“Reported and anticipated workforce reconfiguration during artificial intelligence adoption: Firm-level evidence from Slovakia”

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REPORTED AND ANTICIPATED WORKFORCE RECONFIGURATION DURING ARTIFICIAL INTELLIGENCE ADOPTION: FIRM-LEVEL EVIDENCE FROM SLOVAKIA

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Abstract

Artificial intelligence (AI) is reshaping how firms design work, yet firm-level evidence compresses employment implications into a single net figure that hides simultaneous hiring and cutting within one firm. The study examines how AI adoption stage, self-assessed AI maturity, orientation, and ownership are associated with the incidence and co-occurrence of realized or planned job creation and elimination. The analytical sample is 693 AI-engaged Slovak firms from a cross-sectional survey (351 current users, 211 pilot firms, 131 planning adoption). Two binary items record whether AI-related positions have been introduced or are planned, and whether AI has led or is expected to lead to layoffs. Each item merges realized with planned or expected action, so the outcomes indicate the incidence of an actual or anticipated event, not the number of positions. We applied exact tests, logistic and multinomial logistic regression, and a bivariate probit model with Benjamin-Hochberg false-discovery-rate (FDR) adjustment. Reported or planned creation was more frequent than elimination (18.0% vs. 9.2%; $p < 0.001$), and the two co-occurred well beyond chance (odds ratio 7.23; $\rho = 0.54$). A more advanced adoption stage was associated with a higher incidence of creation (OR 1.49; FDR-adjusted $p = 0.004$), and employee job-threat concern was associated with a higher incidence of elimination (OR 1.58; $p = 0.014$). Foreign ownership was associated with joint occurrence of both outcomes in an exploratory model only (RRR 2.29; unadjusted $p = 0.027$). The study contributes a descriptive typology of four incidence patterns; the cross-sectional design supports associational reading only.

Keywords technological change, human resource management, job creation, employee displacement, workforce planning, Central and Eastern Europe

JEL Classification J23, J24, M12, O33

INTRODUCTION

Artificial intelligence (AI) has moved within a few years from isolated experimentation to routine use in ordinary business functions, and the question of what it does to work has become one of the most prominent issues in economic and managerial debate. That debate remains dominated by a single fear: that machines will remove jobs faster than the economy can replace them. Estimates that large shares of jobs are exposed to automation (Frey & Osborne, 2017), and that most occupations contain tasks accessible to large language models (Eloundou et al., 2024; Lazaroiu et al., 2024), keep that fear in view, while the productivity gains reported by adopters keep the opposite expectation alive.

The employment consequences of AI are not, however, decided in the aggregate. They are decided inside organizations, where managers choose which tasks to delegate to software, which roles to redesign,

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which positions to open, and which to discontinue. Theory suggests that these choices work in two directions at once. In the task-based account, automation displaces labor from tasks in which capital gains an advantage, while the creation of new tasks and roles reinstates labor demand, and which force prevails is an empirical question (Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2019, 2020). Management scholarship reaches a similar conclusion from a different starting point: automation and augmentation are interdependent rather than alternative strategies, and firms cannot cleanly separate them in practice (Raisch & Krakowski, 2021).

Both lines of reasoning point to a possibility that empirical work rarely accommodates. Within one and the same organization, some positions may be created while others are eliminated during the same episode of technological change. A firm may report the creation of data-analyst and AI-coordinator positions while also reporting the elimination of clerical or customer-support roles. Such co-occurrence indicates workforce reconfiguration, but it does not reveal whether the firm's total employment expanded or contracted. Yet the workforce consequences of AI are usually recorded as one quantity, a net gain or a net loss of jobs. A single net figure cannot distinguish a firm whose workforce is stable from a firm in which creation and elimination offset one another, and it therefore conceals precisely the reallocation that managers and policymakers have to organize.

A further difficulty compounds this one. Survey instruments that ask firms about AI-related workforce change frequently merge what has already happened with what is intended or expected, so that the resulting indicators register the occurrence of an event without fixing it in time. Under such conditions, statements about how many jobs AI creates or removes, or about which direction of change prevails, exceed what the underlying measurement can support. The scientific problem is therefore twofold. First, the co-occurrence of job creation and job elimination within the same firm needs to be identified and described in its own right rather than netted out. Second, the conditions under which each pattern arises need to be examined with claims restricted to what binary, temporally combined indicators of incidence can actually establish.

1. LITERATURE REVIEW AND HYPOTHESES

1.1. Displacement, reinstatement, and the automation-augmentation question

The economics of automation rests on a task view of production. Routine, codifiable tasks are the easiest to mechanize, and historically their automation complemented non-routine cognitive and manual work, a pattern that helps to explain job polarization (Acemoglu & Autor, 2011; Autor et al., 2003; Goos et al., 2014). Acemoglu and Restrepo (2019) make the resulting tension explicit: automation produces a displacement effect by removing workers from automated tasks, while the creation of new tasks produces a reinstatement effect that restores labor demand. Which of the two dominates varies by technology. Industrial robots reduced employment and wages in exposed U.S. commuting zones (Acemoglu & Restrepo, 2020), a clear displacement case. AI need not behave in the same way, because much of its current value lies in prediction and language tasks that can complement workers. The theory thus implies co-occurrence rather than a single direction: displacement and reinstatement are simultaneous properties of the same technological shift, and there is no reason for them to be mutually exclusive within an individual firm.

Generative AI has sharpened the debate. Exposure studies estimate that about 80% of U.S. workers have at least 10% of their tasks open to large language models, with white-collar and higher-wage occupations among the most exposed (Eloundou et al., 2024). Field and experimental studies, by contrast, more often find augmentation: a generative-AI assistant raised customer-support productivity by 14% on average and by 34% for novices (Brynjolfsson et al., 2025), and a writing experiment reduced task time by 40% while raising

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quality by 18%, narrowing the gap between weaker and stronger performers (Noy & Zhang, 2023). Comparable patterns are reported for AI use in European service industries (Mura & Stehlíková, 2025), and worker-level evidence indicates that exposure to digital automation is accompanied by greater motivation to retrain rather than by immediate displacement (Śledziewska et al., 2025). Brynjolfsson (2022) cautions that designing AI to imitate people, what he calls the Turing trap, tilts the technology toward substitution and away from the complementarities that raise the value of labor.

Management research treats automation and augmentation as a strategic choice rather than a forecast. Raisch and Krakowski (2021) argue that the two form an interdependent paradox: firms cannot cleanly separate them, and delegating too much to machines can erode the human capability on which augmentation depends. Formal analysis refines the choice, showing that the optimal mix depends on the type of human-AI complementarity, with automation favored when tasks are complementary across activities and augmentation favored when complementarity lies within a task (Fügener et al., 2026). Evidence on digital transformation in firms points in the same direction, associating it with an upgrading of human capital rather than with straightforward substitution (Yu, 2025; Yu & Qi, 2025). Taken together, this literature implies that augmentation and automation are better observed as two properties that a single firm may display at once than as two ends of one scale.

1.2. Firm-level evidence and the conditions shaping AI-related workforce change

Firm-level studies complicate the simple displacement story without unanimously overturning it. In the United States, AI investment is associated with faster growth in revenue, employment, and product innovation, and with a shift toward more educated and technical staff (Babina et al., 2024). In Germany, AI use is associated with higher productivity, and the association grows with the intensity of use rather than with the mere fact of adoption (Czarnitzki et al., 2023; Rammer et al., 2022). Across more than 12,000 EU and U.S. firms, Aldasoro et al. (2026) find that AI adoption raises short-run labor productivity by about 4%, but they attribute the gain to capital deepening rather than to net hiring, report unchanged employment in the short run, and reach these results only after instrumenting adoption to address the selection of capable firms into AI. Broader firm-level work on digital transformation reports similar heterogeneity in organizational outcomes (He et al., 2026). That selection caveat applies to any study, the present one included, that observes only AI-engaged firms.

The findings converge on two points: consequences concentrate among larger, more capable, internationally exposed firms (Aldasoro et al., 2026), and they grow with the depth of use rather than with adoption as such (Czarnitzki et al., 2023). Both are consistent with the argument that AI delivers value only alongside complementary and often intangible investments in data, processes, and skills, which take time to build and which national accounts measure poorly (Angeloska et al., 2021; Brynjolfsson et al., 2021). Related service-sector research adds that technology-task fit, rather than the availability of technology, predicts actual use and subsequent performance-related outcomes (Zouair et al., 2025). What these strands share is a shift of the analytical question away from whether firms adopt AI and toward how deeply it is embedded in work processes, which is why an indicator of deployment stage is theoretically preferable to a binary indicator of adoption. Aggregate accounts of labor-market outcomes, by contrast, necessarily work with net quantities (Hasan et al., 2025; Ramanauskė & Muliuolytė, 2026) and cannot reveal within-firm recomposition.

