employer power, workers with stronger digital skills may be less likely to hold job displacement beliefs.

H2: Greater digital skills are associated with lower job displacement belief among employees.

3.2 Models

In order to test our hypotheses, a survey-weighted logistic regression model with country fixed effects is used, where job displacement belief is the

dependent binary variable, digital monitoring and evaluation and self-assessed job-related digital skill sufficiency are the focal independent variables, occupational AI exposure, reported informing about digital management tools, and workplace technology attitudes are additional substantive regressors, and demographic and workplace characteristics (age, gender, education, social class, community type, sector and firm size) are control variables. The fullest main specification is given by Equation (1).

$$\begin{aligned}\Pr(\text{Job Displacement Belief}_i = 1 \mid X_i) = F(&\beta_0 + \beta_1 \text{Digital monitoring and evaluation}_i \\ &+ \beta_2 \text{Occupational AI exposure}_i \\ &+ \beta_3 \text{Workplace technology attitudes}_i + \beta_4 \text{Reported informing about digital management tools}_i + \beta_5 \text{Job-related digital skills}_i \\ &+ \beta_6 \text{Demographic and workplace controls}_i + \beta_7\ \text{CountryFE}_i)\end{aligned} \quad (1)$$

where $\Pr(\text{Job Displacement Belief}_i = 1 \mid X_i)$ denotes the conditional probability that respondent i exhibits the binary job-displacement-belief outcome, and F() denotes the logistic cumulative distribution function.

The empirical strategy is organized as a sequence of progressively richer specifications, what makes it possible to assess how the estimated association between digital monitoring and evaluation and job displacement belief changes as conceptually distinct blocks of covariates are introduced.

The sequence of models is summarized in Table 3.1. It begins with digital monitoring and evaluation because the core argument of the thesis is derived from the labour-discipline framework, country fixed effects are included because both job displacement belief and workplace digital-management practices may vary systematically across labour-market contexts. As next step

occupational AI exposure (group level) is added because the thesis explicitly distinguishes a workplace-governance channel from a separate technical-exposure channel emphasized in the literature. Demographic and workplace controls are then introduced to reduce the magnitude of the main variables, as they absorb part of the association related to individual or workplace characteristics.

Table 3.1 Sequential specification design for the main models M1-M6

Variable	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**
Outcome: Job displacement belief	Yes	Yes	Yes	Yes	Yes	Yes
Digital monitoring and evaluation	Yes	Yes	Yes	Yes	Yes	Yes
Occupational AI exposure (group level)		Yes	Yes	Yes	Yes	Yes
Workplace technology attitudes				Yes	Yes	Yes
Reported informing about digital management tools					Yes	Yes
Job-related digital skills						Yes
Demographic and workplace controls			Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Then M4 adds workplace technology attitudes in order to distinguish the governance channel from a broader attitudinal channel, as the association between digital monitoring and evaluation and job displacement belief may partly reflect general orientations toward workplace technologies rather than digital monitoring and evaluation as such. M5 adds reported informing about digital management tools after workplace technology attitudes because attitudes capture workers' broader views, while informing captures a more specific workplace communication channel. Informing may shape how workers

interpret monitoring, but it may also be partly determined by the way digital monitoring is implemented. Finally, to test H2 M6 adds job-related digital skills.

M3 is the baseline adjusted specification for H1 because it includes occupational AI exposure and demographic and workplace controls. M4 and M5 are more conditional specifications that examine whether the monitoring-belief association remains after accounting for broader workplace technology attitudes and reported informing about digital management tools. M5 is therefore treated as the final fully adjusted conditional specification for H1, while M6 is the final main specification for H2. Both models are used as the reference models for robustness and diagnostics checks.

First, robustness checks examine whether the substantive interpretation of the main findings depends on particular operational choices, they vary the coding of the variables, and also compare weighted and unweighted specifications. Second, standard diagnostics are used to assess the adequacy of the main model, these include checks for multicollinearity, separation, functional form, and influential observations.

The analytical weight used in this thesis is the Eurobarometer weight w1, which is the standard national post-stratification weight, designed to adjust national samples to their population structure treating individual respondents as the unit of analysis and applying this weight to each observation. The analysis does not additionally account for primary sampling units or strata, because these design identifiers are not included in the analytical dataset used for the thesis, and therefore, the reported standard errors should be interpreted as approximate survey-weighted standard errors based on the available Eurobarometer weight.

Chapter 4

DATA

4.1 Data source

Data from Eurobarometer 101.4 / Special Eurobarometer 554, collected in April-May 2024 across 27 European countries, is used in this thesis (European Commission, 2025). The survey contains information on workers' beliefs, workplace digital management practices, whether respondents were informed about such tools, self-assessed digital skills, and a broad set of demographic and workplace characteristics.

4.2 Variables

The variables are drawn from a survey block on digital technologies and AI, and since the wording of this introductory block shapes how respondents interpret the subsequent questions, it is reported in full in Appendix A. The operationalisation, survey questions, response categories, and coding of all survey variables used in the analysis are reported in Appendix B.

The dependent variable in the main analysis is a binary measure of job displacement belief based on the survey item asking respondents whether they agree that "robots and artificial intelligence steal people's jobs." Agreement with this statement can be interpreted as a broad indicator of job displacement belief, although not as a direct measure of personal job insecurity. Related literature suggests that broader automation-related perceptions may translate into more personalized employment threat. In particular, Gödöllei and Beck (2023) show that employees' perception that their work is automatable is empirically distinct from, yet strongly positively related to, automation-related job insecurity in both a

survey ($\beta = 0.74$, $p < .001$) and an experiment ($\beta = 0.40$, $p < .001$). Similarly, Brougham and Haar (2020) theorize the perceived threat of technological disruption as "a key component or factor shaping job insecurity" and find that it had a direct positive effect on job insecurity ($\beta = 0.62$, $p < 0.001$), while also reporting a substantial correlation between perceived technological disruption and job insecurity in the combined sample ($r = 0.51$, $p < .01$). Moreover, in the context of digital monitoring, this connection is especially relevant. If digital monitoring increases the credibility of employer oversight and dismissal threats, workers in more intensively monitored workplaces may interpret AI and digital technologies as part of a broader shift in employer power. As a result, they may be more likely to agree with the statement that "AI and robots steal jobs," even if the item does not directly ask about their own job insecurity. Taken together, these findings suggest that broader automation-related beliefs may be empirically connected to more personal insecurity perceptions, making the use of agreement with "AI and robots steal jobs" as a broad job-displacement-belief measure plausible, though still imperfect.

For the H2 analysis, digital skills are operationalized using self-assessed job-related digital skill sufficiency, used as an empirical proxy for the broader theoretical concept of digital skills. The resulting variable therefore captures perceived job-related digital skill sufficiency rather than an objective skills test. In addition to the main explanatory variables, the analysis includes a set of demographic, social, and workplace controls, which are included to account for broader differences in labour-market position and work context.

4.3 Occupational AI exposure

For the descriptive analysis in this subsection, I refer to the outcome as AI job displacement belief rather than broad job displacement belief, because the

underlying survey item specifically asks whether "AI and robots steal jobs", this narrower label is more precise for the present comparison between occupation-level AI exposure and the outcome, but in the later regression analysis I return to the broader term.

To construct the exposure measure, I relied on the 4-digit ISCO-08 occupation-level scores provided in Gmyrek et al. (2025). Its methodology combines a representative sample of 29,753 occupational tasks from the polish occupational classification system, 52,558 task-level assessments of the perceived automation potential of 2,861 tasks, expert validation and AI-assisted prediction for tasks described in the technical documentation of ISCO-08 occupations. Because the Eurobarometer data do not provide fully harmonised 4-digit occupation codes, it was necessary to approximate the correspondence between the survey occupation categories and the external ILO exposure index, so I therefore implemented three alternative mapping strategies. The first approach identified the occupations in the ILO index that most closely represented each Eurobarometer category. The second mapped all occupations from the external index into the Eurobarometer categories, using sectoral information as an additional criterion to improve the quality of assignment. The third relied on direct mapping between the Eurobarometer occupation categories and the nearest ISCO-08 occupational groups. All three approaches showed almost the same results, that's why only results based on the third approach were reported, as this one is the least dependent on discretionary researcher judgement, and therefore minimises potential classification error (the detailed construction is documented in Appendix C).

At first glance, one might expect a simple positive pattern: occupations with higher AI exposure should show stronger AI job displacement belief, but Figure 4.1 does not show such a straightforward relationship. Some relatively highly exposed occupation groups, especially more white-collar groups, display only

moderate levels of AI job displacement belief, while some less exposed groups show comparatively high concern.

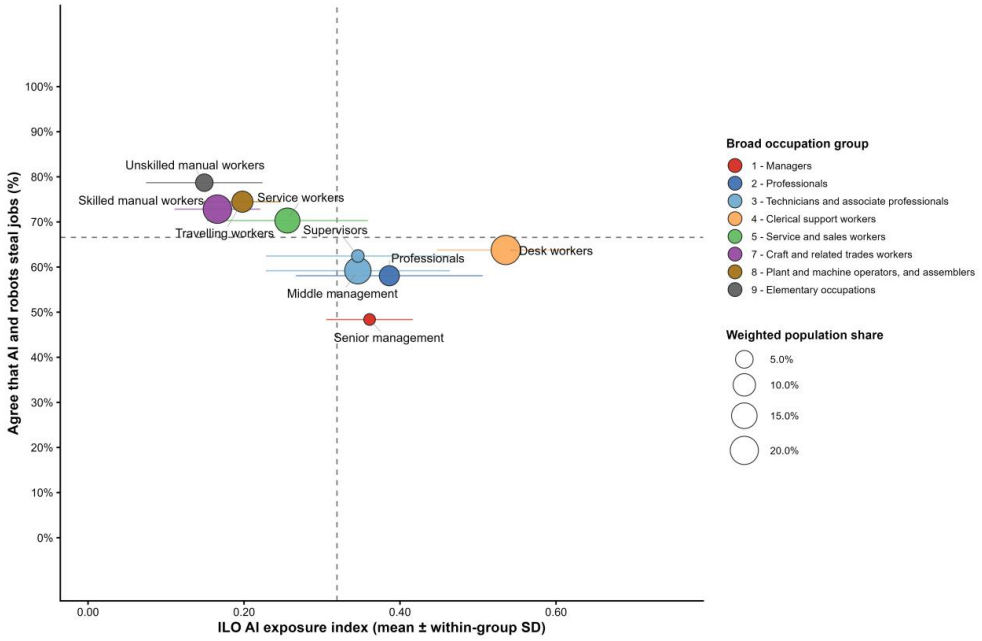


Figure 4.1 Occupational AI exposure and AI job displacement belief across broad occupation groups

Source: Data for index was taken from Gmyrek et al. (2025), author's calculations

Note: Each bubble is one broad occupation category. Horizontal bars show within-group heterogeneity in the ILO exposure score. Bubble size is weighted population share. Dashed lines is overall weighted means.

Several explanations may account for this pattern. First, the ILO index measures the technical exposure of occupational tasks to AI, not workers' subjective beliefs about whether jobs will disappear, so technical exposure is only one input into job displacement belief, which may also depend on how AI is introduced, whether it is seen as complementary or substitutive, and how secure workers perceive their employment situation to be. Second, high exposure does not

necessarily imply expected job loss, as in some relatively exposed white-collar occupations, AI may be perceived more as a tool that assists work than as a direct substitute for the worker. Third, workers in more exposed occupations may have more direct contact with digital tools and therefore more realistic expectations about what current AI systems can do, while workers in less exposed occupations may rely more on general public narratives about technological job loss. Fourth, those narratives may themselves reflect an older automation intuition that manual or routine jobs are the main ones at risk. This interpretation is plausible in light of the rapid later diffusion of AI in European business: Eurostat (2025) reports that 20.0% of EU enterprises with 10 or more employees used AI technologies in 2025, up from 13.5% in 2024, 8.1% in 2023, and 7.7% in 2021. Taken together, this suggests that respondents may not yet have interpreted AI risk in the same way it is often discussed now, especially with respect to white-collar exposure.

4.4 Construction of the analytical samples

The empirical analysis is restricted to employees. Table 4.1 summarizes the construction of the analytical samples.

Table 4.1 Construction of the analytical samples

Sample	N	Excluded	Restriction
Eurobarometer 101.4	26,404	—	—
Employees	11,904	14,500	Exclude non-employed respondents
Sample A	10,200	1,704	Drop missing on core variables
Sample B	9,434	766	Drop missing on digital skills

Starting from the full Eurobarometer 101.4 sample of 26,404 respondents, restricting the data to employees reduces the sample to 11,904 observations. The main estimation sample, Sample A, is then constructed by dropping observations with missing values on the core variables used in the H1 analysis, leaving 10,200 observations, what implies the loss of 1,704 observations (about 14.3% of the employee sample). Because including the digital-skills variable would require dropping a further 766 observations, a separate sample was defined for the H2 analysis in order to avoid imposing this additional reduction on the main H1 models. The resulting Sample B therefore contains 9,434 observations and is used only for specifications that include digital skills. Appendix D compares the profile of Sample A and Sample B, and the two samples are very similar in their weighted demographic and workplace composition.

4.5 Descriptive statistics of main variables

Table 4.2 reports the weighted distributions of the main discrete analytical variables. More than half of respondents agree that "robots and Artificial Intelligence steal people's jobs" indicating that job displacement belief is widespread. The main governance variable, digital monitoring and evaluation, is skewed toward the lower end of the scale, what suggests that intensive digital monitoring is not the modal experience in the employee sample, but is still sufficiently common to support meaningful comparison across categories. The distribution of attitude toward robots and AI in the workplace is more concentrated in the positive range, while the weighted shares for informed about digital management tools are relatively balanced and the distribution of sufficient digital skills for job is concentrated in the upper part of the scale.

Table 4.2 Distributions of the main discrete variables

Variable	Category	%
Robots and Artificial Intelligence steal people's jobs	Disagree	34.2%
Robots and Artificial Intelligence steal people's jobs	Agree	65.8%
Digital monitoring and evaluation	Never / n/a	39.2%
Digital monitoring and evaluation	Never / rarely	9.3%
Digital monitoring and evaluation	Rarely	16.0%
Digital monitoring and evaluation	Rarely / often	12.1%
Digital monitoring and evaluation	Often	14.3%
Digital monitoring and evaluation	Often / all the time	5.1%
Digital monitoring and evaluation	All the time	4.1%
Attitude toward robots and AI in the workplace	Very positive	17.2%
Attitude toward robots and AI in the workplace	Fairly positive	55.2%
Attitude toward robots and AI in the workplace	Fairly negative	21.2%
Attitude toward robots and AI in the workplace	Very negative	6.4%
Informed about digital management tools	No disclosure / n/a	46.6%
Informed about digital management tools	Any disclosure	53.4%
Sufficient digital skills for job	Totally disagree	6.2%
Sufficient digital skills for job	Tend to disagree	14.1%
Sufficient digital skills for job	Tend to agree	46.0%
Sufficient digital skills for job	Totally agree	33.7%

Notes: % is share of valid responses, computed using survey weights. All variables are based on Sample A, except for "sufficient digital skills for job," which is based on Sample B.

Table 4.3 reports the weighted prevalence of job displacement belief across main discrete variables. For digital monitoring and evaluation, the pattern is not monotonic across the full scale, but it is clearly higher at the upper end. At the same time, the prevalence in the never category is also relatively high, indicating that the relationship is not simply linear even at the descriptive level and may combine workers with genuinely no exposure to digital monitoring and workers for whom the monitoring items were less applicable.

The weighted prevalence of job displacement belief for attitude toward robots and AI in the workplace increases steadily from 48.7% among respondents with very positive attitudes toward robots and AI in the workplace to 82.3% among those who are very negative, what suggests that attitude toward robots and AI in the workplace are closely related to the belief that "AI and robots steal jobs". For informed about digital management tools, the prevalence of job displacement belief is lower among respondents reporting any disclosure than among those reporting no disclosure / not applicable.

