When Technology Manages: Workers Demands and Union Responses to AI and Emerging Digital Tools*

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Abstract

AI and other digital technologies are reshaping work, yet their effects on labor-market institutions are still not well understood. Research on technology and unions has focused largely on robots, leaving open how newer digital tools influence worker organizing and collective bargaining. We argue that technology matters not only because it can replace labor, but because it changes how work is organized. We distinguish among displacement, augmentation, and monitoring technologies, and show that each type affects workplace interaction, job stability, and managerial control in different ways. These changes, in turn, shape both workers demand for collective protection and their ability to organize. They also create different bargaining priorities, including training, shared implementation, limits on surveillance, and job security. We test these ideas with a two-level design. First, using European Social Survey data from 15 countries between 2012 and 2024, we match occupations to emerging technologies and assess links to union membership, working conditions and political attitudes. Second, we analyze over 40,000 Canadian collective agreements from 1993 to 2025 with text analysis and an LLM-based AI exposure measure. Results show varied effects: some technologies raise unionization, while others weaken it and worsen worker outcomes significantly for many employees.

Key words: AI, digital technologies, labor unions, working conditions, collective bargaining.

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1 Introduction

AI and other digital technologies are rapidly transforming work, yet their implications for labor-market institutions remain underexplored. Much research examines how automation affects jobs and wages, and the limited literature on organized labor has focused mainly on robotization. We know far less about how newer digital tools, including platform intermediation, monitoring systems, and AI applications, reshape unions' strength, organization, and political voice. This is a critical gap: by bargaining over wages and working conditions, unions reduce inequality and set labor standards economy-wide (Ahlquist 2017; Becher and Stegmueller 2021), and by mobilizing workers, they enhance democratic participation (Iversen and Soskice 2015; Becher and Stegmueller 2019; Frymer and Grumbach 2021; Gonzalez-Rostani 2024a). If technological change erodes union capacity, it could weaken not only workplace protections but also equality and civic engagement. This paper addresses that concern by posing two key questions. First, how are emerging digital technologies affecting workers' conditions and union membership? Second, how are trade unions responding to these developments through collective bargaining?

Our core argument is that technology affects unions by reorganizing the labor process, not only by changing labor demand. We distinguish among displacement, augmentation, and monitoring technologies. These forms of technological change shape both the grievances workers experience and whether those grievances can be organized collectively. Unionization is most likely when workers face a common threat but remain in stable employment relationships with coworker interaction and channels of voice. By contrast, technologies that individualize evaluation, fragment workers, or shift jobs into weakly organized settings are more likely to generate alienation than durable organization. The same logic implies distinct bargaining agendas: augmentation encourages bargaining over training and joint implementation; monitoring generates demands for transparency, contestability, and limits on surveillance; and displacement centers bargaining on notice, redeployment, and job security.

To investigate these claims, we combine micro-level survey analysis with textual analysis of union contracts. Using Western European survey data from 2012 to 2024, we measure occupational exposure to various families of emerging technologies and show that their effects are heterogeneous. Exposure to machine learning, manufacturing, and remote monitoring is associated with higher union membership; by contrast, food-ordering platforms are associated with lower unionization, consistent with the more precarious working conditions and lower levels of worker interaction that typically characterize such technologies. More broadly, when considering exposure to digital technologies as a whole and classifying the associated risks as augmenting, displacing, or monitoring, we find that exposure to augmentation and monitoring is associated with greater unionization, whereas exposure to displacement is associated with lower unionization. We then examine more than 40,000 Canadian collective bargaining agreements (CBAs) from 1993 to 2025 using text-as-data methods and show that contractual responses likewise vary by type of exposure. Furthermore, we document that during the recent AI period, augmentation is associated with more language on training, worker-oriented protections, and joint governance, whereas displacement is associated with fewer proactive safeguards.

This study makes several contributions to the political economy of labor and technology. First, it extends the literature on technology and organized labor beyond robotization by showing that the institutional consequences of technological change depend on what technologies do in the labor process, not only on whether they automate tasks (Agnolin et al. 2025; Agnolin 2025; Leduc and Liu 2024; Gonzalez-Rostani 2024a; Becher and Stegmueller 2025). We show that the impact of new technologies on union membership is not uniformly negative - it varies by technology type and organizational context - thus extending recent arguments that the consequences of automation need not be uniform.