Why firms differ in how AI reshapes their workforce is addressed by adoption frameworks. The technology-organization-environment framework (Tornatzky & Fleischer, 1990) and diffusion theory (Rogers, 2003) locate adoption in technological, organizational, and environmental conditions. Organizational readiness for AI is itself multidimensional (Jöhnk et al., 2021), and a systematic review concludes that it rests above all on IT infrastructure, top-management support, and organizational culture (Ali & Khan, 2025). An implication central to this study is that how ready a firm believes itself to be need not correspond to what it has actually deployed. Adoption research in service settings supports the distinction: generative-AI adoption intentions are shaped by perceived usefulness, ease of use, attitudes, and subjective norms (Fang et al., 2025), and the adoption of contactless services depends on perceived usefulness, security, value, and customer experience rather than on the availability of innovation alone (Burkett & Recuero Virto, 2025). Perceived readiness and AI adoption stage are therefore conceptually distinct, and the second, being closer to observable organizational practice, is the more plausible correlate of workforce change. This distinction motivates measuring adoption stage and self-assessed maturity separately.

A second condition is the organization's orientation toward AI. Digital and AI transformation is commonly experienced as both promise and threat, which produces ambivalence inside organizations (Vrontis et al., 2022). Where leaders express confidence, fund training, and frame AI as part of strategy, the technology is more likely to be used to extend what people already do; research on service firms similarly links leadership and intrinsic motivation to organizational innovation (Abdulmawla et al., 2025). Where employees are widely believed to fear for their jobs, a long-recognized component of technostress (Tarafdar et al., 2007; Roy & Vasa, 2024), the substitution reading becomes more salient and, plausibly, more likely to be acted upon. Ownership adds an environmental dimension: foreign-owned subsidiaries often import parent-company practices and efficiency targets, which may accompany both skilled hiring and rationalization, a channel of particular relevance in Central and Eastern Europe (CEE), where multinational subsidiaries account for a large share of activity. Within management scholarship, an applied literature on AI in human resource management has grown quickly (Budhwar et al., 2023; Vrontis et al., 2022), mapping the rise of AI-driven enterprise management (Xue et al., 2025) and documenting both the promise of AI in human resource functions and its slow, uneven uptake (Grigoryan et al., 2025; Gayathiri & Prabu, 2025). Together, these arguments suggest that orientation is likely to be associated with whether reductions are reported, whereas deployment stage is likely to be associated with whether any workforce change is reported at all.

1.3. The Central and Eastern European and Slovak setting

CEE is a distinctive setting. Slovak firms have been described as cautious and comparatively slow digital adopters, partly because the economy long competed on cost rather than at the technological frontier (Grenčíková et al., 2019), and innovation performance across the Visegrád countries remains uneven (Hanáčková & Takáč, 2024). Even so, Industry 4.0 research in Slovakia anticipates more positions created than lost and an upward shift in the skills demanded, although a sizeable minority of firms expect reductions (Grenčíková et al., 2020). Across the region, digital adoption among small and medium-sized enterprises is often shallow and operational rather than strategic, and AI diffusion is uneven across countries and sectors (GLOBSEC, 2026). Czech evidence from accommodation platforms shows digitalization advancing but segmented by user expectations and trust (Křečková et al., 2025), and methodological work on regional service industries points to the same unevenness (Kubičková et al., 2026). Firm-level, AI-specific evidence on workforce outcomes in CEE remains scarce, and much of the regional management literature is bibliometric or focused on attitudes rather than on the joint structure of job creation and job elimination (Fan, 2025; Hassan et al., 2026).

Three observations follow from this literature. Theoretically, displacement and reinstatement are simultaneous properties of the same technological change, so creation and elimination should be expected to co-occur within organizations rather than to exclude one another. Empirically, firm-level consequences appear to depend on the depth of deployment rather than on adoption as such, and on how an organization is oriented toward the technology, while most available evidence comes from advanced economies. Methodologically, however, the joint occurrence of creation and elimination inside a firm has rarely been observed directly, because workforce outcomes are typically recorded as a single net quantity, and the augmentation-automation distinction has remained largely conceptual or has been examined at the level of tasks and occupations rather than firms.

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The unresolved problem is therefore not the existence of a new mechanism, since the displacement-and-reinstatement duality already implies co-occurrence, but its firm-level identification and description in a setting where such evidence is absent, with claims disciplined by what the available measurement can support. This is the gap addressed here: the joint distribution of reported or planned AI-related job creation and job elimination is observed in an under-researched CEE economy, and firm characteristics associated with each pattern of incidence are examined, without inferring the number of positions involved or the prevailing direction of employment change.

The aim of this study is to examine how AI adoption stage, self-assessed AI maturity, organizational orientation toward AI, and ownership are associated with the reported incidence and the co-occurrence of realized or planned AI-related job creation and job elimination among firms already engaged with AI in an emerging EU economy. Three questions follow from this aim. How frequently is each of the two outcomes reported in this segment of the economy? Do the two outcomes occur together within firms more often than their separate frequencies would imply? And do the firm characteristics associated with reporting any workforce change differ from those associated with reporting elimination? All three questions concern the incidence of realized or planned events, not the number of positions involved or the net change in employment.

The following hypotheses are examined. Each is formulated as an expected association, in line with the observational, cross-sectional design, and each refers to indicators that combine realized with planned or expected change.

H_1: *Among AI-engaged firms, reported or planned AI-related job creation is more frequent than reported or planned AI-related job elimination.*

H_2: *Reported or planned AI-related job creation and reported or planned AI-related job elimination are positively associated within firms, net of observed firm characteristics.*

H_3: *A more advanced AI adoption stage is associated with a higher probability that a firm reports each of the two outcomes: realized or planned job creation, and realized or planned job elimination.*

H_{4a}: *Organizational AI enthusiasm is associated with a lower probability that a firm reports realized or planned job elimination.*

H_{4b}: *Perceived employee job-threat concern is associated with a higher probability that a firm reports realized or planned job elimination.*

H_5: *Foreign-owned firms are more likely than domestically owned firms to report the joint occurrence of both outcomes, that is, to fall into the Reconfigurer category.*

H_6: *AI adoption stage is associated with the reported incidence of realized or planned workforce change, whereas self-assessed AI maturity shows no comparable association; the relative strength of the two associations is examined descriptively and is not tested formally.*

2. METHODS

2.1. Research design, data source, and analytical sample

The study uses a cross-sectional, observational, non-experimental design based on a single-wave organization-level survey. All variables, including the two outcomes, were recorded at one point in time, and no exogenous variation in AI adoption is available. The analysis therefore identifies associations between firm characteristics and reported workforce outcomes; it does not identify causal effects, and no temporal ordering between predictors and outcomes can be established.

The data come from the AI-ImpactSK organization-level survey of firms operating in Slovakia (Černý et al., 2026), an openly licensed dataset of 816 unique firms and 621 variables covering firm and respondent characteristics, AI maturity, adoption status and intensity, functional applications, perceived barriers, and sentiment toward AI. The target population is firms operating in Slovakia. The analytical file records one response per firm. The released CSV version, which contains 816 unique firms, was used; the accompanying SPSS file contained duplicated rows (1,514 records for 816 firms) and was not used. The research protocol was approved by the Ethics Committee of the Bratislava University of Economics and Business (EKEUBA 5/2025).

Two items in the adoption block define the outcomes and, by the survey's branching logic, were shown only to firms that use, are piloting, or plan to adopt AI. The 123 firms that neither use nor plan to use AI were not asked these questions and are excluded; no other exclusion criteria were applied. The analytical sample is therefore 693 AI-engaged firms: 351 current users (50.6%), 211 pilot firms (30.4%), and 131 firms planning to adopt AI (18.9%). Relative to the excluded non-adopters, firms in the analytical sample are larger, report higher sales, and are more AI-mature (all $p < 0.05$), which restricts generalizability to the AI-engaged segment of the economy. The analytical sample contains no missing values on any modeled variable, so no imputation was required.

2.2. Outcome measures and their temporal reference

The two outcomes are recorded by the items "Have you introduced or do you plan to introduce new job positions due to AI?" and "Has the implementation of AI led to employee layoffs, or do you plan to do so?" each answered yes or no and coded 1 = yes. Throughout this paper, the first is referred to as reported or planned job creation and the second as reported or planned job elimination. Each item is an indicator of incidence: it records whether an event of the relevant kind has occurred or is intended, and nothing further.