Table 4.3 Prevalence of job displacement beliefs across main discrete variables

Variable	**Category**	**%**
Digital monitoring and evaluation	Never / n/a	70.1%
Digital monitoring and evaluation	Never / rarely	59.2%
Digital monitoring and evaluation	Rarely	60.2%
Digital monitoring and evaluation	Rarely / often	59.4%
Digital monitoring and evaluation	Often	66.9%
Digital monitoring and evaluation	Often / all the time	69.3%
Digital monitoring and evaluation	All the time	72.8%
Informed about digital management tools	No disclosure / n/a	70.6%
Informed about digital management tools	Any disclosure	61.7%
Attitude toward robots and AI in the workplace	Very positive	48.7%
Attitude toward robots and AI in the workplace	Fairly positive	65.1%
Attitude toward robots and AI in the workplace	Fairly negative	76.5%
Attitude toward robots and AI in the workplace	Very negative	82.3%
Sufficient digital skills for job	Totally disagree	65.9%
Sufficient digital skills for job	Tend to disagree	66.6%
Sufficient digital skills for job	Tend to agree	69.8%
Sufficient digital skills for job	Totally agree	57.8%

Notes: % is weighted prevalence, computed using survey weights. All variables are based on Sample A, except for "sufficient digital skills for job," which is based on Sample B.

The descriptive pattern for sufficient digital skills for job in Sample B is more complex. Job displacement belief is highest among respondents who tend to

agree that they have sufficient digital skills for their job, somewhat lower among those who tend to disagree or totally disagree, and lowest among those who totally agree.

Appendix E reports summary statistics for the main variables introduced in subsections 4.2-4.3, using the continuous or binary codings applied in the empirical analysis, what complements the categorical distributions presented above by showing how the same variables are represented in the regressions.

4.6 Correlation structure of main variables

Figure 4.2 presents the pairwise correlation matrix for the main analytical variables, calculated for Sample B, which is the fullest common sample in which all variables are jointly observed. Overall, the correlations are moderate rather than extreme, which suggests that the variables capture related but distinct dimensions of the empirical setting.

First, digital monitoring and evaluation is positively correlated with informed about digital management tools (r=0.41), indicating that workers in more digitally managed settings are also more likely to report some form of disclosure about these tools, but is negatively correlated with attitude toward robots and AI in the workplace (r=-0.20). Since higher values on the attitude variable indicate more negative views, this implies that more intensive monitoring is modestly associated with less negative workplace AI and robots attitudes at the descriptive level. Although this may seem somewhat unintuitive at first, but one possible explanation that workers exposed to more intensive monitoring are more likely to work in relatively digitalized environments and therefore to have greater familiarity with workplace technologies, which may in turn be associated with more positive attitudes toward them.

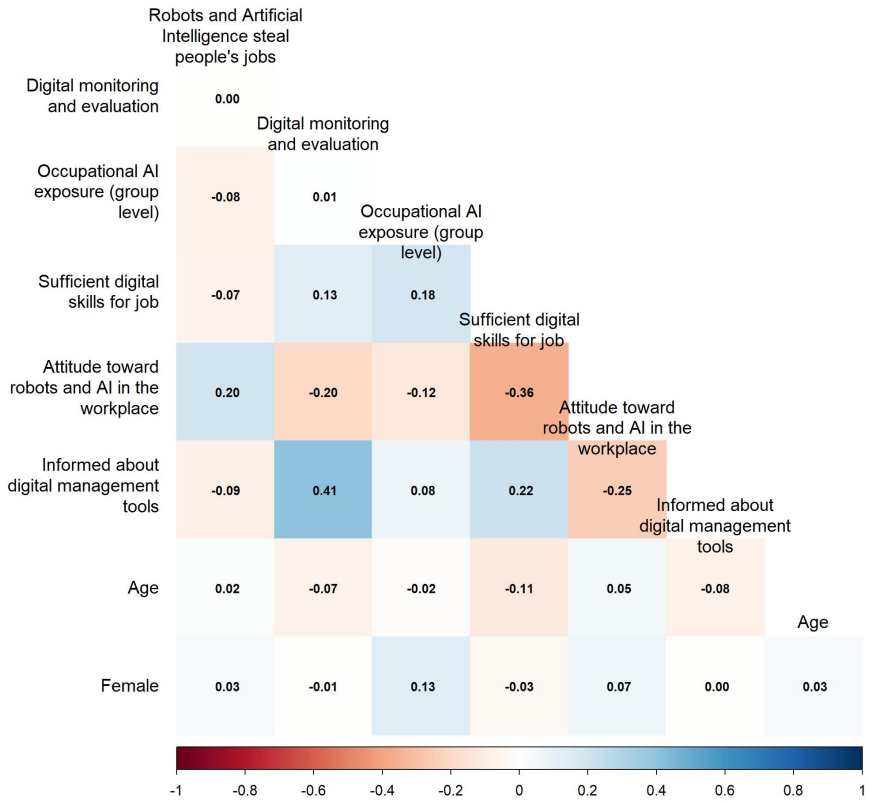


Figure 4.2 Weighted correlation matrix for main variables
Notes: Results are based on sample B.

Second, the strongest simple relationship with the outcome appears for attitude toward robots and AI in the workplace, which is positively correlated with the job-displacement-belief variable (r=0.20), what is consistent with the descriptive evidence reported in the previous subsection. Informed about digital management tools is negatively correlated with the outcome (r=-0.09), while Digital monitoring and evaluation itself is essentially uncorrelated with the outcome at the simple bivariate level (r=0.00), what already suggests that any association between monitoring and job displacement belief may depend on conditioning on other variables.

Third, sufficient digital skills for job is negatively correlated with attitude toward robots and AI in the workplace (r=-0.36), implying that workers who report stronger digital skill sufficiency also tend to hold less negative workplace technology attitudes, and is also positively correlated with occupational AI exposure (r=0.18).

Finally, occupational AI exposure (group level) is only weakly correlated with the outcome (r=-0.08) and with most of the other variables, what is consistent with the argument developed earlier that occupational AI exposure should be treated as a distinct technical-exposure channel rather than as a direct proxy for workers' perceived displacement risk.

Taken together, the correlation structure supports two conclusions: the main explanatory variables are related in substantively meaningful ways and the absence of very high pairwise correlations suggests that these variables are not simple duplicates of one another.

Chapter 5

ESTIMATION RESULTS

First, the association between digital monitoring and evaluation and job displacement belief is examined, as predicted by H1. Second, an extension specification is used to examine whether the monitoring-displacement relationship varies between informed and uninformed workers. Third, the association between digital skills and job displacement belief is tested, as predicted by H2. Coefficients are presented in Appendix F. The chapter then discusses cross-country variation and patterns of control variables. Robustness checks and model diagnostics are presented in Appendices G and H.

5.1 H1 results

Table 5.1 reports average marginal effects from survey-weighted logistic models estimated on sample A and including fixed effects for 27 countries, where the outcome is the probability of agreeing that "AI and robots steal jobs", which is interpreted in this thesis as a broad proxy for job displacement belief. The association between digital monitoring and evaluation and job displacement belief changes sign across the five specifications. The movement from negative in M1-M2 to zero in M3 is consistent with the inclusion of demographic and workplace controls, which absorb the initial negative association, and the subsequent movement from zero in M3 to positive values in M4-M5 occurs once attitudes and informing are added. Monitoring is negatively correlated with negative attitudes toward robots and AI in the workplace ($r = -0.22$ based on sample A) and positively correlated with being informed about digital management tools ($r = 0.43$ based on sample A), while both attitudes and informing are themselves strongly associated with job displacement belief. Once these correlated variables

are held constant, the monitoring coefficient shifts from zero into positive territory, meaning that the estimated monitoring association depends on whether these variables are included in the model.

Table 5.1 Average marginal effects for main variables in models M1-M5

Variable	**M1**	**M2**	**M3**	**M4**	**M5**
Digital monitoring and evaluation	-0.013*	-0.012*	-0.009	0.006	0.014*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Occupational AI exposure (group level)		-0.233* * *	-0.137* * *	-0.099*	-0.096*
		(0.035)	(0.039)	(0.039)	(0.039)
Attitude toward robots and AI in the workplace				0.092* * *	0.088* * *
				(0.007)	(0.007)
Informed about digital management tools					-0.044* * *
					(0.011)
Demographic and workplace controls	No	No	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	10200	10200	10200	10200	10200
Weighted N	10757.66	10757.66	10757.66	10757.66	10757.66
Tjur's R2	0.061	0.065	0.080	0.100	0.102
AUC	0.635	0.643	0.659	0.679	0.682

Notes: *** p < 0.001; ** p < 0.01; * p < 0.05.

In M5, a one-unit increase in monitoring intensity is associated with a 1.4 percentage point increase in job displacement belief, compared with an 8.8 percentage point increase for a one-unit increase in negative attitudes and a 4.4 percentage point decrease for being informed, and across the full 1 to 4 monitoring scale, the implied difference is approximately 4 percentage points, which helps explain why the coefficient is specification-sensitive.

Occupational AI exposure is negative across all specifications and remains statistically significant in the fully conditioned model (M5: AME = -0.096, SE = 0.039, $p < 0.05$), indicating that workers in more AI-exposed occupations are, on average, less likely to report job displacement beliefs. Because the exposure index does not span a full unit across the observed sample, the substantive difference over the observed range is smaller than the raw coefficient suggests, at approximately 3.7 percentage points. This negative association also underscores the limits of exposure indices discussed in Section 2.2, that technical substitutability does not translate directly into worker perceptions of displacement risk. Also it is in line with analysis of data in Section 4.4 that workers in more exposed occupations may encounter AI more often as complementary tool, may hold more realistic expectations about current AI capabilities, or may work in contexts where exposure is interpreted differently, but the data do not allow these interpretations to be distinguished.

To examine functional form, Table 5.2 adds the corresponding dummy specifications of M1 and M5, S1 and S2, using "rarely / often" (the midpoint on the digital monitoring and evaluation scale) as the reference category.

Table 5.2 Average marginal effects for main variables in models S1-S2

Variable	**S1**	**S2**
Occupational AI exposure (group level)		-0.093*
		(0.039)
Attitude toward robots and AI in the workplace		0.090* * *
		(0.007)
Informed about digital management tools		-0.034* *
		(0.011)
Digital monitoring and evaluation: Never	0.102* * *	0.063* * *
	(0.017)	(0.017)
Digital monitoring and evaluation: Never / rarely	0.022	0.009

Table 5.2 — Continued

Variable	S1	S2
	(0.023)	(0.022)
Digital monitoring and evaluation: Rarely	0.009	0.001
	(0.020)	(0.019)
Digital monitoring and evaluation: Rarely / often	Ref.	Ref.
	Ref.	Ref.
Digital monitoring and evaluation: Often	0.051* *	0.064* * *
	(0.020)	(0.019)
Digital monitoring and evaluation: Often / all the time	0.090* * *	0.107* * *
	(0.026)	(0.024)
Digital monitoring and evaluation: All the time	0.130* * *	0.162* * *
	(0.030)	(0.026)
Demographic and workplace controls	No	Yes
Country fixed effects	Yes	Yes
Observations	10200	10200
Weighted N	10757.66	10757.66
Tjur's R2	0.069	0.108
AUC	0.649	0.689

Notes: *** p < 0.001; ** p < 0.01; * p < 0.05.

In both dummy specifications (Figure 5.1), the lower-to-middle categories remain close to the reference group, while the upper monitoring categories are clearly positive and statistically significant, what shows that the upper-tail pattern is already visible in the simplest specification and becomes clearer in the fully conditioned model. These contrasts are larger than the linear AME of +1.4 pp (comparing Model M5 and S2), because the underlying relationship is non-linear or monotonic threshold due to the positive coefficient for the "never" category in both dummy specifications.The dummy specifications also help explain why the linear monitoring coefficient changes sign across models, as in the linear M1 coefficient being pulled downward by the irregular zero-monitoring category, while the later specification makes the upper-tail increase more visible.

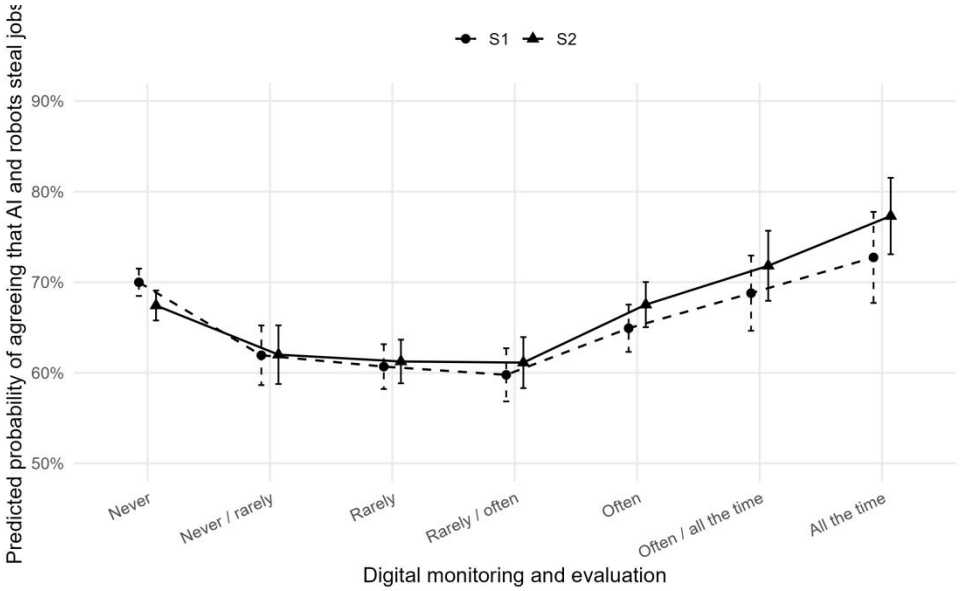


Figure 5.1 Predicted probability of job displacement belief across digital monitoring and evaluation intensity

Notes: Vertical bars show 95% confidence intervals. Digital monitoring and evaluation categories is based on models S1 and S2.

Taken together, the evidence for H1 is limited, conditional, and non-linear. Digital monitoring and evaluation is not positively associated with job displacement belief across the full model sequence and becomes positive and statistically significant only after controlling for attitudes toward AI and robots in the workplace and whether workers are informed about digital management tools, while the dummy specifications show that a more strongly positive relationship is already visible in the upper monitoring categories in the simplest model and becomes clearer in the fully conditioned specification. At the same time, robustness check (Appendix G) shows that the association does not extend to the strictest version of the outcome, since the monitoring coefficient becomes indistinguishable from zero, so the digital monitoring is associated with job

displacement belief in a bounded, conditional, and non-uniform way rather than as a robust positive linear relationship across all specifications.

5.2 Alternative specifications of the informing variable

To examine whether different forms of information about digital management tools are associated with job displacement belief in the same way, two additional specifications are estimated in Table 5.3. Model R11 recodes the informing variable as a 0-3 ordinal scale, while Model S3 treats the same variable categorically. In R11, each additional level of information is associated with a 2.6 percentage point lower probability of holding job displacement belief (AME = -0.026, SE = 0.005, $p < 0.001$). However, the categorical specification shows that this basic notification alone is not statistically distinguishable from no disclosure, while detailed explanation is associated with a 4.1 percentage point lower probability (AME = -0.041, SE = 0.015, $p < 0.01$), and access to data/results is associated with an 8.3 percentage point lower probability (AME = -0.083, SE = 0.016, $p < 0.001$). The other focal variables remain very similar across specifications and model fit changes only marginally. Overall, these results suggest that the negative association between information and job displacement belief is robust, but the categorical model indicates that more substantive forms of information, especially access to data or results, are more strongly associated with lower job displacement belief.