Second, we advance the measurement of technological exposure. Rather than relying on a single aggregate automation risk score, we develop a taxonomy of workplace technologies that extends Prytkova et al.'s work. Our fine-grained approach identifies the specific innovations, from machine learning algorithms to IoT-enabled devices, to which workers are exposed. Because exposure can vary across countries and over time, even within the same occupation, we complement this measure with indicators of the pace of technological adoption. We also introduce a novel LLM-based classification of tasks that evaluates whether digital technologies and AI are likely to displace, augment, or monitor work. Capturing these multidimensional exposures allows us to provide a more detailed account of how technological change shapes workers' daily experiences and collective responses.

Third, we offer one of the first large-scale studies of union strategy as documented in CBAs, getting at the granular textual details of contracts. Labor contracts are a crucial but underutilized source for understanding union influence on workplace outcomes (Freeman and Medoff 1984; Traxler, Blaschke, and Kittel 2001; Arold et al. 2025). Most research on technology and labor relations has relied on qualitative case studies (e.g., Kresge 2025; Rainone 2025); we instead analyze tens of thousands of contracts over three decades. By treating contract texts as data, we show how unions govern technological change through bargaining over training, monitoring, and worker participation, supporting arguments that worker representation can facilitate adaptation to innovation rather than simply resist it (Belloc, Burdin, and Landini 2022; Gingrich, Wu, and Zhang 2026). Together, these contributions deepen our understanding of the link between technology and organized labor, showing that the future of work is not pre-determined by technology alone - it will also be negotiated on the shop floor and at the bargaining table.

2 Related Work: Technology, Work, and Unionization

Automation & Policy Preferences. Work in political economy has linked exposure to technological change with both voting behavior and mass preferences. Surveys and panel studies show that individuals who feel negatively affected by automation tend to support populist parties, right-wing in the Global North (e.g., Anelli, Colantone, and Stanig 2021; Kurer 2020; Milner 2021; Gonzalez-Rostani 2026, 2024b) and left-wing in the Global South (Boix, Gonzalez-Rostani, and Owen 2025), and exhibit signs of political disengagement (Gonzalez-Rostani 2024a). A second strand connects technological disruption to higher demand for social insurance and redistribution (Busemeyer et al. 2023; Busemeyer and Tober 2023; Kurer and Häusermann 2022; Thewissen and Rueda 2019; Haslberger, Gingrich, and Bhatia 2024) as well as support for policies that slow or redirect change, including trade and technology restrictions (Bicchi, Kuo, and Gallego 2024; Gallego et al. 2022; Chaudoin and Mangini 2025; Gonzalez-Rostani 2024b).

Most of this literature treats automation as a single labor-market shock centered on displacement risk. That perspective has been productive, but it leaves less room to examine how distinct workplace technologies reshape autonomy, evaluation, and social interaction on the job. We build on this literature by connecting political attitudes to differentiated forms of technological exposure and to the working conditions through which those exposures are experienced.

Measuring Exposure to Emerging Digital Technologies. A central challenge in this literature is measurement. Most studies rely on a single automation risk indicator, whether based on regional robot exposure (e.g., Acemoglu and Restrepo 2020), occupation characteristics, such as routine task intensity (Goos, Manning, and Salomons 2014; Frey and Osborne 2017; Arntz, Gregory, and Zierahn 2017), cognitive task content (e.g., Autor, Levy, and Murnane 2003), or workers' perceived risk of job loss from technology (Borwein et al. 2025; Busemeyer et al. 2023; Gallego et al. 2022; Kurer and Häusermann 2022; Gonzalez-Rostani and Tober 2025). These measures are informative, but most are tailored to substitution and job loss. They are less well suited to technologies that reorganize work through monitoring, coordination, or platform intermediation, and they compress heterogeneous tools into a single score.

We address this gap with two complementary measures. First, we construct an occupation-level exposure profile across six technology families using text embeddings that link occupational descriptions to patent data (Prytkova et al. 2025). Second, we introduce an original AI exposure measure based on task-level judgments of whether current AI is more likely to augment, monitor, or displace work. This design lets us compare forms of technological change that are usually bundled together under the umbrella of automation.