The temporal reference of these indicators differs systematically across firms, and the questionnaire does not allow the two temporal modes to be separated. For firms that only plan to adopt AI, an affirmative answer can refer solely to an expectation or an intention, because no deployment has yet taken place. For pilot firms and current users, an affirmative answer may refer to a change already carried out, to a change that is intended, or to both, since the wording of each item joins the two with "or." No follow-up item records which of the two applies, and no date of the reported change is available. Each outcome is therefore a combined indicator of a realized or planned event, and every result reported below must be read in that sense. Statements about realized workforce change alone cannot be derived from these data, including for the subsample of current users.

Neither item records the number of positions concerned. Consequently, the number of positions created, the number of positions eliminated, the ratio between them, the net change in employment, and the prevailing direction of workforce change all lie outside the scope of the measurement. Terms describing amount, magnitude, or net direction are accordingly avoided throughout.

2.3. The four-category typology

Cross-classifying the two binary indicators yields four mutually exclusive categories. Static comprises firms reporting neither creation or planned creation nor elimination or planned elimination. Augmenter comprises firms reporting creation or planned creation without elimination or planned elimination. Reducer comprises firms reporting elimination or planned elimination without creation or planned creation. Reconfigurer comprises firms reporting the joint occurrence of both indicators.

The category names are analytical shorthand for combinations of incidence. They do not express the number of positions involved, the relative size of creation and elimination, the net change in employment, or whether the reported changes have already been carried out. A firm classified as a Reconfigurer has reported both creation or planned creation and elimination or planned elimination; how many positions each involved, which of the two predominated, and whether either has yet occurred cannot be determined from these data. The four categories are referred to below as incidence patterns.

2.4. Predictors and control variables

AI adoption stage: From the single adoption item, firms are ordered from planning (1), through piloting (2), and use in specific processes (3), to use across multiple areas (4). The three planning horizons offered in the questionnaire (within one, two, or three or more years) are collapsed into a single planning category, so stage 1 denotes firms that intend to adopt but have not yet deployed. The variable captures the stage of AI engagement, with depth of deployment increasing across its range, and is entered as a standardized score, so odds ratios refer to a one-standard-deviation increase.

Self-assessed AI maturity: The mean of seven ordinal maturity items covering culture, strategy, organization, technology, data, ethics, and privacy (Cronbach's $\alpha = 0.91$ in the analytical sample). Maturity is a self-assessment of perceived readiness and is used to contrast perceived readiness with the stage of AI adoption. The two variables are entered jointly, and no test of the equality of their coefficients is reported.

Orientation: Organizational AI enthusiasm is the mean of four positively framed sentiment items capturing excitement, management confidence, a dedicated AI budget and training plan, and strategic alignment ($\alpha = 0.82$). Perceived employee job-threat concern is a single item recording the respondent's assessment that employees are widely worried that AI threatens their jobs. The two are modeled separately because a combined index that reverse-coded negatively framed items cohered poorly ($\alpha = 0.59$), which is consistent with enthusiasm and threat being distinct rather than opposite constructs. Both use agreement scales. The questionnaire describes these batteries as six-point scales, whereas the released data record them on a five-point scale (1-5); the released coding is used, with reverse-coding computed accordingly.

Perceived barriers: The mean of 20 barrier-severity items ($\alpha = 0.95$).

Firm characteristics: Firm size (number of employees, ordinal), net sales (ordinal), firm age, ownership (domestic private, foreign company registered in Slovakia, state-owned, mixed; a foreign-ownership indicator is used), sector (NACE, grouped; indicators for manufacturing and for knowledge-intensive activities, the latter combining information and communication, finance, and professional and scientific activities), and the respondent's managerial level. Reference categories are domestic ownership for the ownership indicator and the residual sector group, which is neither manufacturing nor knowledge-intensive, for the two sector indicators. Continuous and ordinal predictors are standardized, so their odds ratios refer to a one-standard-deviation change; this treats ordinal scales as interval, a simplification noted as a limitation for the coarser variables. Binary predictors are entered as indicators. A separate breadth measure, the number of functional areas using AI, was available only for current users and pilot firms and not for planners; because coding planners as zero would conflate "no areas" with "not asked," breadth is not included in the models.

2.5. Analytical strategy

The analysis begins with the prevalence of each outcome, reported with Wilson confidence intervals, and with the distribution of the four incidence patterns. H_1 is tested with McNemar's exact test for correlated proportions (McNemar, 1947), which compares the two marginal rates within the same firms. H_2 is examined in three ways. First is the 2×2 association between the outcomes (Fisher's exact odds ratio). Second is a logistic regression of reported or planned job elimination on reported or planned job creation with the full set of controls. Third is a bivariate probit model estimated by maximum likelihood, whose error correlation ρ summarizes how the two latent propensities move together once observables are held constant (Greene, 2018). Because both outcomes are reported by the same respondent on the same instrument, ρ may reflect shared-method variance or a common unobserved shock, such as a restructuring or a change of ownership, in addition to substantive co-occurrence. It is therefore read as consistent with reconfiguration rather than as evidence of it, and a Harman single-factor test on the perceptual items is reported as a partial check on common-method variance.

Associations with firm characteristics (H_3 to H_6) are examined with separate logistic regressions for each outcome, reporting odds ratios with 95% confidence intervals, and with a multinomial logistic regression of the four incidence patterns (reference = Static), reporting relative risk ratios. The nominal significance level is 5%.

Because nine coefficients are tested in each logistic model, p-values in those models are adjusted with the Benjamini–Hochberg false-discovery-rate procedure, and both unadjusted and adjusted values are reported; an association is treated as robust only if it remains significant at a 5% FDR threshold. The multinomial estimates are not FDR-adjusted and rest on small cells (Reconfigurer, n = 35; Reducer, n = 29), which yields few events per parameter, so they are reported as exploratory throughout. Analyses were carried out in Python using statsmodels, with the bivariate probit implemented as a custom maximum-likelihood model. Collinearity was checked with variance inflation factors. All numerical outputs are archived in an accompanying results registry.

Four sensitivity checks address the composition of the sample and the rarity of one outcome. First, the models are re-estimated on the 562 firms that use or pilot AI, and then on the 351 current users only, in order to examine whether the associations hold among firms with actual deployment; because the outcome items do not distinguish realized from planned change, these subsamples reduce but do not remove the temporal ambiguity, and their results cannot be read as pertaining to realized change alone. Second, adoption stage is included in every model, so the associations of orientation, ownership, and firm characteristics are estimated conditional on the stage of deployment. Third, further controls (net sales, firm age, respondent seniority) are added, and the strategy subdimension is substituted for the maturity composite. Fourth, because reported or planned job elimination is the rarer outcome, that model is re-estimated with Firth's penalized likelihood. Two analyses are not reported. No separate outcome model is estimated for the 131 firms that only plan to adopt AI, and no formal test of the equality of the adoption-stage and maturity coefficients is reported, so their relative predictive strength is not established.

3. RESULTS

3.1. Sample composition and the incidence of the two outcomes

Among the 693 AI-engaged firms, 125 (18.0%; 95% CI 15.4–21.1) report AI-related creation or planned creation of positions and 64 (9.2%; 95% CI 7.3–11.6) report AI-related elimination or planned elimination; 154 firms (22.2%) report at least one of the two. The distribution of incidence patterns (Table 1) is dominated by Static firms (539; 77.8%), followed by Augmenters (90; 13.0%), Reconfigurers (35; 5.1%), and Reducers (29; 4.2%).

Among the 154 firms reporting at least one outcome, creation-oriented patterns predominate: 58.4% are Augmenters and a further 22.7% are Reconfigurers, leaving 18.8% as Reducers. Figure 1 shows the two incidence rates with 95% Wilson confidence intervals.

Table 1. Composition of the analytical sample and incidence of the two outcomes

Group	Category	N	Share of the analytical sample (%)
AI adoption stage	Current users (AI used in specific processes or across multiple areas)	351	50.6
	Pilot firms	211	30.4
	Planning to adopt AI (not yet deployed)	131	18.9
Outcome incidence	Reported or planned job creation	125	18.0 [15.4–21.1]
	Reported or planned job elimination	64	9.2 [7.3–11.6]
	At least one of the two outcomes	154	22.2
Incidence pattern	Static (neither outcome)	539	77.8
	Augmenter (creation only)	90	13.0
	Reconfigurer (both outcomes)	35	5.1
	Reducer (elimination only)	29	4.2
Total	Analytical sample	693	100.0

Note: Shares are percentages of the analytical sample of 693 AI-engaged firms.