Table 5.3 Average marginal effects for main variables in models R11 and S3

Variable	**R11**	**S3**
Digital monitoring and evaluation	0.016* *	0.015*
	(0.006)	(0.006)
Occupational AI exposure (group level)	-0.096*	-0.097*

Table 5.3 — Continued

Variable	R11	S3
	(0.039)	(0.039)
Attitude toward robots and AI in the workplace	0.088* * *	0.089* * *
	(0.007)	(0.007)
Informed about digital management tools (0-3 scale)	-0.026* * *	
	(0.005)	
Informed about DM tools: No disclosure / n/a		Ref.
		Ref.
Informed about DM tools: Basic notification only		-0.013
		(0.014)
Informed about DM tools: Detailed explanation		-0.041* *
		(0.015)
Informed about DM tools: Data/results access		-0.083* * *
		(0.016)
Demographic and workplace controls	Yes	Yes
Country fixed effects	Yes	Yes
Observations	10200	10200
Weighted N	10757.66	10757.66
Tjur's R2	0.103	0.103
AUC	0.685	0.685

Notes: *** p < 0.001; ** p < 0.01; * p < 0.05.

5.3 Monitoring and informing: an interaction extension

Model E1 (Appendix F) extends the fully adjusted conditional specification (M5) by adding an interaction between digital monitoring and evaluation and being informed about digital management tools, testing whether the monitoring-job-displacement belief association differs between workers who were informed and those who were not informed about the digital tools used in their workplace.

Figure 5.2 plots the predicted probability of agreeing that "robots and AI steal people's jobs" across the range of digital monitoring intensity, separately for

workers who were informed and those who were not about digital management tools.

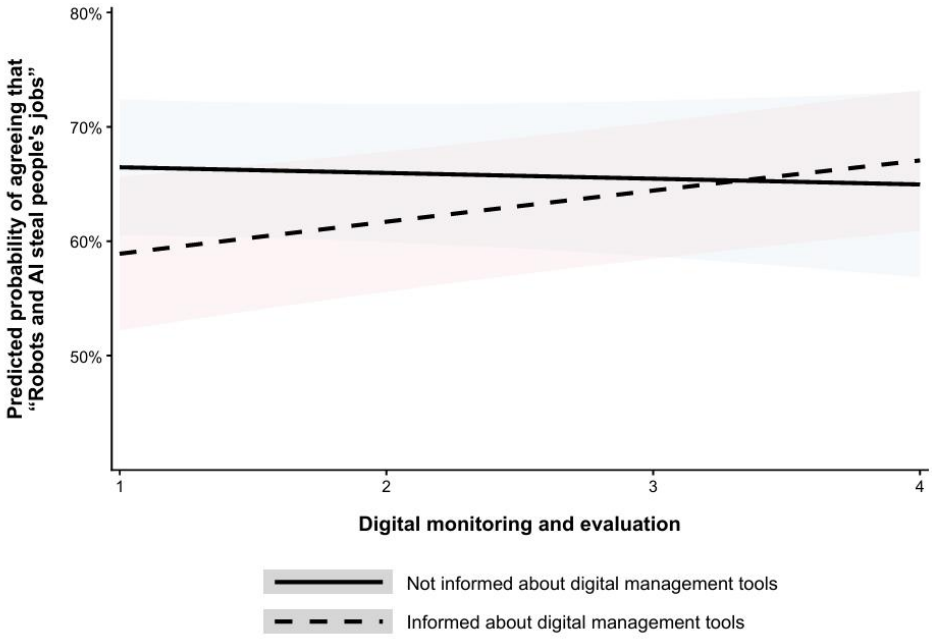


Figure 5.2 Predicted probability of job displacement belief by digital monitoring and evaluation intensity and informing about digital management tools
Notes: Shaded areas show 95% confidence intervals. The model E1 is estimated with centered digital monitoring and evaluation, but shown here on the original 1-4 scale ("never" to "all the time").

At low levels of monitoring, informed workers have a lower predicted probability of job displacement belief than non-informed workers and as monitoring intensity increases, this gap narrows, with the predicted probability rising more steeply for informed workers while remaining relatively flat for non-informed workers; finally, by the highest monitoring levels, the two groups converge. This is consistent with the theoretical argument developed in Section 2.4, which holds that workplace digital monitoring may matter more to workers'

beliefs when digital management practices are more visible to them. At the same time, being informed about digital management tools is not the same as directly measuring awareness of monitoring itself, and the figure shows considerable overlap in the confidence intervals across much of the monitoring range.

5.4 H2 results

To test the second hypothesis, the model M5 was first re-estimated (M5b) on the reduced sample B (Table 5.4). The main variables change only marginally and model fit declines slightly, so these comparisons indicate that sample restriction alone does not materially alter the main pattern of results.

When the variable "sufficient digital skills for the job" is added linearly in M6, it enters positively and is statistically significant (AME = 0.024, SE = 0.007, $p < 0.001$), contrary to the hypothesized direction. Therefore, H2 is not supported in its original linear form.

To assess whether this positive linear coefficient masks a more complex underlying pattern, supplementary specification S4 replaces the linear digital-skills term with category dummies, using "tend to agree" as the reference category, and the results show that the relationship is highest in the intermediate "tend to agree" category rather than at either end of the skill-confidence distribution. Thus, all three non-reference categories exhibit lower job displacement belief than the reference group, so the ordering across categories is not monotonic in skill confidence.

One possible interpretation is that workers who totally agree they have sufficient digital skills feel relatively protected from displacement, which is consistent with the outside-options argument developed in Section 2.5.

Table 5.4 Average marginal effects for main variables in models M5-M6 & S4

Variable	M5	M5b	M6	S4
Digital monitoring and evaluation	0.014*	0.018* *	0.017* *	0.017* *
	(0.006)	(0.006)	(0.006)	(0.006)
Sufficient digital skills for job			0.024* * *	
			(0.007)	
Sufficient digital skills for job: Totally agree (ref. Tend to agree)				-0.042* * *
				(0.012)
Sufficient digital skills for job: Tend to disagree (ref. Tend to agree)				-0.086* * *
				(0.016)
Sufficient digital skills for job: Totally disagree (ref. Tend to agree)				-0.143* * *
				(0.023)
Occupational AI exposure (group level)	-0.096*	-0.081*	-0.093*	-0.095*
	(0.039)	(0.041)	(0.041)	(0.041)
Attitude toward robots and AI in the workplace	0.088* * *	0.093* * *	0.100* * *	0.101* * *
	(0.007)	(0.007)	(0.007)	(0.007)
Informed about digital management tools	-0.044* * *	-0.045* * *	-0.049* * *	-0.049* * *
	(0.011)	(0.011)	(0.012)	(0.012)
Demographic and workplace controls	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Observations	10200	9434	9434	9434
Weighted N	10757.66	9987.25	9987.25	9987.25
Tjur's R2	0.102	0.101	0.102	0.107
AUC	0.682	0.680	0.682	0.688

Notes: *** p < 0.001; ** p < 0.01; * p < 0.05.

By contrast, the especially high job displacement belief among the "tend to agree" group may reflect workers whose current digital skills appear adequate for current tasks but are less certain that those skills will remain sufficient as

technologies continue to evolve. The lower job displacement belief among workers who tend to disagree or totally disagree that they have sufficient digital skills is not predicted by the outside-options mechanism, and one possible explanation is that workers who disagree or totally disagree may not interpret digital skills as central to their work or may differ in other unobserved ways; however, the data do not allow it to be tested directly. The remaining coefficients in M6 and S4 are broadly stable, which strengthens confidence that the digital-skills results do not overturn the model's main findings.

Overall, the theoretical argument developed in Section 2.5, that digital skills provide outside options that protect workers from displacement concerns, is not supported in its original monotonic linear form. At the same time, the categorical results suggest that the outside-options argument may help explain part of the pattern, as workers who totally agree that they have sufficient digital skills show lower job displacement beliefs than workers who tend to agree. However, the theory does not explain why workers at the opposite end of the skill-confidence distribution also lie below the intermediate "tend to agree" category; the findings therefore do not support H2 as originally formulated.

5.5 Country differences

Figure 5.3 shows substantial cross-country heterogeneity in adjusted job displacement belief after controlling for the full set of covariates included in M5. The adjusted predicted probability ranges from 43.5% in the Netherlands to 81.5% in Cyprus, with a spread of 38 percentage points, but regional clustering does not provide a clear explanatory pattern. The persistence of substantial country-level variation after individual controls is consistent with prior findings that cross-national differences shape automation-related beliefs (Dekker et al. 2017; Kozak et al. 2020) and with interpreting the outcome as a job-

displacement-belief measure whose intensity is shaped by national context alongside individual and workplace characteristics.

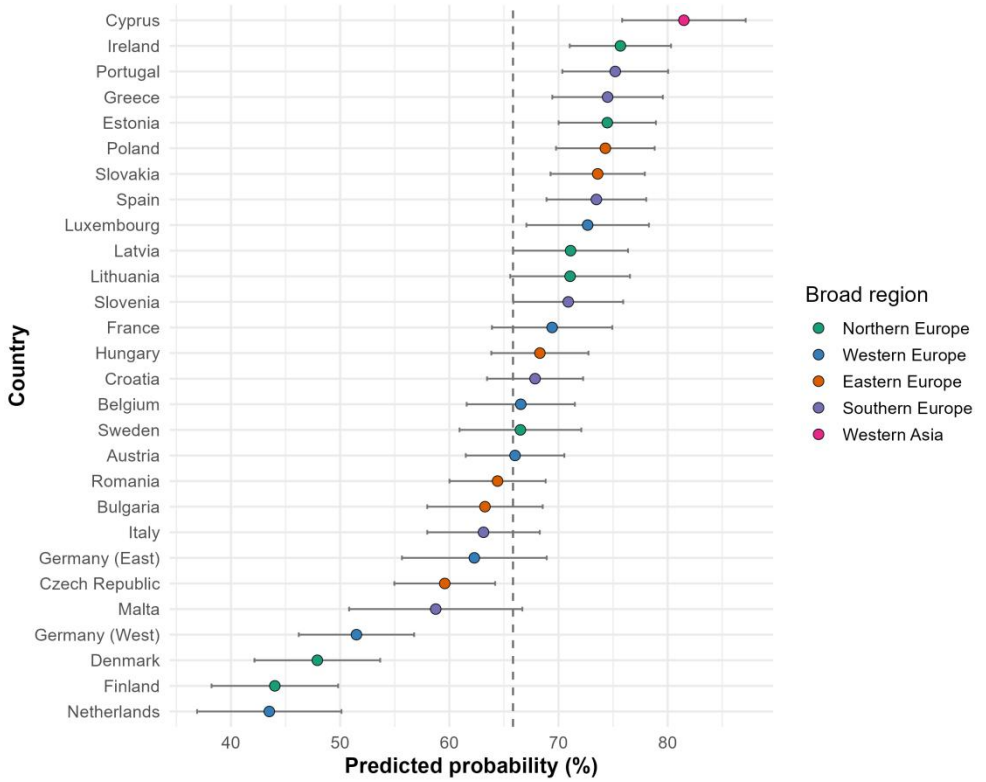


Figure 5.3 Predicted probability of job displacement belief by country
Notes: Bars indicate 95% confidence intervals, the dashed line shows the overall adjusted mean, and colors denote broad regions. Countries are based on model M5.

Following Dekker et al. (2017), who show that country-level fear of robots is higher where unemployment is greater and lower where trade-union density is stronger, elements of a comparable pattern appear in Figure 5.3. Countries with low adjusted job displacement belief, such as the Netherlands, Denmark, Finland, and Germany, tend to combine some form of stronger institutional protection with low or moderate unemployment, while countries with higher job

displacement belief, such as Cyprus, Greece, Portugal, Spain, Poland, and Slovakia, tend to show weaker institutional indicators, higher unemployment, or both. There are also notable exceptions, suggesting that institutional protection, operating through multiple channels rather than formal union density alone, is more closely aligned with the country pattern than unemployment alone, although neither indicator fully accounts for the cross-national variation.

5.6 Demographic and workplace controls

Relative to the omitted category of medium education (ISCED 3-4), high education is consistently associated with lower job displacement belief, whereas low education is associated with higher job displacement belief but is not statistically distinguishable from the reference group. Female respondents show a small but persistent positive association with job displacement belief, and age is also weakly positive, with no clear evidence of curvature from the age-squared term. These patterns are broadly consistent with earlier literature showing that automation-related concerns are socially structured rather than evenly distributed across the workforce (Dekker 2017; Kozak et al., 2020).

Relative to the middle class, working-class respondents are more likely to report job displacement beliefs, while upper-middle-class respondents are substantially less likely to do so. The coefficients for the lower-middle-class category are negative, and those for the higher-class category are positive, but neither is robustly distinguishable from zero. In rural areas, both small and large towns tend to have higher job displacement beliefs, but the large-town coefficient is not statistically significant, whereas the small-town coefficient is significant only in some specifications. Relative to the omitted services sector, agriculture and transport/logistics tend to show higher job displacement beliefs, while the public sector and manufacturing tend to show lower job displacement beliefs; however,

these sectoral differences are generally not robust, and the manufacturing coefficient is statistically significant in only a few models. For firm size, none of the coefficients is statistically significant: solo workers and workers in the largest firms tend to have lower job displacement beliefs than workers in the omitted category of firms with 2-9 employees, whereas the intermediate firm-size categories tend to have higher job displacement beliefs. The solo category should be interpreted with particular caution, since its presence in an employee-only sample is somewhat unexpected but represents less than 3% of the estimation sample. Overall, these control patterns suggest that job displacement belief is structured more systematically by socioeconomic position and demographic characteristics than by community type, sector, or firm size.

5.7 Limitations

The data are cross-sectional, so the models identify conditional associations rather than causal effects. The most basic concern is omitted variable bias, as workers in more intensively monitoring workplaces may differ from other workers in unobserved ways that also shape job displacement belief. Also workers who already hold stronger job displacement beliefs may be more likely to report workplace governance as intensive, which would mechanically strengthen the observed association even if governance were not the sole source of that belief.

Measurement error in the digital monitoring and evaluation composite creates a further ambiguity: if reporting error is systematic, for example, if more fearful workers overstate both governance intensity and displacement concern, the estimated association could instead be biased upward. Moreover, variables such as workplace technology attitudes or reported informing about digital management tools may themselves be partly shaped by digital monitoring and

evaluation, so conditioning on them may remove part of the association that the thesis is substantively interested in tracing, what may involve overadjustment in some later specifications.

One of main limitations is that the dependent variable captures a broad indicator for job displacement belief rather than direct personal job insecurity, as the item asks whether AI and robots steal jobs, so it reflects a general belief about technology-related employment loss rather than a respondent's own perceived probability of losing their job. For this reason, the outcome is informative about broad displacement concerns, but it should not be interpreted as a direct measure of personal employment insecurity.

Digital monitoring and evaluation are based on respondents' reports about whether digital technologies are used to monitor activities and assess performance in their workplace experience, this measure therefore captures perceived exposure to such practices rather than an externally verified record of workplace monitoring. The same logic is applied to almost all other main variables. In addition, a large share of respondents is concentrated at the lowest point of the scale (39% fall into the never category), which also limits variation at the bottom of the distribution and may make the relationship harder to identify through a simple linear specification.

What is more, sufficient digital skills for job is based on self-assessment rather than on an objective skills test, that's why this measures perceived digital skill sufficiency for the respondent's job, which may differ from actual capability. This is still substantively relevant for the thesis, since perceived skills may shape workers' confidence and sense of outside options, but it remains an indirect measure of underlying skill.

Finally, occupational AI exposure (group level) is an occupation-level proxy matched from an external index rather than an individual-level measure of actual

exposure inside a given workplace, therefore captures the technical exposure of occupational tasks to AI-related transformation, but not the precise technological environment experienced by each respondent.

These limitations do not invalidate the analysis, but they are important for interpreting the results with appropriate caution.

C h a p t e r 6

CONCLUSIONS AND POLICY RECOMENDATIONS

Using individual-level data from Eurobarometer 101.4, covering 10,200 employees in April-May 2024 across 27 European countries, we document that the relationship between workplace digital monitoring and evaluation and broad job displacement belief is conditional rather than uniformly positive. Also the results show that digital monitoring and evaluation is not a phenomenon confined to platform work, as more than 60% of employees at least some exposure to digital monitoring or performance evaluation in their last workplace.