The Role of Unions and CBAs. Trade unions matter because they shape both labor-market outcomes and political voice. Collective bargaining compresses wage dispersion and structures distributive conflict (Freeman and Medoff 1984; Farber et al. 2021; Jäger, Naidu, and Schoefer 2025; Hall and Soskice 2001; Iversen 1999). A broader literature shows that unions also mobilize participation, elevate workplace issues in national politics, and make elected officials more responsive to non-elite workers (Ahlquist 2017; Rosenfeld 2019; Kaplan and Naidu 2025; Kerrissey and Schofer 2013; Hertel-Fernandez 2025; Becher and Stegmueller 2021), even if the magnitude of these political effects remains debated (Yan 2025). For that reason, technological change matters not only for jobs and wages, but also for the institutions that organize worker representation.

Classic comparative political economy accounts already suggest that technological change can unsettle labor-market institutions. Analyses of the move away from Fordist production argued that widening productivity differences made solidaristic wage bargaining harder to sustain and encouraged decentralization (Pontusson and Swenson 1996; Iversen 1999). In a related model, skill-biased technological change weakens support for unions among workers who bear more of the costs of wage compression (Acemoglu, Aghion, and Violante 2001). Yet the recent empirical literature on technology and unions has focused overwhelmingly on industrial robots. Work on the United States and Europe finds that robotization has negative average effects on union strength, operating in part through employment shifts out of highly organized sectors (Balcazar 2022; Agnolin et al. 2025; Leduc and Liu 2024). Related evidence also shows that unions can buffer some of the broader political fallout from automation shocks (Gonzalez-Rostani 2024a).

This evidence is important, but it leaves open whether findings based on robotization travel to other emerging technologies, such as monitoring systems, platform intermediation, embedded digital tools, or newer AI applications.

At the same time, more recent work emphasizes that automation need not uniformly erode organized labor. When new technologies involve fixed capital and reduce firms' ability to relocate, workers' leverage may increase rather than fall (Becher and Stegmueller 2025). Evidence from European establishments similarly suggests that employee representation can facilitate the adoption of advanced technologies through training and organizational adaptation (Belloc, Burdin, and Landini 2022). The institutional effects of technological change are therefore conditional, not mechanically negative.

We build on this literature in two connected ways. First, we extend the analysis from robotization to a broader set of emerging digital technologies, including tools associated with monitoring, platform work, logistics, embedded systems, and AI, which may affect unions through channels other than labor substitution alone. Second, we shift attention from union density to governance. Union power cannot be inferred from membership alone; bargaining coverage and contract content are also central to labor-market outcomes (Traxler, Blaschke, and Kittel 2001; Baccaro and Howell 2017; Visser 2016; Cazes, Garnero, Martin, et al. 2019; Arold et al. 2025). A growing industrial-relations literature shows that unions bargain over technology through training provisions, consultation rights, limits on monitoring, and rules for algorithmic management (Kresge 2025; Montreuil and Foucher 2023; Rainone 2025; Borelli et al. 2025; Doellgast et al. 2025; De Stefano and Taes 2023; Brunnerová et al. 2024). Yet this evidence is still dominated by case studies, inventories of selected agreements, and survey snapshots. We therefore analyze collective bargaining agreements at scale and relate contractual responses to distinct forms of technological exposure, rather than treating technology as a single shock.

3 Displacement, Augmentation, and Monitoring: A Theory of Technology and Unionization

We argue that technologies matter for unions because they reorganize the labor process. They change who performs tasks, how performance is evaluated, how visible managerial control becomes, and whether workers encounter one another as a collectivity or as isolated individuals. This premise is consistent with recent work arguing that workers respond not to technology in the abstract, but to technology as it is governed and deployed in concrete workplaces (Gingrich, Wu, and Zhang 2026; Bankins et al. 2024; Marsh, Vallejos, and Spence 2022). We therefore treat emerging digital tools as heterogeneous interventions in work organization rather than as a single "automation shock." Technological change is not only a labor-demand shock; it is also a workplace-governance shock.

We organize this heterogeneity around three ideal types: *displacement*, *augmentation*, and *monitoring*. Displacement technologies substitute for labor or move tasks out of established jobs. Augmentation technologies complement labor while leaving workers in place. Monitoring technologies expand managerial oversight, performance measurement, and algorithmic control. These categories are analytically distinct because they distribute risk, discretion, and interdependence differently across workers. This functional typology is preferable to narrow umbrella labels such as "AI," because the same underlying technology can weaken unions through replacement, strengthen labor's bargaining position through complementarity, or discipline workers through surveillance depending on how it is deployed (Gingrich, Wu, and Zhang 2026; De Stefano and Taes 2023). The key implication is that technological change affects unionization through two linked but separable steps: it first shapes workers' grievances and then shapes whether those grievances can be organized collectively.