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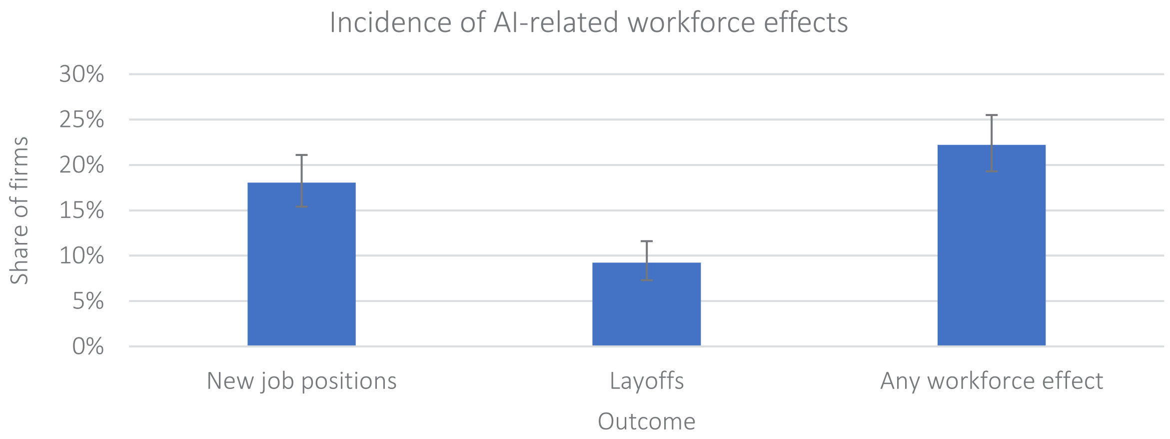

Figure 1. Incidence of reported or planned AI-related job creation and job elimination (N = 693), with 95% Wilson confidence intervals

3.2. Relative frequency of the two outcomes (H_1)

Reported or planned job creation is about twice as frequent as reported or planned job elimination (125 versus 64 firms, a ratio of 1.95 to 1). The off-diagonal cells are asymmetric: 90 firms report creation without elimination, whereas 29 report elimination without creation. McNemar's exact test rejects equality of the two marginal rates ($p < 0.001$), which supports H_1. The result concerns the incidence of the two events among AI-engaged firms: the items count firms rather than positions, so they do not establish a net headcount gain, and part of the reported change may not yet have taken place. With that qualification, the pattern is consistent with the reinstatement-leaning firm-level evidence from advanced economies (Babina et al., 2024) and with Slovak Industry 4.0 expectations (Grenčíková et al., 2020).

3.3. Co-occurrence of the two outcomes (H_2)

The two outcomes are far from mutually exclusive. Their 2×2 association is strong (Fisher's exact odds ratio 7.23, 95% CI 4.21–12.41; $\chi^2(1) = 61.4$ with continuity correction, $p < 0.001$; $\varphi = 0.30$). Among firms reporting creation or planned creation, 28.0% also report elimination or planned elimination, compared with 5.1% among firms reporting no creation (Figure 2). The association persists under control: in a logistic regression of elimination on creation with the full covariate set, the odds ratio for creation is

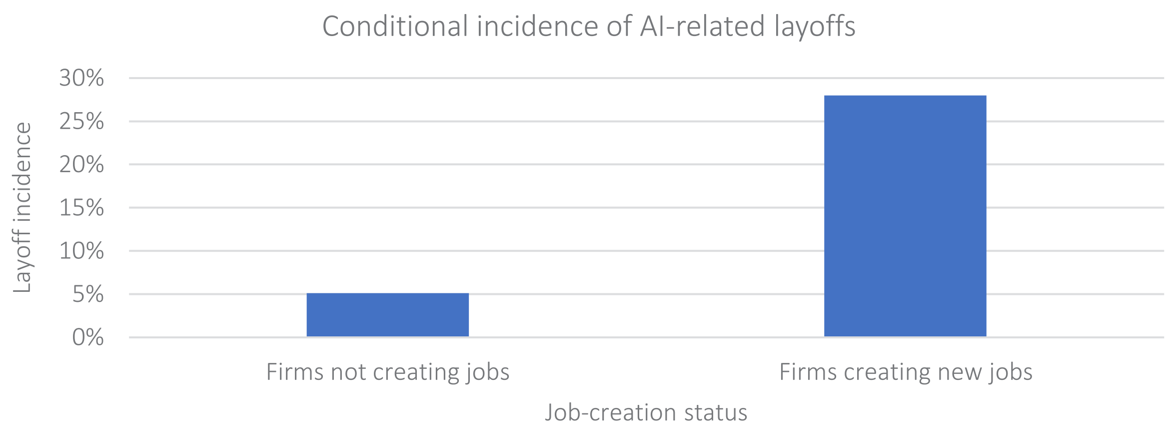

Figure 2. Conditional incidence of reported or planned AI-related job elimination by job-creation status, with measures of association

6.37 (95% CI 3.63–11.18, $p < 0.001$). The bivariate probit points the same way, with an error correlation of $\rho = 0.54$ (95% CI 0.39–0.67) and a likelihood-ratio test rejecting independence of the two equations (LR = 41.6, $p < 0.001$). Net of firm size, sector, ownership, self-assessed maturity, adoption stage, orientation, and perceived barriers, the two propensities remain positively correlated, which supports H_2.

This is read as consistent with within-firm reconfiguration, subject to two qualifications. Because both outcomes come from the same respondent, part of ρ may reflect shared-method variance, for instance an AI-salient respondent answering yes to both items. A Harman single-factor test on the 36 perceptual items is partly reassuring: the first unrotated factor accounts for 29.9% of variance, below the 50% threshold that would signal a dominant method factor, although this test does not bear directly on the two binary outcome items. A common unobserved shock, such as a reorganization or a change of owner, could also raise the reported incidence of both outcomes together. Within these limits, the data are consistent with firms reconfiguring their workforce rather than only reducing or only expanding it, which gives firm-level empirical content to the displacement-and-reinstatement account of automation and to the automation-augmentation paradox.

3.4. Firm characteristics associated with each outcome (H_3, H_{4a}, H_{4b}, H_6)

Adoption stage is the clearest correlate of reported or planned job creation: a one-standard-deviation increase is associated with odds higher by about one half (OR 1.49, 95% CI 1.19–1.86, $p < 0.001$), and this is the only association with creation that remains significant after FDR adjustment ($q = 0.004$). Table 2 reports the two logistic regressions with odds ratios, 95% confidence intervals, and unadjusted and FDR-adjusted p-values.

The predicted probability of reporting creation rises across stages, from about 10% at the planning stage to about 27% among firms using AI across multiple areas, and the predicted probability of reporting elimination from about 5% to about 12% (Figure 3).

For reported or planned job elimination, the association with adoption stage is weaker and does not survive adjustment (OR 1.33, 95% CI 1.00–1.79, $p = 0.053$, $q = 0.159$). H_3 is therefore supported for reported or planned job creation and is not supported for reported or planned job elimination at the adjusted significance level; Figure 4 plots the odds ratios for both models. Adoption stage is associated with whether firms report any realized or planned creation of positions; the number of positions involved was not measured.

Organizational orientation is associated primarily with the elimination outcome. Perceived employee job-threat concern is associated with a higher incidence of reported or planned job elimination (OR 1.58, 95% CI 1.19–2.10, $p = 0.002$, $q = 0.014$), which supports H_{4b} and is the most robust orientation result; its association with creation does not reach the adjusted threshold (OR 1.23, 95% CI

Table 2. Logistic regressions for reported or planned AI-related job creation and job elimination

Predictor	Reported or planned job creation: OR [95% CI]	p (q)	Reported or planned job elimination: OR [95% CI]	p (q)
Firm size	0.93 [0.75, 1.14]	0.471 (0.706)	0.93 [0.71, 1.23]	0.625 (0.804)
Foreign ownership	1.39 [0.92, 2.12]	0.119 (0.267)	1.42 [0.82, 2.47]	0.215 (0.387)
Knowledge-intensive sector	1.14 [0.71, 1.83]	0.587 (0.755)	1.54 [0.83, 2.86]	0.172 (0.387)
Manufacturing sector	0.63 [0.36, 1.11]	0.111 (0.267)	0.79 [0.37, 1.66]	0.531 (0.797)
Self-assessed AI maturity	1.01 [0.79, 1.29]	0.937 (0.937)	1.03 [0.75, 1.43]	0.837 (0.942)
AI adoption stage	1.49 [1.19, 1.86]	< 0.001 (0.004)	1.33 [1.00, 1.79]	0.053 (0.159)
Organizational AI enthusiasm	0.88 [0.70, 1.10]	0.253 (0.456)	0.70 [0.52, 0.95]	0.022 (0.098)
Perceived employee job-threat concern	1.23 [1.00, 1.51]	0.050 (0.224)	1.58 [1.19, 2.10]	0.002 (0.014)
Perceived barriers	1.04 [0.85, 1.26]	0.703 (0.791)	1.00 [0.77, 1.30]	0.998 (0.998)
Firms (N)	693		693	
Firms reporting the outcome (n)	125		64	
Pseudo-R²	0.043		0.052	

Note: Odds ratios with 95% confidence intervals.