The evidence for H1, that greater digital monitoring and evaluation is associated with stronger job displacement belief, is mixed. The simple bivariate association between digital monitoring and evaluation and job displacement belief runs opposite to the predicted direction, but once workplace attitudes toward AI and robots and reported informing about digital management tools are introduced as controls, the association turns positive in the predicted direction: a one-unit increase along the four-point monitoring scale is associated with a 1.4 percentage point increase in job displacement belief, implying a difference of roughly 4 percentage points between workers who report "never" monitoring and those who report monitoring "all the time." The models in which digital monitoring and evaluation are entered as categorical dummy variables show that the job displacement belief differs only marginally between the low and lower-middle monitoring categories ("never / rarely", "rarely", and "rarely / often"), and rises clearly only from "often" upwards, reaching a difference of approximately +13 percentage points at the highest monitoring category (relative to the lower-middle reference). These specifications also help explain why the simple bivariate association is negative, as the "never" category behaves irregularly. Taken

together, these results suggest that digital monitoring and evaluation is associated with job displacement belief in a conditional/non-uniform way. For the disciplinary framework (Shapiro and Stiglitz 1984; Bowles 1985; Belloc et al. 2023), the evidence is consistent with the theory only in a bounded form: the monitoring-belief relationship becomes more clearly positive at higher monitoring intensities, which is consistent with the idea that employer oversight may matter more for worker perceptions when it is sufficiently salient. Moreover, the association is more positive among workers who report being informed about digital management tools, although this evidence is suggestive rather than definitive.

This leads to a first tentative policy implication, that regulatory attention may therefore be most warranted for high-intensity monitoring systems, rather than for monitoring practices in general. At the same time, Kellogg, Valentine, and Christin (2020) acknowledge that earlier research has emphasised the economic and operational value of algorithmic tools for employers, including improved decision-making, coordination, organisational learning, and efficiency. So a balanced approach would therefore not prohibit digital monitoring as such, but to strengthen worker power through institutional channels. Evidence supporting this direction comes from Grund, Sliwka, and Titz (2024), who suggest that collective bargaining and works councils may act as substitutes in protecting employees' interests when management practices are introduced.

The findings also indicate that when workers have more information about digital management practices, their job displacement belief is lower: workers who are informed about digital management tools with a detailed explanation are around 4 percentage points less likely to hold a job displacement belief, while the association becomes stronger as disclosure deepens, reaching around 8 percentage points among workers who report access to the data used or to the results. This pattern supports a second policy implication: transparency

requirements, such as obligations to disclose the use of digital monitoring, evaluation, or algorithmic management tools, may be a relevant policy lever, helping workers better understand how digital systems are used in their workplace, although the quality and content of disclosure would likely matter.

For the outside-options framework (Manning 2003), the findings are harder to reconcile with the original prediction. The non-monotonic relationship between the digital-skills proxy and job displacement belief captures only part of the framework: the highest skill-confidence category is associated with lower job displacement belief, which is consistent with the outside-options argument, but the lowest skill-confidence category is also associated with lower job displacement belief, which is not. This suggests that self-assessed digital skill sufficiency reflects something broader than labour-market outside options alone. Plausible interpretations include weaker engagement with digitally intensive tasks among workers who do not see themselves as digitally skilled, sorting into occupations where digital skills are less central.

For the displacement-concerns literature (Dekker et al. 2017; Kozak et al. 2020; Włoch et al. 2025), the thesis extends earlier work, which has tended to focus on country-level effects or individual demographic characteristics, by showing that workplace factors are also empirically associated with job displacement belief. The thesis also reproduces the broader patterns identified in this literature regarding the role of education, labour-market position, and cross-national context.

Finally, the findings are consistent with the distinction made in the occupational-exposure literature between technical task exposure and perceived employment threat. Occupation-level exposure indices, such as those reported by Gmyrek et al. (2025), are best interpreted as measures of how closely occupational tasks align with the capabilities of AI systems, rather than as direct indicators of future job

loss. In this thesis, occupational AI exposure at the group level is negatively associated with job displacement belief in the main models, and the descriptive evidence across occupational groups also shows no simple positive relationship between technical exposure and job displacement belief.

Last but not least, several limitations of the thesis should be noted. The cross-sectional design identifies conditional associations rather than causal effects, the dependent variable captures broad indicator for job displacement belief rather than personal job insecurity, and both monitoring and digital skills are self-reported and may share reporting frames with the outcome in ways that bias the conditional positive association upward. The most productive next step is panel data linking workplace monitoring measures to subsequent personal insecurity and labour-market outcomes, combined with explicit country-level institutional interactions.

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APPENDIX A

Definition of digital technologies, including Artificial Intelligence from a survey: "Digital technologies refer to technologies that use data and computing to help people do their work more efficiently. They include hardware such as smartphones, laptops or robots, and software, such as smartphone applications, video conferencing tools, collaboration platforms, or project management tools in the workplace. Artificial Intelligence refers to computer systems capable of performing tasks that typically require human intelligence. It is used, for instance, in driverless cars or drones, in healthcare to improve medical diagnoses, and in various other applications such as answering questions and offering support to users on websites or call centres. Artificial Intelligence can also be used in workplaces, for example to monitor and evaluate workers or automatically assign them certain tasks. Artificial Intelligence can also be used to create new content such as images, text, or music as well as to answer questions and assist with tasks such as composing emails or essays. ChatGPT is the best-known example."

APPENDIX B

Table B.1 Coding of variables

Methodological variable	**Empirical measure**	**Survey question**	**Survey responses**	**Coding**
Job displacement belief	Agreement with the statement that "AI and robots steal people's jobs"	Please tell me to what extent you agree or disagree with each of the following statements. ...Robots and Artificial Intelligence steal people's jobs.	[1] Totally agree; [2] Tend to agree; [3] Tend to disagree; [4] Totally disagree; [5] Not applicable; [6] Don't know.	Responses are recoded into a binary indicator equal to 1 for respondents who agree or totally agree, and 0 for those who disagree or totally disagree, with "not applicable" and "don't know" treated as missing.
Digital monitoring and evaluation	Digital monitoring and evaluation	Have the following activities ever been performed by digital technologies, including Artificial Intelligence, in your current or previous workplaces? For each activity, please refer to your most recent	[1] Yes, all the time; [2] Yes, often; [3] No, rarely; [4] No, never; [5] Not applicable; [6] Don't know.	Each item is measured on a four-point frequency scale, and the combined index ranges from 1 (never) to 4 (all the time), with intermediate half-

Methodological variable	Empirical measure	Survey question	Survey responses	Coding
		workplace experience. ...Monitoring workers' activities; ....Assessing workers' performance, including imposing sanctions or attributing rewards.		point values reflecting averages across the two items, also responses coded as not applicable are treated as equivalent to never, since they indicate the absence of the relevant digital monitoring or evaluation practice in the respondent's workplace experience.
Workplace technology attitudes	Attitude toward robots and AI in the workplace	How positively or negatively do you perceive the use of robots and Artificial Intelligence in the workplace? By robots we mean machines designed to perform tasks which are normally performed by humans. They can perform them by	[1] Very positive; [2] Fairly positive; [3] Fairly negative; [4] Very negative; [5] Don't know.	Each item is measured on a four-point scale, and the index ranges from 1 (very positive) to 4 (very negative), "don't know" treated as missing.

Methodological variable	Empirical measure	Survey question	Survey responses	Coding
		themselves or, often, working together with a human. For example, robots that can perform surgery together with a surgeon or automatic tills in supermarkets.		
Reported informing about digital management tools	Informed about digital management tools	Did your employer inform you about the use of digital technologies, including Artificial Intelligence, to manage activities in your workplace?	[1] Yes, you have made them aware of it, but without further details; [2] Yes, and you have given them a detailed explanation, including information about benefits, drawbacks, and their rights; [3] Yes, and you have given them access to their personal data; [4] Yes, and you have given them the results of any automated analysis that concerns them; [5] No, you have not made them aware of it; [6] Don't know.	Responses are recoded into a binary indicator that distinguishes any disclosure from no disclosure / not applicable.
Digital skills	Sufficient digital skills for job	To what extent do you agree or disagree with the following statements regarding your skills in the use of the most recent digital	[1] Totally agree; [2] Tend to agree; [3] Tend to disagree; [4] Totally disagree; [5] Not applicable; [6] Don't know.	Each item is measured on a four-point scale, and the index ranges from 1 (totally disagree) to 4 (totally agree),

Methodological variable	Empirical measure	Survey question	Survey responses	Coding
		technologies, including Artificial Intelligence? Think about, for example, using smart appliances at home that you can control remotely for heating, cooking, or cleaning; using apps on your smartphone to handle your daily schedule; or using websites to manage your tasks at work. You consider yourself to be sufficiently skilled in the use of digital technologies to do your job.		"not applicable" and "don't know" treated as missing.
Social class	Social class	Do you see yourself and your household belonging to…?	[1] The working class of society; [2] The lower middle class of society; [3] The middle class of society; [4] The upper middle class of society; [5] The higher class of society; [6] Other; [7] None; [8] Refusal; [9] Don't know.	Coded as a categorical variable; "other", "none", "refusal" and "don't know" are treated as missing.
Community type	Community	Would you say you live	[1] Rural area or village; [2]	Coded as a

Methodological variable	Empirical measure	Survey question	Survey responses	Coding
	type	in a...?	Small or middle sized town; [3] Large town.	categorical variable.
Sector	Sector	What sector, business or industry is the company or organisation where you work mainly active in?	[1] Agriculture, forestry and fishing, [2] Manufacturing; [3] Logistics; [4] Service, including retail trade, accommodation, transportation, food services; [5] Public sector; [6] Other; [7] Don't know.	Coded as a categorical variable; "other" and "don't know" are treated as missing.
Firm size	Firm size	Including yourself, how many people in total work at your workplace, that is at the local site where you work?	[1] 1; [2] 2-9; [3] 10-49; [4] 50-250; [5] More than 250; [6] Don't know but less than 10 people; [7] Don't know but 10 people or more; [8] Refusal; [9] Don't know.	Coded as a categorical variable; "don't know but less than 10 people" coded as "2-9"; "don't know but 10 people or more" coded as "10-49"; "refusal" and "don't know" are treated as missing.
Gender	Gender	How would you describe yourself?	[1] Man; [2] Woman; [3] None of the above / Non binary / Do not recognize yourself in above categories; [4] Prefer not to say.	Coded as a categorical variable; "none of the above / non binary / do not recognize yourself in above categories" and

Methodological variable	Empirical measure	Survey question	Survey responses	Coding
				"prefer not to say" are treated as missing.
Country	Country	Country code	[1] AT; [2] BE; [3] BG; [4] CY; [5] CZ; [6] DE-E; [7] DE-W; [8] DK; [9] EE; [10] ES; [11] FI; [12] FR; [13] GR; [14] HR; [15] HU; [16] IE; [17] IT; [18] LT; [19] LU ; [20] LV; [21] MT; [22] NL; [23] PL; [24] PT; [25] RO; [26] SE; [27] SI; [28] SK.	Coded as a categorical variable.
Education	Education	What is the highest level of education you completed?	[1] Did not attend school/ Did not finish Primary School (MQF Level 1); [2] Primary school (MQF Level 1); [3] SEC (O'Levels) Grades 6-7 (MQF Level 2)/ Trade school; [4] SEC (i.e. O'Levels) Grades 1-5 (MQF Level 3); [5] National Diploma/ Matriculation Certificate (Advanced Level, Intermediate Level i.e. A'Levels) (MQF Level 4)/ Apprenticeship; [6] Higher National Diploma/ Foundation Degree/ Undergraduate Diploma/ Undergraduate Certificate (MQF Level 5); [7]	Coded as a categorical variable with three education groups: low education = categories [1]-[3], medium education = categories [4]-[5] and [10]-[11], and high education = categories [6]-[9]; "refusal" and "don't know" are treated as missing.

Methodological variable	Empirical measure	Survey question	Survey responses	Coding
			Bachelor's Degree (MQF Level 6); [8] Master's Degree/ Post-graduate Diploma/ Post-graduate Certificate (MQF Level 7); [9] Doctoral Degree/ PhD (MQF Level 8); [10] Education up to ISCED 4 completed abroad; [11] Education ISCED 5 and above completed abroad; [12] Refusal; [13] Don't know.	
Age	Age	How old are you?	NA	Coded as a continuous variable.

APPENDIX C

Table C.1 Mapping of Eurobarometer occupation categories to ISCO-08 groups and occupational AI exposure scores

Eurobarometer code	Eurobarometer occupation category	Assigned ISCO-08 group	AI exposure score	Within-group SD	Weighted job-displacement-belief prevalence	Weighted population share	N
10	Employed professional (employed doctor, lawyer, accountant, architect)	2 - Professionals	0.386	0.120	58.1%	7.3%	815
11	Employed position, general management, director or top management (managing directors, director, general, other director)	1 - Managers	0.361	0.055	48.4%	2.8%	332
12	Employed position, middle management, other management (department head, junior manager, teacher, technician)	3 - Technicians and associate professionals	0.346	0.118	59.2%	16.7%	1,896
13	Employed position, working mainly at a desk	4 - Clerical support workers	0.536	0.088	63.8%	22.3%	2,580
14	Employed position, not at a desk but travelling (salesmen, driver, etc.)	8 - Plant and machine operators, and	0.198	0.050	74.5%	8.5%	980

Eurobarometer code	Eurobarometer occupation category	Assigned ISCO-08 group	AI exposure score	Within-group SD	Weighted job-displacement-belief prevalence	Weighted population share	N
		assemblers					
15	Employed position, not at a desk, but in a service job (hospital, restaurant, police, fireman, etc.)	5 - Service and sales workers	0.256	0.103	70.3%	14.1%	1,679
16	Employed position, supervisor	3 - Technicians and associate professionals	0.346	0.118	62.5%	2.8%	325
17	Employed position, skilled manual worker	7 - Craft and related trades workers	0.166	0.055	72.8%	20.7%	2,389
18	Other employed (unskilled) manual worker, servant	9 - Elementary occupations	0.149	0.075	78.7%	4.9%	573

APPENDIX D

Table D.1 Sample characteristics of the two main analytical samples

Characteristic	**Sample A**	**Sample B**
Unweighted sample size	10200	9434
Weighted sample size	10757.66	9987.25
Age, weighted mean (SD)	42.99 (11.95)	42.82 (11.86)
Women, weighted share	48.8%	48.8%
Education		
Low (ISCED 0-2)	12.0%	10.9%
Medium (ISCED 3-4)	45.7%	45.2%
High (ISCED 5-8)	42.3%	44.0%
Subjective social class		
Working	20.1%	18.8%
Lower middle	14.5%	14.5%
Middle	55.4%	56.3%
Upper middle	9.0%	9.4%
Higher	0.9%	1.0%
Community type		
Rural	32.1%	31.8%
Small town	35.6%	35.8%
Large town	32.3%	32.4%
Sector		
Agriculture	2.8%	2.7%
Manufacturing	18.5%	18.2%
Logistics	7.6%	7.7%
Services	44.4%	44.0%
PublicSector	26.7%	27.4%
Firm size		
Solo / self-employed	2.5%	2.3%
2-9 employees	24.4%	24.0%
10-49 employees	38.8%	38.7%
50-250 employees	21.1%	21.4%

Characteristic	Sample A	Sample B
250+ employees	13.3%	13.7%

APPENDIX E

Table E.1 Main variable descriptive statistics for Sample A and Sample B

Sample	Variable	Mean	Std. Dev.	25th pct.	Median	75th pct.	Min	Max
Sample A	Robots and Artificial Intelligence steal people's jobs	0.658	0.474	NA	NA	NA	0.000	1.000
Sample A	Digital monitoring and evaluation	1.923	0.927	1.000	2.000	2.500	1.000	4.000
Sample A	Occupational AI exposure (group level)	0.320	0.138	0.166	0.346	0.386	0.149	0.536
Sample A	Attitude toward robots and AI in the workplace	2.168	0.782	2.000	2.000	3.000	1.000	4.000
Sample A	Informed about digital management tools	0.534	0.499	NA	NA	NA	0.000	1.000
Sample A	Age	42.990	11.954	34.000	43.000	52.000	17.000	86.000
Sample A	Woman	0.488	0.500	NA	NA	NA	0.000	1.000
Sample B	Robots and Artificial Intelligence steal people's jobs	0.651	0.477	NA	NA	NA	0.000	1.000
Sample B	Digital monitoring and evaluation	1.964	0.931	1.000	2.000	2.500	1.000	4.000
Sample B	Occupational AI exposure (group level)	0.326	0.137	0.198	0.346	0.386	0.149	0.536
Sample B	Sufficient digital skills for job	3.071	0.849	3.000	3.000	4.000	1.000	4.000
Sample B	Attitude toward robots and AI in the workplace	2.136	0.766	2.000	2.000	3.000	1.000	4.000
Sample B	Informed about digital management tools	0.558	0.497	NA	NA	NA	0.000	1.000
Sample B	Age	42.818	11.863	33.000	43.000	52.000	17.000	83.000
Sample B	Woman	0.488	0.500	NA	NA	NA	0.000	1.000

Notes: All statistics are computed using survey weights.