At the center of the theory is a distinction between demand for collective protection and realized collective organization. Workers do not unionize simply because conditions deteriorate. Collective action requires at least four conditions. First, workers must perceive a common stake, whether in job security, autonomy, fairness, or privacy. Second, they must retain enough interaction and workplace social capital to solve collective-action problems. Third, they must remain embedded in employment relationships stable enough to sustain mobilization. Fourth, existing channels of voice matter: where workers already have unions, consultation rights, or even informal mechanisms of input, technological change is more likely to become an object of bargaining than unilateral managerial control (Gingrich, Wu, and Zhang 2026; O'Brady and Doellgast 2021; De Stefano and Taes 2023). As Naidu (2022) emphasizes, dense workplace networks are a precondition for successful organizing, while Ferguson (2016) shows how more fragmented organizing environments make mobilization harder. Our core theoretical claim follows directly: technologies that worsen work while preserving common exposure, coworker contact, employment stability, and channels of voice can generate unionization, whereas technologies that worsen work while fragmenting workers are more likely to generate alienation without durable organization.

First, *displacement technologies* primarily affect the *possibility* and *location* of unionization because they alter where and under what terms people work. The aggregate expectation is negative: if automation removes workers from unionized settings or reallocates employment toward more weakly organized sectors, unions should decline. This logic is consistent with evidence linking robot exposure to weaker union presence and lower bargaining power in the United States and Western Europe (Balcazar 2022; Agnolin et al. 2025; Leduc and Liu 2024). But the same threat can have the opposite effect among workers who remain in concentrated and relatively stable workplaces. When exposure to replacement is visible, shared, and not immediately translated into exit, workers may seek unions as a form of collective insurance. Umblijs, Schøne, and Finseraas (2025) provide evidence of precisely this dynamic in Norwegian manufacturing, and Becher and Stegmueller (2025) similarly show that automation can increase organizing incentives where production remains anchored and workers retain leverage. At the same time, unions do not simply react to automation; they can also shape the process of technological change itself, as Kostøl and Svarstad (2023) show in their analysis of how unions affect firms' occupational structure and relative wages, in particular, contributing to raising the relative wage of routine workers over non-routine workers. We therefore expect displacement to depress unionization overall, but to stimulate organizing among protected insiders facing a salient replacement threat.

Second, *augmentation technologies* change the content of conflict more than the existence of employment. When digital tools complement labor, require training, or deepen interdependence across workers, they preserve workers inside the production process while raising the value of their knowledge. Under these conditions, the central issue is less whether workers disappear than who controls implementation, training, classification, and the distribution of productivity gains. This is why augmentation should be the form of technological change most compatible with proactive unionism. Bankins et al. (2024) find more positive worker responses where AI improves job design and learning rather than merely disciplining labor, and Belloc, Burdin, and Landini (2022) show that worker representation can facilitate advanced technology adoption through training and organizational adaptation. Our expectation, then, is that augmentation should be associated less with organizational breakdown than with bargaining over how new technologies are governed.

Third, *monitoring technologies* intensify grievances most directly because they redistribute discretion from workers to management without necessarily severing the employment relation. Surveillance systems, remote monitoring, and algorithmic performance management make control more continuous, individualized, and data-driven. In that sense, they are especially likely to produce demands for collective protection around privacy, due process, pace, and fairness. The empirical literature supports this mechanism: König (2025) reviews electronic monitoring research and finds little consistent productivity gain but more worker strain and weaker job attitudes; Glavin, Bierman, and Schieman (2024) link workplace surveillance to psychological distress and lower job satisfaction through job pressure, reduced autonomy, and privacy violations; and O'Brady and Doellgast (2021) show that collective voice can make monitoring fairer and less exhausting. Yet monitoring also has a second, countervailing effect. Because it individualizes evaluation and can weaken everyday coworker contact, it may make organization harder even as grievances become sharper, a point also emphasized in research on algorithmic management and platform work (Bankins et al. 2024; Marsh, Vallejos, and Spence 2022). We therefore expect monitoring technologies to raise the demand for union protection broadly, but to increase realized unionization only where workers retain shared organizational spaces or occupational communities.

The framework also extends beyond unionization to labor politics. Unions are not only bargaining institutions; they are political intermediaries that mobilize workers, aggregate grievances, and translate workplace conflict into demands for compensation and regulation. When technological change weakens unions, it can therefore erode not only workplace voice but also the organizational infrastructure through which workers seek policy protection. Technological change thus has indirect political effects through its consequences for the organizations that represent worker interests.