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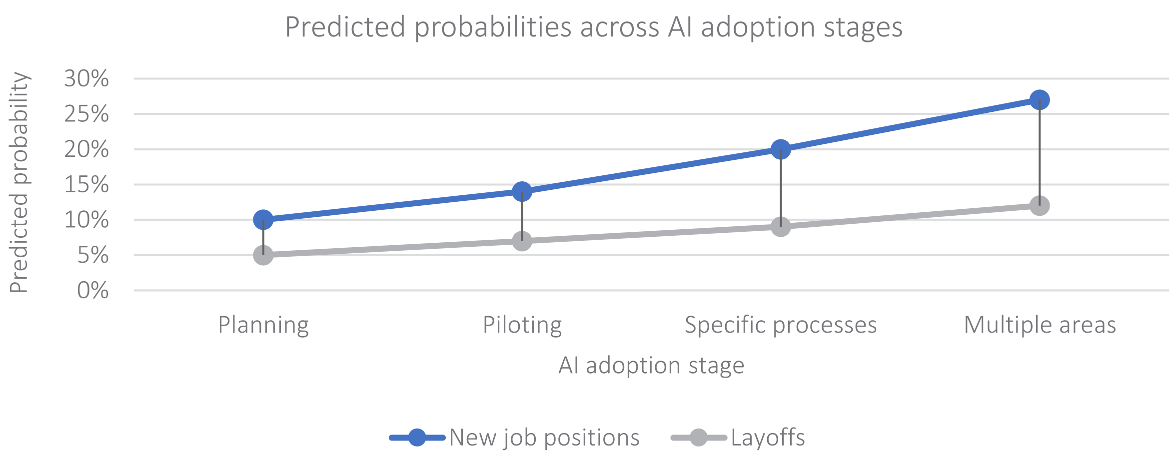

Figure 3. Predicted probability of reporting AI-related job creation and job elimination (realized or planned) across AI adoption stages

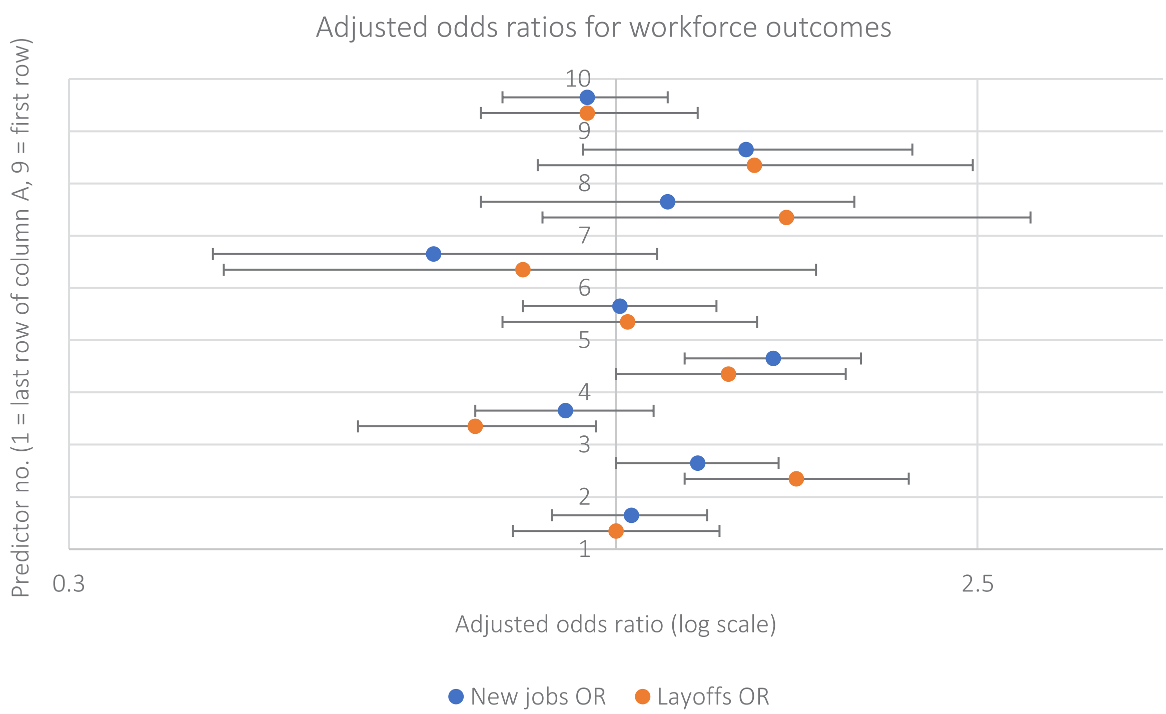

Figure 4. Adjusted odds ratios for reported or planned AI-related job creation and job elimination

1.00–1.51, $p = 0.050$, $q = 0.224$) and is not interpreted. Organizational AI enthusiasm is associated with a lower incidence of reported or planned job elimination in the unadjusted model (OR 0.70, 95% CI 0.52–0.95, $p = 0.022$), but this association does not remain significant after FDR adjustment ($q = 0.098$). H_{4a} is therefore not supported at the 5% FDR level, and the association is reported as an unadjusted, exploratory finding only.

Self-assessed AI maturity is not associated with either outcome once adoption stage and orientation are included (creation OR 1.01, 95% CI 0.79–1.29, $p = 0.937$; elimination OR 1.03, 95% CI 0.75–1.43, $p = 0.837$), and the analysis did not provide sufficient evidence of an association for firm size, sector, ownership, or perceived barriers in these models. Adoption stage and self-assessed maturity thus show different patterns of association with the two outcomes: the first is associated with the incidence of reported or planned creation, whereas for the second the analysis did not provide sufficient evidence of an association. Their relative predictive strength was not formally established, because no test of the equality of the two coefficients was carried out. H_6 is accordingly treated as partially supported with respect to the two distinct patterns of association and as untested with respect to relative strength. The explanatory power of both models is modest (McFadden pseudo-R^2 = 0.043 for creation and 0.052 for elimination), so they identify characteristics associated with a somewhat higher or lower probability of reporting an outcome rather than a closely determined process.

3.5. Firm characteristics associated with the four incidence patterns (H_5)

The multinomial model (Table 3; Figure 5) contrasts each of the three active patterns with Static firms; because the Reconfigurer and Reducer cells are small and the *p*-values are not adjusted for multiple testing, these estimates are exploratory. Augmenters are distinguished almost entirely by adoption stage (RRR 1.49, 95% CI 1.16–1.93, p = 0.002). Reconfigurers combine adoption stage (RRR 1.52, 95% CI 1.03–2.25, p = 0.037) with foreign ownership (RRR 2.29, 95% CI 1.10–4.78, p = 0.027), lower organizational AI enthusiasm (RRR

Table 3. Multinomial logistic regression of the four incidence patterns relative to Static firms

Predictor	Augmenter RRR [CI] (p)	Reconfigurer RRR [CI] (p)	Reducer RRR [CI] (p)
Firm size	0.98 [0.78,1.25] (0.898)	0.82 [0.58,1.17] (0.281)	1.12 [0.74,1.69] (0.595)
Foreign ownership	1.15 [0.71,1.86] (0.579)	2.29 [1.10,4.78] (0.027)	0.85 [0.37,1.94] (0.698)
Knowledge-intensive sector	1.32 [0.77,2.28] (0.315)	1.00 [0.44,2.29] (1.000)	3.18 [1.25,8.11] (0.015)
Manufacturing sector	0.79 [0.42,1.49] (0.469)	0.36 [0.11,1.13] (0.079)	1.76 [0.62,4.96] (0.288)
Self-assessed AI maturity	1.01 [0.77,1.33] (0.946)	0.99 [0.65,1.53] (0.975)	1.06 [0.67,1.68] (0.808)
AI adoption stage	1.49 [1.16,1.93] (0.002)	1.52 [1.03,2.25] (0.037)	1.27 [0.82,1.95] (0.282)
Organizational AI enthusiasm	0.99 [0.76,1.29] (0.935)	0.63 [0.43,0.92] (0.016)	0.85 [0.54,1.34] (0.484)
Perceived employee job-threat concern	1.23 [0.97,1.55] (0.094)	1.46 [1.00,2.11] (0.047)	1.96 [1.27,3.03] (0.002)
Perceived barriers	1.09 [0.87,1.36] (0.468)	0.95 [0.66,1.36] (0.772)	1.09 [0.76,1.58] (0.630)

Note: Reference category = Static (neither outcome reported).