APPENDIX F

Table F.1 Survey-weighted logit coefficients for the main specifications

Variable	**M1**	**M2**	**M3**	**M4**	**M5**	**M5b**	**M6**	**E1**
Constant	0.761***	0.744***	0.746***	-0.386*	-0.292	-0.311	-0.362*	-0.209
	(0.121)	(0.121)	(0.142)	(0.166)	(0.167)	(0.172)	(0.173)	(0.158)
Digital monitoring and evaluation	-0.063*	-0.057*	-0.046	0.028	0.070*	0.088**	0.084**	
	(0.026)	(0.026)	(0.026)	(0.027)	(0.029)	(0.030)	(0.030)	
Digital monitoring and evaluation (centred)								-0.022
								(0.048)
Digital monitoring and evaluation (centred) × Informed about digital management tools								0.139*
								(0.059)
Sufficient digital skills for job							0.119***	
							(0.034)	
Occupational AI exposure (group level)		-1.108***	-0.664***	-0.491*	-0.472*	-0.398*	-0.455*	-0.469*
		(0.169)	(0.190)	(0.192)	(0.193)	(0.199)	(0.200)	(0.193)
Attitude toward robots and AI in the workplace				0.455***	0.436***	0.455***	0.491***	0.436***
				(0.035)	(0.035)	(0.037)	(0.038)	(0.035)

Variable	M1	M2	M3	M4	M5	M5b	M6	E1
Informed about digital management tools					-0.216* * *	-0.218* * *	-0.240* * *	-0.196* * *
					(0.055)	(0.056)	(0.057)	(0.055)
Education: Low			0.092	0.059	0.051	0.004	0.032	0.050
			(0.087)	(0.088)	(0.088)	(0.094)	(0.095)	(0.088)
Education: High			-0.260* * *	-0.218* * *	-0.208* * *	-0.187* *	-0.200* * *	-0.208* * *
			(0.058)	(0.059)	(0.059)	(0.060)	(0.061)	(0.059)
Social class: Working class			0.216* *	0.174*	0.163*	0.177*	0.184*	0.157*
			(0.071)	(0.072)	(0.072)	(0.075)	(0.075)	(0.072)
Social class: Lower middle class			0.004	-0.034	-0.039	-0.023	-0.014	-0.041
			(0.072)	(0.073)	(0.073)	(0.076)	(0.076)	(0.073)
Social class: Upper middle class			-0.414* * *	-0.366* * *	-0.357* * *	-0.332* * *	-0.336* * *	-0.357* * *
			(0.085)	(0.086)	(0.086)	(0.088)	(0.088)	(0.086)
Social class: Higher class			0.019	0.075	0.074	0.106	0.081	0.069
			(0.227)	(0.223)	(0.222)	(0.222)	(0.222)	(0.221)
Community type: Small town			0.108	0.131*	0.129*	0.082	0.079	0.131*
			(0.061)	(0.062)	(0.062)	(0.064)	(0.064)	(0.062)
Community type: Large town			0.050	0.093	0.089	0.048	0.049	0.088
			(0.062)	(0.062)	(0.062)	(0.065)	(0.065)	(0.062)
Sector: Agriculture			0.070	0.057	0.046	0.010	0.017	0.038
			(0.154)	(0.160)	(0.160)	(0.167)	(0.167)	(0.160)
Sector: Manufacturing			-0.163*	-0.140*	-0.148*	-0.115	-0.109	-0.147*
			(0.068)	(0.069)	(0.070)	(0.072)	(0.073)	(0.070)

Variable	M1	M2	M3	M4	M5	M5b	M6	E1
Sector: Transport and logistics			0.129	0.124	0.125	0.135	0.142	0.129
			(0.096)	(0.098)	(0.098)	(0.100)	(0.101)	(0.098)
Sector: Public sector			-0.041	-0.052	-0.055	-0.061	-0.061	-0.056
			(0.062)	(0.062)	(0.062)	(0.064)	(0.064)	(0.062)
Firm size: Solo / self-employed			-0.036	-0.085	-0.090	-0.124	-0.127	-0.103
			(0.156)	(0.159)	(0.158)	(0.170)	(0.170)	(0.159)
Firm size: 10-49 employees			0.034	0.026	0.031	0.014	0.012	0.032
			(0.063)	(0.064)	(0.064)	(0.067)	(0.067)	(0.065)
Firm size: 50-250 employees			0.065	0.063	0.075	0.044	0.037	0.074
			(0.076)	(0.077)	(0.077)	(0.080)	(0.080)	(0.077)
Firm size: 250+ employees			-0.155	-0.111	-0.103	-0.133	-0.143	-0.103
			(0.087)	(0.087)	(0.088)	(0.090)	(0.090)	(0.088)
Age			0.006* *	0.005*	0.005*	0.004	0.005*	0.005*
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age squared			0.000	0.000	0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female			0.160* *	0.118*	0.119*	0.124*	0.132*	0.119*
			(0.049)	(0.049)	(0.049)	(0.051)	(0.051)	(0.049)
Belgium	0.064	0.089	0.094	0.055	0.025	-0.031	-0.020	0.050
	(0.160)	(0.160)	(0.163)	(0.161)	(0.161)	(0.168)	(0.168)	(0.161)
Bulgaria	-0.002	-0.009	-0.106	-0.111	-0.127	-0.123	-0.139	-0.110
	(0.158)	(0.159)	(0.163)	(0.163)	(0.163)	(0.168)	(0.169)	(0.163)
Cyprus	0.944* * *	0.991* * *	0.972* * *	0.881* * *	0.854* * *	0.785* * *	0.767* *	0.865* * *
	(0.219)	(0.219)	(0.222)	(0.224)	(0.226)	(0.233)	(0.234)	(0.225)

Variable	M1	M2	M3	M4	M5	M5b	M6	E1
Czech Republic	-0.269	-0.202	-0.285	-0.258	-0.291	-0.340*	-0.332*	-0.284
	(0.146)	(0.147)	(0.151)	(0.149)	(0.149)	(0.153)	(0.154)	(0.149)
Germany (East)	0.018	-0.024	-0.126	-0.159	-0.171	-0.249	-0.242	-0.157
	(0.187)	(0.186)	(0.190)	(0.187)	(0.187)	(0.194)	(0.196)	(0.186)
Germany (West)	-0.574* * *	-0.583* * *	-0.651* * *	-0.641* * *	-0.638* * *	-0.602* * *	-0.605* * *	-0.620* * *
	(0.148)	(0.150)	(0.159)	(0.158)	(0.159)	(0.164)	(0.164)	(0.159)
Denmark	-1.039* * *	-1.012* * *	-0.927* * *	-0.751* * *	-0.790* * *	-0.821* * *	-0.844* * *	-0.773* * *
	(0.159)	(0.160)	(0.165)	(0.164)	(0.165)	(0.169)	(0.171)	(0.165)
Estonia	0.348*	0.348*	0.379*	0.446* *	0.426* *	0.418*	0.403*	0.434* *
	(0.161)	(0.161)	(0.165)	(0.165)	(0.165)	(0.170)	(0.171)	(0.165)
Spain	0.520* *	0.501* *	0.408*	0.400*	0.372*	0.348*	0.312	0.392*
	(0.163)	(0.163)	(0.168)	(0.166)	(0.166)	(0.170)	(0.171)	(0.166)
Finland	-1.087* * *	-1.084* * *	-1.034* * *	-0.947* * *	-0.956* * *	-1.015* * *	-1.045* * *	-0.936* * *
	(0.167)	(0.166)	(0.169)	(0.167)	(0.167)	(0.172)	(0.173)	(0.167)
France	0.298	0.289	0.274	0.189	0.163	0.086	0.073	0.183
	(0.173)	(0.173)	(0.178)	(0.177)	(0.177)	(0.184)	(0.186)	(0.178)
Greece	0.604* * *	0.607* * *	0.555* *	0.490* *	0.428*	0.435*	0.419*	0.440*
	(0.177)	(0.177)	(0.180)	(0.178)	(0.179)	(0.186)	(0.187)	(0.179)
Croatia	0.206	0.220	0.170	0.125	0.087	0.043	0.058	0.092
	(0.148)	(0.149)	(0.152)	(0.152)	(0.152)	(0.157)	(0.157)	(0.152)
Hungary	0.290	0.287	0.156	0.121	0.108	0.108	0.129	0.117
	(0.150)	(0.150)	(0.156)	(0.154)	(0.154)	(0.159)	(0.160)	(0.154)
Ireland	0.508* *	0.525* *	0.493* *	0.520* *	0.493* *	0.455*	0.442*	0.516* *
	(0.169)	(0.170)	(0.174)	(0.172)	(0.172)	(0.178)	(0.178)	(0.172)
Italy	0.036	0.061	-0.057	-0.104	-0.133	-0.143	-0.117	-0.125

Variable	M1	M2	M3	M4	M5	M5b	M6	E1
	(0.154)	(0.155)	(0.162)	(0.161)	(0.161)	(0.165)	(0.166)	(0.161)
Lithuania	0.215	0.216	0.214	0.253	0.246	0.259	0.235	0.262
	(0.175)	(0.175)	(0.180)	(0.179)	(0.179)	(0.189)	(0.189)	(0.180)
Luxembourg	0.230	0.289	0.393*	0.330	0.329	0.208	0.194	0.354
	(0.183)	(0.183)	(0.188)	(0.186)	(0.186)	(0.192)	(0.193)	(0.186)
Latvia	0.291	0.266	0.219	0.265	0.248	0.201	0.173	0.265
	(0.171)	(0.171)	(0.175)	(0.174)	(0.174)	(0.180)	(0.182)	(0.174)
Malta	-0.390	-0.330	-0.327	-0.302	-0.327	-0.371	-0.387	-0.313
	(0.209)	(0.207)	(0.207)	(0.206)	(0.207)	(0.212)	(0.213)	(0.207)
Netherlands	-1.227* * *	-1.160* * *	-0.995* * *	-0.951* * *	-0.978* * *	-1.021* * *	-1.072* * *	-0.953* * *
	(0.178)	(0.178)	(0.181)	(0.181)	(0.181)	(0.184)	(0.186)	(0.181)
Poland	0.480* *	0.457* *	0.401*	0.434* *	0.416*	0.372*	0.376*	0.424*
	(0.159)	(0.160)	(0.165)	(0.165)	(0.166)	(0.172)	(0.172)	(0.166)
Portugal	0.708* * *	0.693* * *	0.549* *	0.493* *	0.466* *	0.436*	0.408*	0.477* *
	(0.170)	(0.170)	(0.176)	(0.176)	(0.176)	(0.184)	(0.184)	(0.176)
Romania	0.102	0.071	0.026	-0.058	-0.074	-0.113	-0.080	-0.062
	(0.144)	(0.145)	(0.148)	(0.148)	(0.147)	(0.151)	(0.151)	(0.148)
Sweden	-0.184	-0.132	-0.089	0.034	0.023	-0.012	-0.072	0.043
	(0.170)	(0.170)	(0.174)	(0.173)	(0.174)	(0.177)	(0.179)	(0.174)
Slovenia	0.202	0.207	0.223	0.239	0.237	0.199	0.171	0.261
	(0.171)	(0.171)	(0.174)	(0.169)	(0.169)	(0.173)	(0.173)	(0.169)
Slovakia	0.354*	0.368*	0.314	0.380*	0.378*	0.306	0.311	0.393*
	(0.156)	(0.157)	(0.160)	(0.159)	(0.160)	(0.164)	(0.165)	(0.160)
Observations	10200	10200	10200	10200	10200	9434	9434	10200
Weighted N	10757.66	10757.66	10757.66	10757.66	10757.66	9987.25	9987.25	10757.66

Variable	M1	M2	M3	M4	M5	M5b	M6	E1
Tjur's R2	0.061	0.065	0.080	0.100	0.102	0.101	0.102	0.102
AUC	0.635	0.643	0.659	0.679	0.682	0.680	0.682	0.682

Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

APPENDIX G

Robustness check

Appendix I summarizes the robustness strategy used in the thesis by showing which modeling choice is changed in each robustness specification, the name of the corresponding robustness model, and the main baseline model to which it is compared. Appendices J and K report fourteen robustness specifications that vary the main coding choices used in the thesis: outcome coding, construction of the digital monitoring variable, measurement of digital skills, treatment of occupational AI exposure, coding of informing about digital management tools, and survey weights. Their purpose is to assess whether the substantive interpretation of the main findings depends on these decisions; they are reported on the logit scale rather than the average marginal effect scale used in the main results, so they are used to compare the direction, statistical significance, and broad stability of the focal associations rather than exact coefficient magnitudes. R1-R2 vary the outcome and therefore test a related rather than the same hypothesis; R3-R14 vary inputs to the same outcome.

In R1, the baseline outcome is replaced with the alternative labor-market-framed item capturing agreement that, due to robots and AI, more jobs will disappear than new jobs will be created. Relative to M5, the monitoring coefficient becomes substantially larger and more statistically significant (0.126 vs 0.070), while occupational AI exposure becomes weaker and no longer significant (-0.370 vs -0.472); attitudes toward AI remain strongly positive but smaller in magnitude (0.301 vs 0.436), and informing remains negative and significant (-0.233 vs -0.216), the monitoring coefficient is therefore stronger for this alternative labour-market-framed item than for the baseline job-displacement-belief item. While in R2, where the outcome is coded strictly so that only respondents who totally agree are coded as one, the monitoring coefficient falls to zero and is no longer

distinguishable from zero, occupational AI exposure becomes more strongly negative (-0.654 vs -0.472), attitudes toward AI become substantially stronger (0.653 vs 0.436), and informing remains negative and significant (-0.205 vs -0.216), what defines an important boundary of the H1 finding: the monitoring association does not extend to the most extreme form of agreement.

In R3, replacing the two-item monitoring composite with a broader digital-management-activities index (hiring workers, allocating tasks to workers, managing worktime schedules, monitoring workers' activities, enforcing safety measures, and assessing workers' performance, including imposing sanctions or attributing rewards) leaves the monitoring coefficient virtually identical to M5 (0.070 vs 0.070), while the remaining core variables are also stable. In R4, a stricter coding of the monitoring variable also leaves the estimate positive and significant (0.066 vs 0.070), with the other main predictors again almost unchanged, while in R5, the two underlying monitoring items are entered separately as digital monitoring of work activities and digital performance assessment, sanctions, and rewards, and both coefficients remain positive (0.039 and 0.032), but neither is individually statistically significant, whereas the composite in M5 is positive and significant (0.070), while occupational AI exposure (-0.472), attitudes (0.436), and informing (-0.216) are effectively unchanged. Taken together, these checks reduce concern that the H1 result is mechanically driven by one arbitrary construction of the monitoring variable, while at the same time, they qualify the interpretation that the association is more consistently detected for the composite monitoring-and-evaluation index than for either individual item alone, so the result should be interpreted as evidence about a broader digital workplace-governance construct.