These mechanisms also imply distinct bargaining agendas. If collective bargaining is one of the main institutional arenas through which workers can govern technological change, then unions should not respond to all technologies in the same way. Where augmentation dominates, bargaining should center on training, upskilling, job ladders, and joint implementation. Where monitoring expands, unions should seek notice, contestability, data governance, and limits on surveillance or automated evaluation. Where displacement risk is salient, unions should emphasize advance notice, redeployment, retraining, and job security. Emerging evidence suggests that these forms of technological governance are already entering collective agreements (Howe et al. 2026; O'Brady and Doellgast 2021). The broader theoretical implication is that technology does not map mechanically onto union decline: its effect depends on whether it generates shared claims under conditions that still permit workers to act collectively.

Table 1 summarizes these expectations for several technology families and maps each family to its dominant theoretical logic.

Table 1: Technology profiles, workplace context, and bargaining agendas

	Technology exposure			Workplace context				
Technology	**Aug.**	**Disp.**	**Monit.**	**Preca-rious**	**Inter-actions**	**Expectation for unionization**	**Bargaining agenda**	**Examples**
Machine Learning & Neural Networks	H	H	M	M	M–L	More compatible with unionization in skilled, stable workplaces where workers remain central to production	Protection under uncertainty: well-being safeguards, transparency, human review, and targeted skill adjustment	Computer vision, model training, data processing
Additive Manufacturing	M–H	H	M–H	L	H	Favorable to proactive unionization: workers remain in place, coordination needs rise, and stable employment supports collective organization	Governed adaptation with transition risk: training and retraining, process-redesign consultation, remedies or mitigation, and bumping or displacement rules	3D printing, prostheses, construction materials
Remote Monitoring & Control Systems	M–H	M	H	L	M–H	Raises demand for protection; stronger unionization where shared worksites and stable employment reduce exit options	Upstream governance of control: training, implementation oversight, data governance, and monitoring limits or exceptions	Factories, buildings, warehouses, remote supervision
Intelligent Logistics	H	H	H	H	M	Ambiguous: shared grievances may be offset by precarity, fragmentation, and performance management reducing collective capacity	Governance under intensified oversight: joint committees, training, workload or data-use rules, and remedies or mitigation	Warehousing, delivery, supply chains
Food Ordering & Vending Systems	L	M–H	M	H	M	Least conducive to unionization: strong grievances coexist with high turnover, dispersion, and app-based control	Defensive adjustment in fragmented settings: union notice, exceptions or limits, transparency, and basic scheduling safeguards	Self-ordering, vending, meal preparation, delivery

Notes: H = high, M = medium, L = low. The table summarizes five selected technologies, their mechanism profiles, workplace context, expected unionization effects, and bargaining agendas. The augmentation, displacement, and monitoring scores come from the LLM-based classification procedure described in Section 4.1.2. Precariousness refers to the relationship between technological exposure and the probability of holding a limited contract, while workplace interactions capture the frequency of contact with colleagues, both estimated from individual-level ESS data.

4 The Impact of Emerging Digital Technologies on Working Conditions and Unionization

In this section, we examine how different digital technologies are associated with workers union membership and reported working conditions. We consider digital tools as heterogeneous, as they reshape tasks and workplace relations in distinct ways that can alter both grievances and opportunities for collective action. Using individual-level survey data, we analyze how exposure to these technologies relates to union membership, working conditions, and political attitudes. Section 5 then shifts to the collective and institutional level, exploring whether and how trade unions address these emerging issues in CBAs.

4.1 Data and measurement

We use individual-level data from Western Europe covering 2012-2024, drawing on waves 6-11 of the European Social Survey (ESS). The sample includes roughly 130,000 respondents in 15 countries.[1] The ESS provides rich sociodemographic information (including detailed occupation and industry of employment), indicators of objective and subjective working conditions, and political attitudes.

4.1.1 Measuring Dependent Variable: Working Conditions and Political Attitudes

We examine two sets of outcomes: (i) unionization and working conditions, and (ii) political preferences and engagement. Table A.1 reports descriptions, coding, and ESS waves for all dependent variables. Unionization is measured with a binary indicator for current union membership (*union member*). To capture the main workplace conditions that we expect to shape the propensity to unionize, we consider two measures for employment stability and the social context of work. Contractual stability is measured with an indicator for limited-term employment (*limited contract*), distinguishing temporary from permanent contracts. The social context of work is captured by the frequency with which respondents interact with colleagues in person (*interaction in person*).[2]

Political outcomes include support for *redistribution*, measured as the agreement that the government should reduce differences in income levels. Political engagement is captured by self-reported turnout in the last national election (*voted*) while satisfaction with the way democracy works in the respondents country (*satisfaction dem.*) serves as an indicator of system support.