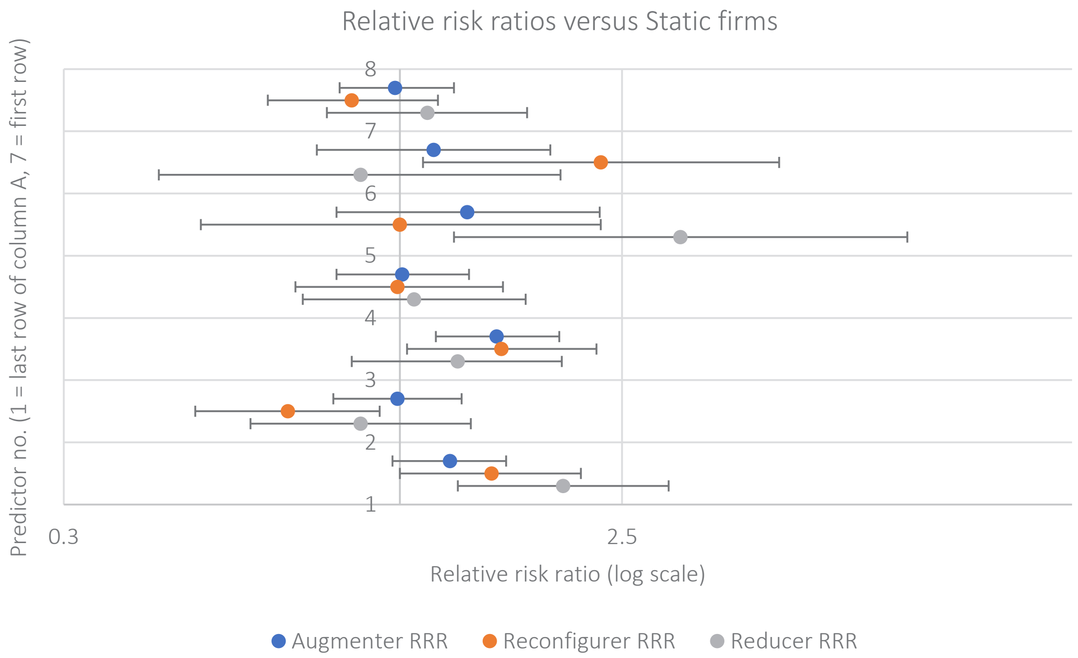

Figure 5. Relative risk ratios for the three active incidence patterns versus Static firms (multinomial logistic regression, 95% confidence intervals, N = 693)

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Augmenter	+0.33	+0.18	+0.15	+0.14	+0.01
Reconfigurer	+0.31	-0.03	-0.35	+0.14	-0.20
Reducer	+0.18	+0.17	+0.13	+0.52	+0.14
Static	-0.09	-0.04	-0.01	-0.06	+0.00
	AI adoption stage	**AI maturity**	**AI enthusiasm**	**Employee fear**	**Firm size**

Figure 6. Standardized predictor profiles of the four incidence patterns (z-scores, N = 693)

0.63, 95% CI 0.43–0.92, p = 0.016), and somewhat higher perceived employee job-threat concern (RRR 1.46, 95% CI 1.00–2.11, p = 0.047).

The association of foreign ownership with membership in the Reconfigure category is consistent with H_5, but it rests on 35 firms and on unadjusted p-values. Thus, H_5 receives tentative, exploratory support rather than robust confirmation. In the two logistic models, the analysis did not provide sufficient evidence of an association between foreign ownership and either outcome taken separately (creation OR 1.39, p = 0.119; elimination OR 1.42, p = 0.215).

Reducers differ in kind: they are not distinguished by adoption stage (RRR 1.27, 95% CI 0.82–1.95, p = 0.282) but by perceived employee job-threat concern (RRR 1.96, 95% CI 1.27–3.03, p = 0.002) and by knowledge-intensive sector (RRR 3.18, 95% CI 1.25–8.11, p = 0.015). The latter rests on only 12 knowledge-intensive Reducer firms and a wide interval and is read as exploratory. Figure 6 displays the standardized predictor profiles of the four patterns.

3.6. Sector patterns

Unadjusted sector rates (Figure 7) are consistent with the multinomial results. Knowledge-

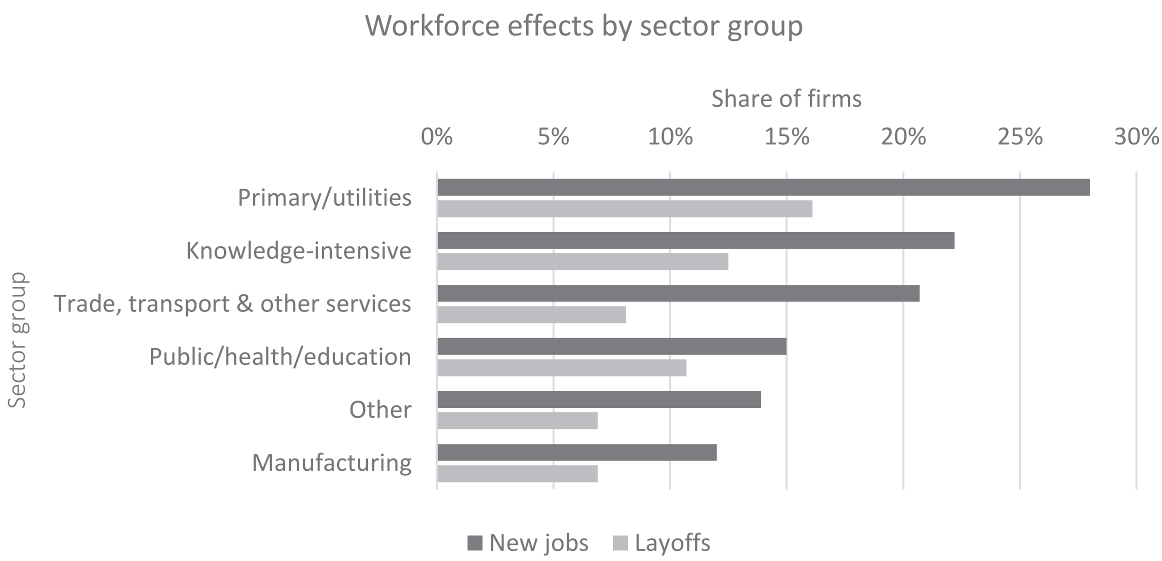

Figure 7. Incidence of reported or planned AI-related job creation and job elimination by sector group (unadjusted, N = 693)

intensive firms show the highest incidence of reported or planned job elimination (12.5%) alongside a high incidence of reported or planned job creation (22.2%), whereas manufacturing, still the core of the Slovak economy, shows a lower incidence of both (12.0% creation and 6.9% elimination). These rates are unadjusted and rest on modest cell sizes, so they are descriptive only.

3.7. Robustness and sensitivity checks

The main associations are stable across specifications (Table 4). Restricting the sample to the 562 firms that use or pilot AI strengthens the association of adoption stage with reported or planned creation (OR 1.73, 95% CI 1.28–2.32, $p < 0.001$) and preserves the orientation associations with reported or planned elimination (enthusiasm OR 0.65, 95% CI 0.48–0.88, $p = 0.005$; employee job-threat concern OR 1.64, 95% CI 1.21–2.21, $p = 0.001$). The conditional co-occurrence of the two outcomes also holds (odds ratio for creation 5.78, 95% CI 3.19–10.49, $p < 0.001$). Restricting the sample further to the 351 current users retains both signals (creation and adoption stage OR 1.84, $p = 0.029$; elimination and employee job-threat concern OR 1.89, $p = 0.001$). Adding net sales, firm age, and respondent seniority leaves the adoption-stage association intact (OR 1.42, 95% CI 1.13–1.77, $p = 0.002$), and substituting the strategy subdimension for the maturity composite changes nothing of substance. Because reported or planned elimination is the rarer outcome (64 firms), that model was re-estimated with Firth's penalized likelihood, with essentially unchanged coefficients (employee job-threat concern OR 1.56, 95% CI 1.18–2.06, $p = 0.002$; adoption stage OR 1.33, 95% CI 1.00–1.77, $p = 0.048$; enthusiasm OR 0.71, $p = 0.021$). Collinearity is not a concern (all variance inflation factors below 1.7). Because the outcome items combine realized with planned change, none of these subsample restrictions isolates realized workforce change, and the estimates for firms with actual deployment should not be read as pertaining to completed adjustments.