In R6, using a broader measure that combines digital skills for the job and everyday life, the digital-skills coefficient becomes substantially larger (0.172 vs 0.119), while the monitoring coefficient remains almost unchanged (0.086 vs

0.084), and the remaining core variables are also stable. In R7, using perceived digital skills for a future job, the digital-skills coefficient remains positive but smaller (0.104 vs 0.119), while the remaining core variables are also stable. In R8, using an alternative version of variable in which "not applicable" responses are coded as "totally disagree", the digital-skills coefficient remains positive (0.084 vs 0.119), while the remaining core variables show modest shifts but remain in the same direction. Across R6-R8, every alternative skill measure produces a positive coefficient, which therefore strengthens the rejection of the original linear H2.

In R9-R10, occupational AI exposure is replaced by occupational-category controls. Because the AI exposure measure is itself derived from occupation, this check asks whether the main results depend on using the index rather than controlling for occupational structure more directly. Relative to M5 and M6, the main coefficients remain essentially unchanged, which indicates that the focal results do not depend on the specific way occupational structure is controlled for. In R11-R12, informing about digital management tools is recoded as a set of levels rather than a binary indicator: the main coefficients remain close to baseline, and the informing variable itself remains negative and highly significant under the alternative coding. Although the coefficients are not directly comparable in magnitude because the parameterizations differ, the substantive conclusion remains unchanged: greater informing remains consistently associated with lower job displacement belief.

R13-R14 re-estimate the main models without survey weights: the monitoring coefficient remains positive and close to baseline in both cases, while the digital-skills coefficient in the M6-type specification becomes larger (0.169 vs 0.119). Model fit declines somewhat in the unweighted specifications, but the substantive interpretation of the focal associations is unchanged; therefore, weighting appears to matter more for precision and some control estimates than for the direction of the main results.

Overall, the positive association between digital monitoring and job displacement belief is bounded in two identifiable ways. First, it disappears under the strictest coding of the outcome (R2), so the monitoring result does not extend to the most extreme level of agreement. Second, it is not cleanly attributable to either individual monitoring item alone (R5), but splitting the two-item composite reduces the variance of each component variable and therefore reduces statistical power. Within these boundaries, however, the monitoring results remain stable across alternative codings of the outcome and the control structure. The digital-skills finding is also robust; alternative skill measures do not recover the negative linear relationship hypothesized by H2, so H2 is rejected across all alternative measures tested.

APPENDIX H

Diagnostics

To ensure comparability across predictors with different degrees of freedom, I examine comparable variance inflation factors: standard VIFs for single-parameter terms and adjusted GVIFs, transformed onto a directly comparable scale, for multi-parameter terms. In M5 and M6, the highest comparable VIF among focal regressors is about 1.362, while in E1, the centered monitoring term and its interaction with informing rise to 3.586 and 3.106, respectively, which is expected in an interaction specification because the interaction term is mechanically related to its component terms even after mean-centering. All remaining focal regressors remain low, and none exceed the commonly cited threshold of 5. These diagnostics indicate that the change in the monitoring coefficient across M3-M5 is better understood as the result of conditioning on correlated covariates than as a consequence of problematic variance inflation from multicollinearity.

In M5, fitted probabilities range from 0.152 to 0.959, with no observations approaching the boundaries that would indicate separation; M6 and E1 show the same pattern (M6: 0.143 to 0.957; E1: 0.148 to 0.955), and country fixed effects also do not appear to induce separation. Across M5, M6, and E1, all country categories retained in the estimation sample preserve within-country variation in the outcome, and no country exhibits a near-degenerate outcome distribution, providing additional evidence against country-driven separation in the main models.

The clearest departure from strict linearity concerns digital monitoring and evaluation; as discussed in Section 5.1, the dummy specification shows a flatter relationship across the lower and intermediate monitoring categories and a more

clearly positive association at higher monitoring intensity, together with an irregular zero-monitoring category. The digital skills proxy also departs from a simple linear pattern, since the supplementary categorical specification indicates a non-monotonic relationship, whereas the linear specification for attitudes toward robots and AI in the workplace remains adequate, as the dummy specification shows a broadly monotonic pattern. For occupational AI exposure, adding quadratic and cubic terms provides some evidence of higher-order curvature at the joint level, but the individual higher-order terms are not precisely estimated and do not materially change the substantive interpretation of the exposure effect. Supplementary functional-form specifications are reported in Appendix L. Overall, these checks suggest that the main findings are not driven by severe functional-form misspecification, although the linear monitoring coefficient should be read as an average summary rather than a uniform dose-response effect.

Influence diagnostics do not indicate that the main results are driven by a small number of unusual observations. In each of the three main specifications (M5, M6, and E1), only two observations are jointly flagged by the screening rule based on leverage, Cook's distance, and Pearson residuals, representing about 0.02% of the estimation sample in each case, none of the focal regressors, including digital monitoring and evaluation, occupational AI exposure, sufficient digital skills for job, informing about digital management tools, and attitudes toward robots and AI in the workplace, exceeds the DFBETA screening threshold in any model. Taken together, these diagnostics suggest that the interpretation of the focal coefficients is not sensitive to individual influential cases.

Last but not least, models M5, M6 and E1 appear well calibrated in-sample, with small bin-level deviations and no strong systematic overprediction or underprediction.

APPENDIX I

Table I.1 Summary of robustness checks

What is varied	Robustness model	Base model	Short description of what changes
Outcome coding	R1	M5	Replaces the baseline job-displacement-belief outcome with the broader item on whether more jobs will disappear than be created due to robots and AI.
Outcome coding	R2	M5	Uses a stricter outcome coding in which only respondents who totally agree are coded as 1.
Digital monitoring and evaluation	R3	M5	Replaces the 2-item monitoring composite with a broader digital-management-activities index.
Digital monitoring and evaluation	R4	M5	Uses a stricter coding of the monitoring variable in which "not applicable" responses are not treated as equivalent to "never."
Digital monitoring and evaluation	R5	M5	Replaces the monitoring composite with its two underlying items entered separately.
Sufficient digital skills for job	R6	M6	Replaces the main digital-skills item with a broader measure combining digital skills for job and everyday life.
Sufficient digital skills for job	R7	M6	Replaces the main digital-skills item with perceived digital skills for a future job.
Sufficient digital skills for job	R8	M6	Replaces the main digital-skills item with an alternative version in which "not applicable" responses are coded as "totally disagree."
Occupational AI exposure / occupational structure	R9	M5	Replaces occupational AI exposure (group level) with occupational-category controls.

What is varied	Robustness model	Base model	Short description of what changes
Occupational AI exposure / occupational structure	R10	M6	Replaces occupational AI exposure (group level) with occupational-category controls.
Reported informing about digital management tools	R11	M5	Replaces the binary informing variable with a levels-coded informing measure.
Reported informing about digital management tools	R12	M6	Replaces the binary informing variable with a levels-coded informing measure.
Survey weights	R13	M5	Re-estimates the main H1 model without survey weights.
Survey weights	R14	M6	Re-estimates the main H2 model without survey weights.

APPENDIX J

Table J.1 Survey-weighted logit coefficients for the robustness specifications on outcome coding, digital monitoring and evaluation, and digital-skills measures

Variables with alternative coding for robustness checks	**Robots and Artificial Intelligence steal people's jobs**		**Digital monitoring and evaluation**			**Sufficient digital skills for job**		
Base model	**M5**	**M5**	**M5**	**M5**	**M5**	**M6**	**M6**	**M6**
Variable	**R1**	**R2**	**R3**	**R4**	**R5**	**R6**	**R7**	**R8**
Constant	0.087	-2.378* * *	-0.265	-0.266	-0.292	-0.448*	-0.351	-0.297
	(0.175)	(0.178)	(0.176)	(0.170)	(0.167)	(0.176)	(0.180)	(0.168)
Digital management activities index			0.070*					
			(0.034)					
Digital monitoring and evaluation (strict coding)				0.066*				
				(0.030)				
Digital monitoring and evaluation	0.126* * *	0.000				0.086* *	0.086* *	0.064*
	(0.030)	(0.034)				(0.030)	(0.031)	(0.030)
Digital monitoring of work activities					0.039			
					(0.032)			
Digital performance assessment, sanctions, and rewards					0.032			

Variables with alternative coding for robustness checks	Robots and Artificial Intelligence steal people's jobs		Digital monitoring and evaluation			Sufficient digital skills for job		
Base model	**M5**	**M5**	**M5**	**M5**	**M5**	**M6**	**M6**	**M6**
Variable	**R1**	**R2**	**R3**	**R4**	**R5**	**R6**	**R7**	**R8**
					(0.034)			
Occupational AI exposure (group level)	-0.370	-0.654* *	-0.462*	-0.442*	-0.472*	-0.525* *	-0.448*	-0.501* *
	(0.200)	(0.218)	(0.197)	(0.195)	(0.193)	(0.201)	(0.201)	(0.194)
Sufficient digital skills for job and everyday life						0.172* * *		
						(0.039)		
Sufficient digital skills for future job							0.104* *	
							(0.034)	
Sufficient digital skills for job, future job, everyday life, and online learning								0.084* *
								(0.029)
Attitude toward robots and AI in the workplace	0.301* * *	0.653* * *	0.431* * *	0.440* * *	0.436* * *	0.523* * *	0.481* * *	0.457* * *
	(0.036)	(0.038)	(0.036)	(0.036)	(0.035)	(0.039)	(0.039)	(0.036)
Informed about digital management tools	-0.233* * *	-0.205* * *	-0.234* * *	-0.216* * *	-0.216* * *	-0.240* * *	-0.260* * *	-0.240* * *
	(0.057)	(0.059)	(0.058)	(0.055)	(0.055)	(0.058)	(0.058)	(0.056)
Education: Low	-0.150	0.106	0.087	0.059	0.051	0.044	0.022	0.076
	(0.089)	(0.089)	(0.091)	(0.090)	(0.088)	(0.096)	(0.094)	(0.089)

Variables with alternative coding for robustness checks	Robots and Artificial Intelligence steal people's jobs		Digital monitoring and evaluation			Sufficient digital skills for job		
Base model	**M5**	**M5**	**M5**	**M5**	**M5**	**M6**	**M6**	**M6**
Variable	**R1**	**R2**	**R3**	**R4**	**R5**	**R6**	**R7**	**R8**
Education: High	-0.212* * *	-0.235* * *	-0.195* *	-0.209* * *	-0.208* * *	-0.202* * *	-0.217* * *	-0.220* * *
	(0.061)	(0.067)	(0.060)	(0.059)	(0.059)	(0.061)	(0.062)	(0.059)
Social class: Working class	0.306* * *	0.140*	0.124	0.194* *	0.163*	0.192*	0.206* *	0.175*
	(0.074)	(0.070)	(0.073)	(0.073)	(0.072)	(0.076)	(0.077)	(0.072)
Social class: Lower middle class	-0.022	-0.168*	-0.048	-0.031	-0.039	-0.003	-0.045	-0.037
	(0.075)	(0.077)	(0.075)	(0.074)	(0.073)	(0.077)	(0.077)	(0.073)
Social class: Upper middle class	-0.180*	-0.027	-0.341* * *	-0.356* * *	-0.356* * *	-0.338* * *	-0.320* * *	-0.358* * *
	(0.087)	(0.112)	(0.088)	(0.087)	(0.086)	(0.088)	(0.090)	(0.086)
Social class: Higher class	-0.489*	0.247	0.096	0.082	0.074	0.079	0.047	0.061
	(0.216)	(0.284)	(0.228)	(0.222)	(0.222)	(0.223)	(0.227)	(0.221)
Community type: Small town	0.042	0.144*	0.112	0.118	0.129*	0.082	0.118	0.125*
	(0.063)	(0.063)	(0.063)	(0.063)	(0.062)	(0.065)	(0.065)	(0.062)
Community type: Large town	0.075	0.020	0.085	0.076	0.089	0.070	0.086	0.095
	(0.064)	(0.066)	(0.064)	(0.063)	(0.062)	(0.065)	(0.066)	(0.062)
Sector: Agriculture	-0.213	0.077	-0.026	0.053	0.046	0.033	0.032	0.037
	(0.150)	(0.154)	(0.160)	(0.165)	(0.160)	(0.169)	(0.167)	(0.161)
Sector: Manufacturing	-0.036	-0.017	-0.139	-0.158*	-0.148*	-0.075	-0.084	-0.151*

Variables with alternative coding for robustness checks	Robots and Artificial Intelligence steal people's jobs		Digital monitoring and evaluation			Sufficient digital skills for job		
Base model	**M5**	**M5**	**M5**	**M5**	**M5**	**M6**	**M6**	**M6**
Variable	**R1**	**R2**	**R3**	**R4**	**R5**	**R6**	**R7**	**R8**
	(0.071)	(0.075)	(0.071)	(0.070)	(0.070)	(0.074)	(0.073)	(0.070)
Sector: Transport and logistics	0.177	0.203*	0.101	0.131	0.124	0.164	0.174	0.118
	(0.100)	(0.100)	(0.099)	(0.099)	(0.098)	(0.102)	(0.102)	(0.098)
Sector: Public sector	0.011	0.009	-0.078	-0.059	-0.055	-0.045	-0.031	-0.059
	(0.064)	(0.069)	(0.064)	(0.063)	(0.062)	(0.065)	(0.065)	(0.062)
Firm size: Solo / self-employed	-0.048	0.243	-0.062	-0.068	-0.090	-0.160	-0.156	-0.069
	(0.166)	(0.148)	(0.162)	(0.164)	(0.158)	(0.170)	(0.168)	(0.159)
Firm size: 10-49 employees	0.059	-0.042	0.035	0.019	0.031	0.000	0.002	0.025
	(0.066)	(0.066)	(0.066)	(0.065)	(0.065)	(0.068)	(0.068)	(0.065)
Firm size: 50-250 employees	-0.003	-0.004	0.066	0.060	0.075	0.021	0.041	0.062
	(0.079)	(0.083)	(0.078)	(0.078)	(0.077)	(0.081)	(0.081)	(0.077)
Firm size: 250+ employees	-0.166	0.099	-0.099	-0.107	-0.103	-0.158	-0.150	-0.121
	(0.089)	(0.097)	(0.090)	(0.088)	(0.088)	(0.091)	(0.091)	(0.088)
Age	0.004*	0.008* * *	0.006* *	0.004*	0.005*	0.005*	0.005*	0.005*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age squared	-0.000	-0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	0.153* *	0.126*	0.138* *	0.117*	0.119*	0.147* *	0.139* *	0.127*