3.8. Positions reported as created or eliminated

Firms' own descriptions are consistent with the quantitative pattern. Of 115 firms describing positions they have introduced or plan to introduce, roughly half name AI-specific or adjacent skilled roles, such as AI specialist, AI developer or engineer, machine-learning programmer, data analyst, and AI coordinator, alongside general IT and marketing roles. Of 56 firms describing positions eliminated or considered at risk, the most frequent are administrative and clerical roles, customer-support and reception roles, with several firms noting that support has moved to AI chatbots, and lower and middle management. These descriptions indicate which kinds of roles firms associate with each outcome; they do not indicate how many positions are involved, and they too combine changes already made with changes anticipated. The contrast is nonetheless consistent with the coexistence of new, complementary, higher-skill roles and the paring of routine, codifiable ones (Acemoglu & Restrepo, 2019; Autor et al., 2003).

Table 4. Sensitivity and robustness checks: Selected focal estimates

Specification	Outcome	Key predictor	OR	p
Current users and pilot firms (N = 562)	Job creation	AI adoption stage	1.73	< 0.001
Current users and pilot firms (N = 562)	Job elimination	Organizational AI enthusiasm	0.65	0.005
Current users and pilot firms (N = 562)	Job elimination	Perceived employee job-threat concern	1.64	0.001
Extended controls (+ net sales, firm age, respondent seniority; N = 693)	Job creation	AI adoption stage	1.42	0.002
Extended controls (+ net sales, firm age, respondent seniority; N = 693)	Job elimination	Perceived employee job-threat concern	1.60	0.001
Current users and pilot firms (N = 562)	Job elimination	Job creation (co-occurrence)	5.78	< 0.001
Firth penalized likelihood (N = 693)	Job elimination	AI adoption stage	1.33	0.048
Firth penalized likelihood (N = 693)	Job elimination	Perceived employee job-threat concern	1.56	0.002
Current users only (N = 351)	Job creation	AI adoption stage	1.84	0.029
Current users only (N = 351)	Job elimination	Perceived employee job-threat concern	1.89	0.001
Firth penalized likelihood (N = 693)	Job elimination	Organizational AI enthusiasm	0.71	0.021

Note: Each row reports one focal estimate from a fully specified model containing the same covariates.

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3.9. Summary of the hypothesis assessment

The empirical findings provide varying levels of support for the proposed hypotheses, ranging from robust confirmation to partial or exploratory support. A consolidated assessment of all hypotheses is presented in Table 5.

Of the seven hypotheses examined, three were supported without qualification. H1 was supported: reported or planned job creation was more frequent than reported or planned job elimination (18.0% vs. 9.2%; McNemar exact $p < 0.001$). H2 was supported: the two outcomes were positively associated within firms (Fisher OR 7.23, 95% CI [4.21, 12.41]; $p < 0.001$). H4b was supported: perceived employee job-threat concern was associated with a higher incidence of reported or planned elimination (OR 1.58 [1.19, 2.10]; $q = 0.014$). Two further hypotheses were partially supported. H3 held for job creation (OR 1.49 [1.19, 1.86]; $q = 0.004$) but not for job elimination (OR 1.33 [1.00, 1.79]; $q = 0.159$). H6 held in that adoption stage was associated with reported or planned job creation (OR 1.49; $q = 0.004$) whereas self-assessed maturity was not (OR 1.01 [0.79, 1.29]; $q = 0.937$), although the relative strength of the two associations was not tested formally. H4a was not supported once the false-discovery rate was controlled: the association between organizational AI enthusiasm and reported or planned elimination ran in the expected direction but did not survive adjustment (OR 0.70 [0.52, 0.95]; unadjusted $p = 0.022$, $q = 0.098$). H5 received tentative support in an exploratory model only: foreign ownership was associated with the joint occurrence of both outcomes (RRR 2.29 [1.10, 4.78]; unadjusted $p = 0.027$), but the estimate rests on 35 firms and was not adjusted for multiple testing, so it is reported as provisional.

4. DISCUSSION

Among AI-engaged Slovak firms, more firms report creating positions than eliminating them, by roughly two to one. As an incidence result for this segment, it is consistent with firm-level evidence

Table 5. Summary of hypothesis assessment

Hypothesis	Expected association	Outcome examined	Estimate	Adjusted significance	Decision
H_1	Creation reported more often than elimination	Marginal rates of the two indicators	18.0% vs. 9.2%	McNemar exact p < 0.001 (single pre-specified test; no FDR adjustment)	Supported
H_2	Positive association between the two indicators within firms	Joint occurrence	Fisher OR 7.23 [4.21–12.41]	p < 0.001 (single pre-specified test)	Supported
H_3	More advanced adoption stage associated with higher incidence	Reported or planned job creation	OR 1.49 [1.19–1.86]	q = 0.004	Supported
H_3	More advanced adoption stage associated with higher incidence	Reported or planned job elimination	OR 1.33 [1.00–1.79]	q = 0.159	Not supported
H_{4a}	Higher enthusiasm associated with lower incidence	Reported or planned job elimination	OR 0.70 [0.52–0.95]	q = 0.098	Not supported (unadjusted p = 0.022; exploratory)
H_{4b}	Higher perceived employee job-threat concern associated with higher incidence	Reported or planned job elimination	OR 1.58 [1.19–2.10]	q = 0.014	Supported
H_5	Foreign ownership associated with joint occurrence of both outcomes	Reconfigurer vs. Static	RRR 2.29 [1.10–4.78]	Not adjusted (p = 0.027); n = 35	Tentatively supported (exploratory)
H_6	Adoption stage associated, self-assessed maturity not	Both outcomes	Stage OR 1.49 [1.19–1.86]; maturity OR 1.01 [0.79–1.29]	q = 0.004 / q = 0.937	Partially supported; relative strength not tested

Note: OR = odds ratio; RRR = relative risk ratio; ρ = error correlation of the bivariate probit; q = Benjamini-Hochberg false-discovery-rate-adjusted p-value.

from the United States and Western Europe that AI adoption tends to coincide with expansion among adopters (Babina et al., 2024), and with Slovak Industry 4.0 expectations (Grenčíková et al., 2020). It does not, on its own, speak to net employment in the economy, both because the items count firms rather than positions and because the sample is selected on AI engagement; the EU-wide finding that AI's productivity gains run through capital deepening rather than through hiring is a useful corrective here (Aldasoro et al., 2026).

Creation and elimination also occur together within firms. Once observable characteristics are held constant, the propensities to report each of the two outcomes remain positively correlated ($\rho = 0.54$). This is read as consistent with reconfiguration rather than with straightforward substitution, while acknowledging that shared-respondent reporting and common unobserved shocks may contribute to the correlation. The reading gives concrete, firm-level content to the displacement-and-reinstatement duality (Acemoglu & Restrepo, 2019) and to the argument that automation and augmentation are interdependent rather than separable (Raisch & Krakowski, 2021). It also suggests that, at the level of the firm, posing the question as augmentation versus automation can mislead, because the two are frequently reported together, which is itself part of the paradox that Raisch and Krakowski describe.

Adoption stage is associated with whether a firm reports any realized or planned workforce change. Firms further along the path from planning to use across multiple areas are more likely to report creation or planned creation of positions and, in the unadjusted model, elimination or planned elimination as well. What this does not establish is how much a workforce changes: the data record the occurrence of an event and not its size, so the association concerns the probability of reporting change rather than its extent. Nor does it establish a prevailing direction, since the two indicators are modeled separately and cannot be combined into a net measure.

An alternative reading of this association deserves explicit attention. Firms with actual deployment have had more time and more opportunity to carry out workforce changes, whereas firms that only plan to adopt AI necessarily answered about changes they expect. Part of the association between adoption stage and reported workforce change may therefore be mechanical, reflecting differential exposure time and differences in the temporal reference of the answers rather than a substantive relationship between depth of deployment and workforce restructuring. The available data cannot separate these interpretations, because the outcome items merge realized with planned change and no date of the reported change is recorded. This possibility is not a confirmed mechanism, but it is a material interpretive constraint, and the association should be read with it in mind.

Organizational orientation is associated primarily with the elimination outcome, and not with the direction of workforce change in any measurable sense. Perceived employee job-threat concern is associated with a higher incidence of reported or planned job elimination, and this is the only orientation association that remains significant after adjustment for multiple testing. Organizational AI enthusiasm is associated with a lower incidence of the same outcome in the unadjusted model, but the association does not survive FDR adjustment and is therefore reported as exploratory; it should not be treated as an established finding until replicated. The relationship between employee concern and elimination is, moreover, open to reverse interpretation: because the item includes planned reductions, employees may already be reacting to announced or anticipated cuts, so the ordering of the two cannot be established from cross-sectional data. What the results support is the narrower statement that orientation is associated with whether reductions are reported, and not that it determines the prevailing direction of net employment change.

Foreign ownership is associated with membership in the Reconfigurer category in an exploratory multinomial model, and not with either outcome taken separately. Read within those limits, the result is consistent with the expectation that multinational subsidiaries in an FDI-dependent economy may import both the skilled roles and the efficiency requirements that accompany AI, so that creation and elimination appear together in the same firm. Other interpretations are equal-

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ly compatible with the estimate: foreign-owned firms may be larger and more complex organizations in which any technological change touches several functions at once; they may have more formalized reporting practices that make workforce consequences more visible to respondents; or they may operate under group-level restructuring programs unrelated to AI. The estimate rests on 35 firms and unadjusted *p*-values and cannot distinguish among these accounts, so it is best read as a hypothesis for replication rather than as an established regional mechanism.

The Reducer pattern is the least expected result and the least certain. These firms are not distinguished by depth of deployment but by perceived employee job-threat concern and, in a small number of cases, by knowledge-intensive activity. The open-text answers point in the same direction, naming administrative, clerical, customer-support, and reception roles as those most often reported as eliminated or at risk, which suggests that reported reductions may appear first in routine service and support functions; a comparable reorganization of customer-facing processes has been documented for self-service technologies in airline services (Duran et al., 2024). If the pattern holds in larger samples, it would be consistent with the view that the current AI wave reaches cognitive, white-collar tasks once considered protected (Eloundou et al., 2024), a different logic from the routine-manual displacement associated with earlier automation (Acemoglu & Restrepo, 2020). Given 29 firms in this category and a wide confidence interval for the sector association, this reading remains exploratory.

The contribution of the typology is descriptive and lies in what it makes visible. Cross-classifying two indicators of incidence separates firms reporting only creation from firms reporting only elimination and from firms reporting both, and it shows that the third group is not negligible: more than one in five firms reporting any AI-related workforce change reports both outcomes together. What the typology captures is a combination of incidence. It does not measure how many positions were involved, which of the two predominated, what the net change in employment was, or whether the reported changes have already been carried out. Category names such as Reconfigurer are analytical shorthand for these combinations and should not be read as descriptions of the size or the net direction of workforce change.

4.1. Theoretical implications

Three implications follow for theory. First, the results extend the binary framing of job creation versus job destruction by showing that, at firm level, the two can be reported together rather than as alternatives; the displacement-and-reinstatement duality (Acemoglu & Restrepo, 2019) and the automation-augmentation paradox (Raisch & Krakowski, 2021) thereby acquire an observable firm-level counterpart in an economy for which such evidence has been unavailable. Second, the descriptive typology of four incidence patterns offers a way of modeling AI-related workforce outcomes as two correlated binary processes instead of one net figure; this is a modeling choice rather than a new mechanism. Third, the results support a conceptual separation between the stage of AI adoption and self-assessed AI maturity: the two behave differently in relation to the same outcomes, which suggests that perceived readiness and realized use should not be used interchangeably as indicators of AI engagement.

Two boundaries of the theoretical contribution should be stated plainly. The study does not identify the net direction or the intensity of workforce restructuring, and no such claim is made; what it identifies is the co-occurrence of two reported events and the characteristics associated with each. It follows that theoretical work in this area requires measurement in which realized and planned changes, and the number of positions involved, are recorded separately, since the substantive questions about reallocation cannot be settled with combined indicators of incidence.

4.2. Practical and policy implications

Several practical implications follow, each limited to what the results support. Because a more advanced AI adoption stage is robustly associated with a higher probability of reporting job creation or planned job creation, workforce planning should anticipate the emergence of new AI-related roles. At the same time, the observed co-occurrence of creation and elimination indicates that

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firms should also prepare for the possibility that some positions may be discontinued. Because the roles most often named as created differ systematically from those named as at risk, reskilling and upskilling programs are most usefully targeted at administrative, clerical, and customer-support functions, where reported reductions concentrate, while recruitment and internal mobility are directed toward data and AI-related roles. Evidence on strategic training supports the contribution of such programs to organizational adaptability and innovation (Oyasor, 2025). Because perceived employee job-threat concern is associated with a higher incidence of reported or planned reductions, early and substantive social dialogue during implementation is advisable, both as a matter of employment practice and because unaddressed concern forms part of the organizational context in which reductions are reported.

For policy, monitoring is likely to be more informative if it distinguishes firms by adoption stage and, critically, distinguishes anticipated from realized workforce consequences, since the two are routinely merged in survey instruments, including the one used here. A substantial share of firms in the region remain at shallow stages of adoption (GLOBSEC, 2026), so support for organizational transformation, and not only for technology acquisition, remains relevant. These recommendations concern the management of reallocation; they should not be read as claims that AI raises or lowers total employment, which the present data cannot address.

4.3. Limitations and future research

The study has several limitations, the most consequential of which concern measurement. The design is cross-sectional and observational; all variables were recorded at a single point in time, and no exogenous variation in adoption is available; all results are therefore associations, and none supports causal interpretation. The two outcome items merge realized with planned or expected action, so the outcomes register the incidence of an actual or anticipated event. Moreover, the temporal reference of an affirmative answer differs systematically across firms: for firms that only plan to adopt AI it can refer solely to expectations, whereas for pilot firms and current users it may refer to either or to both. Restricting the sample to firms with actual deployment reduces but does not remove this ambiguity.

Neither item records the number of positions created or eliminated. It is therefore impossible to compute the net change in employment, to determine which of the two processes predominates in a given firm, or to establish the prevailing direction of restructuring; the four categories describe combinations of incidence only. The outcomes are binary, which discards information about the scale and the timing of change, and one of them is rare (64 firms), which limits precision, particularly in the multinomial model, where the Reconfigurer (n = 35) and Reducer (n = 29) categories yield few events per parameter and where p-values are not adjusted for multiple testing. Several ordinal predictors are treated as interval variables when standardized, a simplification that is most consequential for the coarser scales, and the questionnaire and the released data differ in the number of scale points recorded for the sentiment batteries, as documented in the Methods.

All data are self-reported by a single respondent per firm, so common-method variance, social-desirability bias, and differences in respondents' knowledge of workforce decisions cannot be excluded; the Harman single-factor test mitigates but does not resolve this concern and does not bear directly on the two binary outcome items. Unobserved confounders, such as concurrent reorganization, a change of ownership, or demand shocks, may be associated with both outcomes and may contribute to the observed correlation. The analytical sample is the AI-engaged segment of the economy and is larger, higher-selling, and more AI-mature than the excluded firms, and selection into AI engagement is not modeled, so the findings generalize to firms already involved with AI rather than to the economy as a whole. The Slovak setting is specific: a manufacturing-intensive, FDI-dependent, cost-competitive economy in which digital adoption has been comparatively cautious, so the results should not be transferred to other institutional contexts without replication. Finally, the relative predictive strength of adoption stage and self-assessed maturity was not established, because no formal test of coefficient equality is reported.

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These limitations indicate a clear agenda. Future instruments should measure realized and planned workforce changes as separate items, record the number of positions created and eliminated, and thereby allow the net employment change associated with AI to be computed rather than inferred. Distinguishing occupations and skill levels would show where within the organization creation and elimination occur, and longitudinal or panel data would allow firms to be observed as they move between the four incidence patterns, which is the natural test of whether reconfiguration is a transitional or a stable state. Comparative designs across CEE countries and across sectors would establish how far the patterns reported here are specific to the Slovak setting, and linking managerial responses to administrative employment records would provide an external check on self-reported workforce outcomes. Quasi-experimental designs, or instrumentation of adoption in the manner of Aldasoro et al. (2026), would be required before any causal claim about AI and workforce composition could be made.

CONCLUSION

This study set out to establish how reported or planned AI-related job creation and job elimination are distributed and combined within firms already engaged with AI, and which firm characteristics are associated with each pattern of incidence. The central conclusion is that the two outcomes are not alternatives. They occur together far more often than their separate frequencies would suggest, and the firms that report change of any kind are not the same firms that report reductions: depth of deployment accompanies the reporting of new roles, whereas concern among employees accompanies the reporting of cuts. Taken together, these findings support a shift in how the workforce consequences of AI are conceived at firm level, away from a single expected direction of employment change and toward a process of reallocation in which creation and elimination are managed at the same time.

Three consequences follow. For measurement, indicators that merge realized with planned change, and that record only whether an event occurred, cannot settle questions of magnitude or net direction; instruments should separate the two and record the number of positions involved. For management, workforce planning in adopting firms is better organized around redeployment between functions than around a forecast of net headcount, and the association between perceived job threat and reported reductions gives a practical reason for early social dialogue. For policy, regional monitoring gains little from a single net employment figure and more from tracking adoption stage alongside separately recorded realized and anticipated outcomes. These conclusions remain associational and specific to AI-engaged firms in one CEE economy; whether reconfiguration is a transitional phase of adoption or a durable state, and whether the exploratory result for foreign ownership holds in larger samples, are questions that require the longitudinal and comparative evidence outlined above.

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