Variables with alternative coding for robustness checks	Robots and Artificial Intelligence steal people's jobs		Digital monitoring and evaluation			Sufficient digital skills for job		
Base model	**M5**	**M5**	**M5**	**M5**	**M5**	**M6**	**M6**	**M6**
Variable	**R1**	**R2**	**R3**	**R4**	**R5**	**R6**	**R7**	**R8**
	(0.051)	(0.053)	(0.050)	(0.050)	(0.049)	(0.052)	(0.052)	(0.049)
Belgium	0.296	-0.431*	0.043	0.020	0.025	-0.017	-0.053	0.030
	(0.171)	(0.184)	(0.164)	(0.165)	(0.161)	(0.170)	(0.172)	(0.162)
Bulgaria	-0.151	-0.067	-0.144	-0.124	-0.128	-0.110	-0.157	-0.165
	(0.171)	(0.172)	(0.166)	(0.165)	(0.163)	(0.172)	(0.172)	(0.163)
Cyprus	0.531*	0.501*	0.845* * *	0.820* * *	0.854* * *	0.802* * *	0.861* * *	0.815* * *
	(0.225)	(0.200)	(0.231)	(0.230)	(0.226)	(0.239)	(0.241)	(0.227)
Czech Republic	-0.141	-0.439*	-0.323*	-0.308*	-0.292	-0.325*	-0.322*	-0.304*
	(0.157)	(0.173)	(0.154)	(0.151)	(0.149)	(0.155)	(0.158)	(0.150)
Germany (East)	-0.242	-0.012	-0.217	-0.204	-0.172	-0.223	-0.290	-0.167
	(0.195)	(0.203)	(0.191)	(0.188)	(0.187)	(0.198)	(0.199)	(0.188)
Germany (West)	-0.824* * *	-0.656* * *	-0.665* * *	-0.654* * *	-0.639* * *	-0.546* *	-0.507* *	-0.652* * *
	(0.159)	(0.189)	(0.163)	(0.160)	(0.159)	(0.167)	(0.170)	(0.159)
Denmark	-0.810* * *	-0.760* * *	-0.784* * *	-0.781* * *	-0.791* * *	-0.900* * *	-0.894* * *	-0.815* * *
	(0.168)	(0.219)	(0.173)	(0.167)	(0.165)	(0.174)	(0.177)	(0.167)
Estonia	0.086	0.220	0.450* *	0.422*	0.425* *	0.410*	0.398*	0.409*
	(0.166)	(0.173)	(0.171)	(0.167)	(0.165)	(0.173)	(0.178)	(0.166)
Spain	0.211	0.281	0.394*	0.332*	0.372*	0.307	0.290	0.334*
	(0.169)	(0.162)	(0.171)	(0.168)	(0.166)	(0.173)	(0.175)	(0.167)
Finland	-0.570* * *	-1.296* * *	-1.058* * *	-0.999* * *	-0.957* * *	-1.066* * *	-1.066* * *	-0.987* * *
	(0.168)	(0.246)	(0.176)	(0.170)	(0.167)	(0.175)	(0.178)	(0.168)

Variables with alternative coding for robustness checks	Robots and Artificial Intelligence steal people's jobs		Digital monitoring and evaluation			Sufficient digital skills for job		
Base model	**M5**	**M5**	**M5**	**M5**	**M5**	**M6**	**M6**	**M6**
Variable	**R1**	**R2**	**R3**	**R4**	**R5**	**R6**	**R7**	**R8**
France	0.305	0.184	0.212	0.119	0.163	0.101	0.127	0.164
	(0.187)	(0.175)	(0.185)	(0.180)	(0.177)	(0.189)	(0.188)	(0.179)
Greece	0.219	0.198	0.370*	0.413*	0.428*	0.406*	0.427*	0.403*
	(0.181)	(0.172)	(0.182)	(0.181)	(0.179)	(0.188)	(0.190)	(0.179)
Croatia	-0.128	0.039	0.072	0.069	0.087	0.046	0.031	0.085
	(0.154)	(0.160)	(0.155)	(0.154)	(0.152)	(0.159)	(0.160)	(0.152)
Hungary	0.033	-0.297	0.081	0.104	0.109	0.152	0.121	0.113
	(0.160)	(0.162)	(0.158)	(0.156)	(0.154)	(0.162)	(0.164)	(0.155)
Ireland	0.249	0.421*	0.485* *	0.467* *	0.493* *	0.453*	0.445*	0.477* *
	(0.176)	(0.176)	(0.181)	(0.174)	(0.172)	(0.181)	(0.181)	(0.173)
Italy	-0.058	-0.638* * *	-0.136	-0.143	-0.133	-0.099	-0.150	-0.126
	(0.166)	(0.180)	(0.165)	(0.163)	(0.161)	(0.167)	(0.169)	(0.162)
Lithuania	0.157	0.278	0.203	0.287	0.245	0.238	0.161	0.225
	(0.183)	(0.177)	(0.183)	(0.187)	(0.180)	(0.191)	(0.190)	(0.179)
Luxembourg	0.001	0.075	0.279	0.300	0.329	0.178	0.229	0.305
	(0.188)	(0.194)	(0.191)	(0.189)	(0.186)	(0.195)	(0.196)	(0.188)
Latvia	0.319	0.185	0.280	0.246	0.248	0.154	0.186	0.222
	(0.182)	(0.175)	(0.180)	(0.176)	(0.174)	(0.184)	(0.185)	(0.176)
Malta	-0.316	-0.229	-0.339	-0.353	-0.328	-0.414	-0.432*	-0.352
	(0.215)	(0.252)	(0.213)	(0.208)	(0.207)	(0.215)	(0.220)	(0.208)
Netherlands	-0.988* * *	-0.986* * *	-0.985* * *	-0.984* * *	-0.979* * *	-1.091* * *	-1.058* * *	-1.026* * *

Variables with alternative coding for robustness checks	Robots and Artificial Intelligence steal people's jobs		Digital monitoring and evaluation			Sufficient digital skills for job		
Base model	**M5**	**M5**	**M5**	**M5**	**M5**	**M6**	**M6**	**M6**
Variable	**R1**	**R2**	**R3**	**R4**	**R5**	**R6**	**R7**	**R8**
	(0.181)	(0.244)	(0.186)	(0.183)	(0.181)	(0.188)	(0.192)	(0.182)
Poland	0.350*	-0.463* *	0.454* *	0.411*	0.416*	0.360*	0.404*	0.418*
	(0.172)	(0.179)	(0.170)	(0.168)	(0.166)	(0.173)	(0.179)	(0.167)
Portugal	0.424*	0.037	0.510* *	0.459*	0.466* *	0.403*	0.449*	0.438*
	(0.184)	(0.171)	(0.183)	(0.180)	(0.176)	(0.186)	(0.188)	(0.177)
Romania	-0.240	-0.231	-0.087	-0.083	-0.074	-0.046	-0.125	-0.063
	(0.149)	(0.163)	(0.150)	(0.149)	(0.147)	(0.153)	(0.154)	(0.147)
Sweden	-0.189	0.006	-0.059	0.014	0.023	-0.084	-0.055	-0.030
	(0.175)	(0.197)	(0.179)	(0.175)	(0.174)	(0.180)	(0.182)	(0.175)
Slovenia	0.445*	0.263	0.246	0.232	0.237	0.169	0.206	0.208
	(0.184)	(0.181)	(0.175)	(0.171)	(0.169)	(0.175)	(0.179)	(0.170)
Slovakia	0.698* * *	-0.046	0.356*	0.331*	0.378*	0.318	0.316	0.377*
	(0.178)	(0.172)	(0.164)	(0.161)	(0.160)	(0.168)	(0.172)	(0.161)
Observations	10074	10200	9735	9989	10200	9293	9227	10156
Weighted N	10614.40	10757.66	10248.29	10545.44	10757.66	9848.72	9786.56	10711.52
Tjur's R2	0.083	0.110	0.101	0.103	0.102	0.106	0.104	0.102
AUC	0.667	0.698	0.682	0.683	0.682	0.685	0.684	0.683

Notes: *** p < 0.001; ** p < 0.01; * p < 0.05.

APPENDIX K

Table K.1 Logit coefficients for the robustness specifications on occupational structure, reported informing about digital management tools, and survey weights

Variables with alternative coding for robustness checks	**Occupational AI exposure (group level)**		**Informed about digital management tools**		**Unweighted sample**	
Base model	**M5**	**M6**	**M5**	**M6**	**M5**	**M6**
Variable	**R9**	**R10**	**R11**	**R12**	**R13**	**R14**
Constant	-0.342	-0.408*	-0.259	-0.331	-0.112	-0.211
	(0.175)	(0.181)	(0.168)	(0.174)	(0.156)	(0.162)
Digital monitoring and evaluation	0.071*	0.084* *	0.080* *	0.090* *	0.073* *	0.085* *
	(0.029)	(0.030)	(0.029)	(0.030)	(0.027)	(0.028)
Occupational AI exposure (group level)			-0.477*	-0.456*	-0.415*	-0.421*
			(0.193)	(0.200)	(0.180)	(0.187)
Sufficient digital skills for job		0.121* * *		0.111* *		0.169* * *
		(0.034)		(0.034)		(0.031)
Attitude toward robots and AI in the workplace	0.431* * *	0.487* * *	0.435* * *	0.490* * *	0.391* * *	0.461* * *
	(0.035)	(0.038)	(0.035)	(0.038)	(0.032)	(0.035)
Informed about digital management tools	-0.212* * *	-0.236* * *			-0.275* * *	-0.304* * *
	(0.055)	(0.057)			(0.051)	(0.053)
Informed about digital management tools (coded as levels)			-0.129* * *	-0.132* * *		

Variables with alternative coding for robustness checks	Occupational AI exposure (group level)		Informed about digital management tools		Unweighted sample	
Base model	**M5**	**M6**	**M5**	**M6**	**M5**	**M6**
Variable	**R9**	**R10**	**R11**	**R12**	**R13**	**R14**
			(0.023)	(0.024)		
Education: Low	0.040	0.024	0.051	0.030	0.038	0.032
	(0.090)	(0.096)	(0.088)	(0.095)	(0.081)	(0.087)
Education: High	-0.173* *	-0.167* *	-0.206* * *	-0.199* *	-0.191* * *	-0.190* * *
	(0.062)	(0.064)	(0.059)	(0.061)	(0.054)	(0.056)
Social class: Working class	0.152*	0.175*	0.159*	0.180*	0.144*	0.173*
	(0.072)	(0.076)	(0.072)	(0.075)	(0.066)	(0.069)
Social class: Lower middle class	-0.046	-0.021	-0.039	-0.014	-0.081	-0.056
	(0.073)	(0.076)	(0.073)	(0.076)	(0.066)	(0.069)
Social class: Upper middle class	-0.331* * *	-0.310* * *	-0.356* * *	-0.336* * *	-0.380* * *	-0.353* * *
	(0.087)	(0.089)	(0.086)	(0.088)	(0.080)	(0.082)
Social class: Higher class	0.152	0.158	0.082	0.092	-0.068	-0.069
	(0.222)	(0.222)	(0.221)	(0.221)	(0.222)	(0.225)
Community type: Small town	0.134*	0.084	0.129*	0.079	0.121*	0.078
	(0.062)	(0.065)	(0.062)	(0.065)	(0.056)	(0.058)
Community type: Large town	0.090	0.049	0.086	0.047	0.107	0.080
	(0.062)	(0.065)	(0.062)	(0.065)	(0.057)	(0.059)
Sector: Agriculture	0.057	0.032	0.043	0.016	0.004	-0.006
	(0.163)	(0.169)	(0.161)	(0.167)	(0.144)	(0.150)
Sector: Manufacturing	-0.127	-0.091	-0.147*	-0.108	-0.142*	-0.103
	(0.072)	(0.075)	(0.070)	(0.073)	(0.064)	(0.067)

Variables with alternative coding for robustness checks	Occupational AI exposure (group level)		Informed about digital management tools		Unweighted sample	
Base model	**M5**	**M6**	**M5**	**M6**	**M5**	**M6**
Variable	**R9**	**R10**	**R11**	**R12**	**R13**	**R14**
Sector: Transport and logistics	0.122	0.135	0.132	0.148	0.111	0.120
	(0.098)	(0.101)	(0.098)	(0.101)	(0.089)	(0.092)
Sector: Public sector	-0.054	-0.059	-0.055	-0.061	-0.083	-0.090
	(0.063)	(0.065)	(0.062)	(0.064)	(0.058)	(0.059)
Firm size: Solo / self-employed	-0.092	-0.131	-0.096	-0.134	-0.009	-0.024
	(0.159)	(0.172)	(0.158)	(0.170)	(0.151)	(0.162)
Firm size: 10-49 employees	0.035	0.016	0.026	0.006	0.022	0.011
	(0.065)	(0.067)	(0.065)	(0.067)	(0.059)	(0.061)
Firm size: 50-250 employees	0.077	0.038	0.078	0.039	0.077	0.046
	(0.077)	(0.080)	(0.077)	(0.080)	(0.071)	(0.073)
Firm size: 250+ employees	-0.105	-0.145	-0.111	-0.151	-0.071	-0.105
	(0.088)	(0.090)	(0.088)	(0.090)	(0.082)	(0.084)
Age	0.005*	0.005*	0.005*	0.005*	0.004*	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age squared	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	0.106*	0.123*	0.122*	0.136* *	0.110*	0.127* *
	(0.050)	(0.052)	(0.049)	(0.051)	(0.046)	(0.048)
Occupation: Employed professional	-0.169	-0.159				
	(0.102)	(0.104)				
Occupation: Top management	-0.338*	-0.339*				

Variables with alternative coding for robustness checks	Occupational AI exposure (group level)		Informed about digital management tools		Unweighted sample	
Base model	**M5**	**M6**	**M5**	**M6**	**M5**	**M6**
Variable	**R9**	**R10**	**R11**	**R12**	**R13**	**R14**
	(0.144)	(0.147)				
Occupation: Middle management	0.056	0.057				
	(0.079)	(0.081)				
Occupation: Travelling	0.205*	0.222*				
	(0.101)	(0.105)				
Occupation: Service job	0.091	0.072				
	(0.082)	(0.085)				
Occupation: Supervisor	-0.371*	-0.331*				
	(0.151)	(0.159)				
Occupation: Skilled manual	0.116	0.118				
	(0.084)	(0.087)				
Occupation: Unskilled manual	0.279	0.256				
	(0.147)	(0.161)				
Belgium	-0.008	-0.052	-0.004	-0.050	-0.148	-0.208
	(0.162)	(0.170)	(0.162)	(0.169)	(0.149)	(0.156)
Bulgaria	-0.130	-0.145	-0.154	-0.164	-0.126	-0.154
	(0.164)	(0.170)	(0.163)	(0.169)	(0.155)	(0.160)
Cyprus	0.856* * *	0.765* *	0.823* * *	0.733* *	0.773* * *	0.695* *
	(0.226)	(0.233)	(0.227)	(0.234)	(0.212)	(0.219)
Czech Republic	-0.306*	-0.349*	-0.322*	-0.363*	-0.427* *	-0.465* *
	(0.150)	(0.155)	(0.150)	(0.155)	(0.144)	(0.148)

Variables with alternative coding for robustness checks	Occupational AI exposure (group level)		Informed about digital management tools		Unweighted sample	
Base model	**M5**	**M6**	**M5**	**M6**	**M5**	**M6**
Variable	**R9**	**R10**	**R11**	**R12**	**R13**	**R14**
Germany (East)	-0.148	-0.223	-0.172	-0.243	-0.443* *	-0.500* *
	(0.190)	(0.199)	(0.188)	(0.197)	(0.165)	(0.174)
Germany (West)	-0.645* * *	-0.614* * *	-0.657* * *	-0.627* * *	-0.765* * *	-0.721* * *
	(0.159)	(0.165)	(0.159)	(0.164)	(0.149)	(0.154)
Denmark	-0.822* * *	-0.873* * *	-0.830* * *	-0.882* * *	-0.908* * *	-0.967* * *
	(0.166)	(0.172)	(0.166)	(0.172)	(0.154)	(0.158)
Estonia	0.426*	0.400*	0.396*	0.373*	0.359*	0.316
	(0.167)	(0.173)	(0.165)	(0.171)	(0.160)	(0.166)
Spain	0.365*	0.303	0.334*	0.276	0.296	0.210
	(0.167)	(0.172)	(0.166)	(0.172)	(0.163)	(0.168)
Finland	-0.955* * *	-1.044* * *	-1.005* * *	-1.094* * *	-1.015* * *	-1.132* * *
	(0.168)	(0.174)	(0.168)	(0.174)	(0.161)	(0.166)
France	0.177	0.086	0.127	0.037	0.125	0.026
	(0.178)	(0.186)	(0.178)	(0.186)	(0.164)	(0.171)
Greece	0.396*	0.386*	0.379*	0.373*	0.439*	0.415*
	(0.180)	(0.188)	(0.179)	(0.187)	(0.177)	(0.185)
Croatia	0.096	0.064	0.068	0.040	0.004	-0.022
	(0.153)	(0.158)	(0.152)	(0.157)	(0.142)	(0.146)
Hungary	0.110	0.127	0.101	0.120	0.087	0.109
	(0.155)	(0.162)	(0.154)	(0.160)	(0.146)	(0.151)
Ireland	0.515* *	0.463* *	0.446* *	0.395*	0.415*	0.346*

Variables with alternative coding for robustness checks	Occupational AI exposure (group level)		Informed about digital management tools		Unweighted sample	
Base model	**M5**	**M6**	**M5**	**M6**	**M5**	**M6**
Variable	**R9**	**R10**	**R11**	**R12**	**R13**	**R14**
	(0.173)	(0.179)	(0.173)	(0.178)	(0.166)	(0.172)
Italy	-0.116	-0.100	-0.149	-0.135	-0.187	-0.167
	(0.163)	(0.168)	(0.162)	(0.166)	(0.153)	(0.157)
Lithuania	0.257	0.247	0.213	0.202	0.270	0.250
	(0.180)	(0.190)	(0.180)	(0.190)	(0.167)	(0.176)
Luxembourg	0.325	0.191	0.276	0.139	0.284	0.139
	(0.188)	(0.194)	(0.187)	(0.193)	(0.182)	(0.188)
Latvia	0.269	0.190	0.189	0.113	0.266	0.188
	(0.175)	(0.183)	(0.175)	(0.183)	(0.163)	(0.169)
Malta	-0.283	-0.344	-0.387	-0.448*	-0.461*	-0.520* *
	(0.210)	(0.215)	(0.208)	(0.214)	(0.194)	(0.200)
Netherlands	-1.008* * *	-1.102* * *	-0.999* * *	-1.090* * *	-1.003* * *	-1.136* * *
	(0.182)	(0.186)	(0.183)	(0.187)	(0.166)	(0.170)
Poland	0.403*	0.360*	0.401*	0.360*	0.281	0.226
	(0.167)	(0.174)	(0.166)	(0.173)	(0.152)	(0.157)
Portugal	0.504* *	0.440*	0.439*	0.384*	0.389*	0.323
	(0.177)	(0.185)	(0.176)	(0.184)	(0.171)	(0.179)
Romania	-0.071	-0.080	-0.073	-0.079	-0.101	-0.097
	(0.149)	(0.153)	(0.147)	(0.151)	(0.142)	(0.146)
Sweden	0.011	-0.088	-0.016	-0.110	-0.074	-0.198
	(0.174)	(0.180)	(0.174)	(0.179)	(0.159)	(0.163)

Variables with alternative coding for robustness checks	Occupational AI exposure (group level)		Informed about digital management tools		Unweighted sample	
Base model	**M5**	**M6**	**M5**	**M6**	**M5**	**M6**
Variable	**R9**	**R10**	**R11**	**R12**	**R13**	**R14**
Slovenia	0.226	0.158	0.194	0.127	0.149	0.065
	(0.170)	(0.174)	(0.169)	(0.173)	(0.161)	(0.166)
Slovakia	0.372*	0.304	0.351*	0.279	0.323*	0.254
	(0.161)	(0.166)	(0.160)	(0.166)	(0.151)	(0.156)
Observations	10200	9434	10200	9434	10200	9434
Weighted N	10757.66	9987.25	10757.66	9987.25	10757.66	9987.25
Tjur's R2	0.104	0.104	0.103	0.104	0.095	0.096
AUC	0.685	0.684	0.685	0.684	0.677	0.678

Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

APPENDIX L

Table L.1 Survey-weighted logit coefficients for the supplementary functional-form specifications

Base model	**M1**	**M5**	**M5**	**M6**	**M5**	**M5**	**M5**
Variable	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**
Constant	0.334* *	-0.476* *	-0.272	-0.204	0.104	-0.373*	-0.363*
	(0.125)	(0.172)	(0.168)	(0.176)	(0.154)	(0.171)	(0.172)
Digital monitoring and evaluation: Never	0.479* * *	0.306* * *					
	(0.077)	(0.082)					
Digital monitoring and evaluation: Never / rarely	0.096	0.041					
	(0.101)	(0.104)					
Digital monitoring and evaluation: Rarely	0.040	0.006					
	(0.087)	(0.088)					
Digital monitoring and evaluation: Often	0.233* *	0.311* * *					
	(0.090)	(0.092)					
Digital monitoring and evaluation: Often / all the time	0.419* * *	0.537* * *					
	(0.124)	(0.126)					
Digital monitoring and evaluation: All the time	0.622* * *	0.857* * *					
	(0.152)	(0.150)					

Base model	**M1**	**M5**	**M5**	**M6**	**M5**	**M5**	**M5**
Variable	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**
Informed about digital management tools: Basic notification only			-0.066				
			(0.070)				
Informed about digital management tools: Detailed explanation			-0.203* *				
			(0.072)				
Informed about digital management tools: Data/results access			-0.400* * *				
			(0.074)				
Attitude toward robots and AI in the workplace: Fairly positive					0.498* * *		
					(0.066)		
Attitude toward robots and AI in the workplace: Fairly negative					0.936* * *		
					(0.083)		
Attitude toward robots and AI in the workplace: Very negative					1.213* * *		
					(0.128)		
Use of digital skills at work: Totally agree				-0.209* * *			
				(0.060)			
Use of digital skills at work: Tend to disagree				-0.422* * *			
				(0.076)			

Base model	**M1**	**M5**	**M5**	**M6**	**M5**	**M5**	**M5**
Variable	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**
Use of digital skills at work: Totally disagree				-0.683* * *			
				(0.108)			
Digital monitoring and evaluation			0.073*	0.082* *	0.071*	0.069*	0.069*
			(0.029)	(0.030)	(0.029)	(0.029)	(0.029)
Occupational AI exposure (group level)		-0.464*	-0.483*	-0.470*	-0.472*	-0.834* * *	-2.096* *
		(0.194)	(0.193)	(0.201)	(0.193)	(0.248)	(0.811)
Occupational AI exposure squared						4.333*	1.078
						-1.776	-2.667
Occupational AI exposure cubed							41.716
							-25.643
Attitude toward robots and AI in the workplace		0.448* * *	0.440* * *	0.497* * *		0.432* * *	0.431* * *
		(0.036)	(0.035)	(0.038)		(0.035)	(0.035)
Informed about digital management tools		-0.168* *		-0.242* * *	-0.216* * *	-0.207* * *	-0.208* * *
		(0.055)		(0.057)	(0.055)	(0.055)	(0.055)
Education: Low		0.045	0.053	0.063	0.053	0.029	0.040
		(0.088)	(0.088)	(0.096)	(0.088)	(0.089)	(0.090)
Education: High		-0.207* * *	-0.208* * *	-0.190* *	-0.207* * *	-0.170* *	-0.154*
		(0.059)	(0.059)	(0.061)	(0.059)	(0.061)	(0.062)
Social class: Working class		0.150*	0.160*	0.188*	0.165*	0.141	0.142*
		(0.072)	(0.072)	(0.076)	(0.072)	(0.072)	(0.072)
Social class: Lower middle class		-0.038	-0.037	-0.015	-0.039	-0.043	-0.046

Base model	**M1**	**M5**	**M5**	**M6**	**M5**	**M5**	**M5**
Variable	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**
		(0.073)	(0.073)	(0.076)	(0.073)	(0.073)	(0.073)
Social class: Upper middle class		-0.366* * *	-0.359* * *	-0.316* * *	-0.353* * *	-0.341* * *	-0.331* * *
		(0.087)	(0.087)	(0.088)	(0.086)	(0.087)	(0.087)
Social class: Higher class		0.059	0.086	0.150	0.092	0.111	0.137
		(0.222)	(0.221)	(0.224)	(0.222)	(0.223)	(0.224)
Community type: Small town		0.134*	0.129*	0.075	0.130*	0.129*	0.131*
		(0.062)	(0.062)	(0.065)	(0.062)	(0.062)	(0.062)
Community type: Large town		0.093	0.086	0.040	0.088	0.093	0.094
		(0.063)	(0.062)	(0.065)	(0.062)	(0.062)	(0.062)
Sector: Agriculture		0.024	0.044	0.028	0.048	0.031	0.053
		(0.158)	(0.160)	(0.168)	(0.161)	(0.161)	(0.162)
Sector: Manufacturing		-0.137	-0.146*	-0.110	-0.148*	-0.161*	-0.142*
		(0.070)	(0.070)	(0.073)	(0.070)	(0.070)	(0.071)
Sector: Transport and logistics		0.148	0.134	0.136	0.124	0.115	0.120
		(0.098)	(0.098)	(0.101)	(0.098)	(0.098)	(0.098)
Sector: Public sector		-0.056	-0.055	-0.073	-0.057	-0.042	-0.039
		(0.062)	(0.062)	(0.064)	(0.062)	(0.062)	(0.063)
Firm size: Solo / self-employed		-0.120	-0.098	-0.087	-0.085	-0.096	-0.088
		(0.161)	(0.158)	(0.170)	(0.158)	(0.158)	(0.158)
Firm size: 10-49 employees		0.044	0.022	0.022	0.029	0.038	0.035
		(0.065)	(0.065)	(0.067)	(0.065)	(0.065)	(0.065)
Firm size: 50-250 employees		0.075	0.075	0.048	0.074	0.080	0.080
		(0.077)	(0.077)	(0.080)	(0.077)	(0.077)	(0.077)
Firm size: 250+ employees		-0.110	-0.115	-0.121	-0.100	-0.101	-0.104

Base model	**M1**	**M5**	**M5**	**M6**	**M5**	**M5**	**M5**
Variable	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**
		(0.088)	(0.088)	(0.090)	(0.088)	(0.088)	(0.088)
Age		0.005*	0.005*	0.004*	0.005*	0.005*	0.005*
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age squared		0.000	0.000	0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female		0.119*	0.123*	0.128*	0.118*	0.116*	0.112*
		(0.049)	(0.049)	(0.051)	(0.049)	(0.049)	(0.049)
Belgium	0.126	0.089	-0.006	-0.069	0.019	0.005	-0.011
	(0.160)	(0.162)	(0.162)	(0.169)	(0.161)	(0.161)	(0.162)
Bulgaria	0.047	-0.073	-0.159	-0.136	-0.139	-0.145	-0.141
	(0.158)	(0.163)	(0.163)	(0.169)	(0.163)	(0.163)	(0.163)
Cyprus	0.946* * *	0.858* * *	0.821* * *	0.756* *	0.857* * *	0.850* * *	0.846* * *
	(0.221)	(0.228)	(0.227)	(0.233)	(0.225)	(0.225)	(0.225)
Czech Republic	-0.256	-0.274	-0.320*	-0.340*	-0.294*	-0.300*	-0.306*
	(0.147)	(0.150)	(0.150)	(0.154)	(0.149)	(0.149)	(0.150)
Germany (East)	0.102	-0.086	-0.166	-0.231	-0.176	-0.178	-0.172
	(0.189)	(0.190)	(0.189)	(0.196)	(0.186)	(0.187)	(0.188)
Germany (West)	-0.542* * *	-0.606* * *	-0.662* * *	-0.598* * *	-0.646* * *	-0.633* * *	-0.634* * *
	(0.149)	(0.160)	(0.159)	(0.166)	(0.159)	(0.159)	(0.159)
Denmark	-1.017* * *	-0.759* * *	-0.831* * *	-0.821* * *	-0.787* * *	-0.809* * *	-0.816* * *
	(0.160)	(0.166)	(0.167)	(0.172)	(0.165)	(0.166)	(0.166)
Estonia	0.368*	0.446* *	0.394*	0.395*	0.421*	0.423*	0.421*
	(0.163)	(0.167)	(0.166)	(0.171)	(0.165)	(0.165)	(0.166)
Spain	0.554* * *	0.425*	0.331*	0.349*	0.367*	0.359*	0.358*

Base model	**M1**	**M5**	**M5**	**M6**	**M5**	**M5**	**M5**
Variable	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**
	(0.163)	(0.167)	(0.167)	(0.171)	(0.166)	(0.166)	(0.166)
Finland	-1.044* * *	-0.910* * *	-1.013* * *	-1.016* * *	-0.958* * *	-0.954* * *	-0.963* * *
	(0.166)	(0.168)	(0.169)	(0.174)	(0.167)	(0.167)	(0.167)
France	0.312	0.187	0.124	0.088	0.154	0.172	0.167
	(0.174)	(0.179)	(0.179)	(0.186)	(0.177)	(0.177)	(0.177)
Greece	0.599* * *	0.433*	0.380*	0.433*	0.423*	0.413*	0.398*
	(0.177)	(0.178)	(0.179)	(0.188)	(0.178)	(0.179)	(0.179)
Croatia	0.215	0.103	0.073	0.047	0.079	0.082	0.076
	(0.149)	(0.153)	(0.152)	(0.158)	(0.152)	(0.152)	(0.152)
Hungary	0.316*	0.142	0.101	0.119	0.100	0.091	0.094
	(0.151)	(0.156)	(0.154)	(0.160)	(0.154)	(0.154)	(0.154)
Ireland	0.520* *	0.519* *	0.439*	0.460*	0.495* *	0.492* *	0.500* *
	(0.169)	(0.173)	(0.173)	(0.179)	(0.173)	(0.172)	(0.172)
Italy	0.070	-0.096	-0.145	-0.138	-0.147	-0.138	-0.131
	(0.156)	(0.163)	(0.162)	(0.166)	(0.162)	(0.162)	(0.162)
Lithuania	0.255	0.287	0.207	0.259	0.239	0.245	0.244
	(0.177)	(0.182)	(0.180)	(0.190)	(0.180)	(0.180)	(0.180)
Luxembourg	0.292	0.395*	0.265	0.189	0.321	0.316	0.313
	(0.184)	(0.188)	(0.188)	(0.192)	(0.186)	(0.186)	(0.186)
Latvia	0.328	0.293	0.178	0.172	0.241	0.251	0.252
	(0.172)	(0.176)	(0.176)	(0.182)	(0.175)	(0.174)	(0.174)
Malta	-0.369	-0.300	-0.394	-0.401	-0.331	-0.320	-0.311
	(0.211)	(0.209)	(0.209)	(0.214)	(0.208)	(0.209)	(0.209)
Netherlands	-1.174* * *	-0.915* * *	-0.996* * *	-1.039* * *	-0.981* * *	-0.972* * *	-0.979* * *

Base model	**M1**	**M5**	**M5**	**M6**	**M5**	**M5**	**M5**
Variable	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**
	(0.179)	(0.181)	(0.183)	(0.186)	(0.181)	(0.181)	(0.181)
Poland	0.517* *	0.463* *	0.402*	0.341*	0.408*	0.398*	0.399*
	(0.160)	(0.167)	(0.166)	(0.173)	(0.166)	(0.166)	(0.166)
Portugal	0.706* * *	0.478* *	0.436*	0.406*	0.460* *	0.480* *	0.488* *
	(0.170)	(0.177)	(0.176)	(0.186)	(0.176)	(0.176)	(0.176)
Romania	0.121	-0.050	-0.065	-0.067	-0.085	-0.097	-0.095
	(0.144)	(0.148)	(0.148)	(0.151)	(0.147)	(0.148)	(0.148)
Sweden	-0.195	0.023	-0.024	0.008	0.024	0.012	0.015
	(0.171)	(0.175)	(0.174)	(0.180)	(0.174)	(0.174)	(0.174)
Slovenia	0.244	0.286	0.182	0.159	0.237	0.232	0.229
	(0.170)	(0.169)	(0.170)	(0.174)	(0.169)	(0.169)	(0.169)
Slovakia	0.385*	0.408*	0.344*	0.305	0.372*	0.382*	0.371*
	(0.157)	(0.160)	(0.161)	(0.166)	(0.160)	(0.160)	(0.160)
Observations	10200	10200	10200	9434	10200	10200	10200
Weighted N	10757.66	10757.66	10757.66	9987.25	10757.66	10757.66	10757.66
Tjur's R2	0.069	0.108	0.103	0.107	0.102	0.102	0.102
AUC	0.649	0.689	0.685	0.688	0.682	0.683	0.683

Notes: *** p < 0.001; ** p < 0.01; * p < 0.05.