4.1.2 Measuring Independent Variables: Exposure to Emerging Digital Technologies

Our initial measures of technological exposure come from the *TechXposure* project and database by Prytkova et al. (2025), which quantify industry- and occupation-level exposure to emerging digital technologies. The database clusters patents from 2012-2021 into 40 technologies using sentence-embedding similarity of patent titles and k-means. Then, matches patents to industry

1. Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, and the UK.

2. To further characterize working conditions and potential worker demands, we include several supplementary outcomes in the Appendix. Workplace power and autonomy are captured by respondents' ability to influence firm-level organizational decisions (*influence on decisions*) and to organize their own daily work (*decide daily work*). We also include self-reported job satisfaction (*job satisfaction*) and household income in deciles (*income*).

and occupation descriptions via cosine similarity, weights patent-industry links by citations, and aggregates to the technology level. We employ the harmonized occupation scores at the ISCO four-digit level. This measure is particularly well suited to our purposes because it captures broad variation across a diverse set of technological tools, rather than focusing narrowly on computers or industrial robots as in much of the existing literature.

Departing from Prytkova et al. (2025), who primarily rely on an overall exposure index, we mostly focus on five specific technologies that illustrate distinct pathways through which digitalization can reshape work.[3] These are *Machine learning and neural networks*, *Additive manufacturing*, *Remote monitoring and control systems*, *Intelligent logistics*, and *Food ordering and vending systems.* Machine learning and neural networks capture model training, pattern recognition, and automated classification; additive manufacturing refers to digitally guided fabrication processes, including industrial 3D printing; remote monitoring and control systems capture real-time supervision of equipment, workflows, and workers across factories, buildings, and networked environments; intelligent logistics refers to data-driven coordination of warehousing, routing, delivery, and supply-chain operations; and food ordering and vending systems capture digital ordering, vending, and service platforms used in food preparation, payment, and delivery. Taken together, these five measures span production-centered, supervisory, logistics, and service-platform forms of digital change, allowing us to illustrate how different technologies generate distinct workplace pressures.[4][5]

These five technologies differ not only in where they are deployed, but also in the mechanisms through which they reshape work. Machine learning and additive manufacturing are more strongly associated with augmentation, as they often complement worker tasks while also creating some risk of displacement as production is reorganized. Remote monitoring and control systems operate primarily through monitoring, intensifying surveillance, pace control, and managerial oversight even when workers remain in place. Intelligent logistics combines all three channels, augmenting coordination and workflow management while also expanding performance tracking and the potential substitution of labor. Food ordering and vending systems, by contrast,

3. See Table A.2 for definitions and illustrative examples of each technology type.

4. See Table A.4 for the top five occupations by exposure to each technology. Descriptive summaries are reported in the Appendix. Figure A.1 and Figure A.2 illustrate how exposure varies across occupations, while Figure A.3 reports the correlations among the various exposure indices.

5. Descriptive summaries of these measures are reported in the Appendix. Figure A.1 and Figure A.2 illustrate how exposure varies across occupations: the first displays the distribution of exposure within major ISCO groups, while the second reports average exposure by two-digit occupational categories. Finally, Figure A.3 displays the correlations among the various exposure indices.

are less augmentation-oriented and more closely associated with displacement and control in fragmented service environments.

While these five technologies provide useful illustrations of how emerging digital tools may reshape work, we also leverage the full set of 40 technologies to examine how technological exposure relates to unionization dynamics. Because we expect substantial heterogeneity across technology types, we assess the underlying structure of these relationships by accounting for individuals' simultaneous exposure to multiple technologies and classifying them according to how these technologies transform work activities, namely through augmentation, displacement and monitoring. To construct these measures, we first use a large language model to evaluate each of the 40 technologies in the *TechXposure* taxonomy and assign scores capturing the extent to which each technology is associated to task augmentation, labor displacement or worker monitoring.[6] We then weight occupation-level exposure $\theta_j^{(m)}$ to each technology m by these technology-specific scores and aggregate across technologies:

$$A_\theta = \sum_{m=1}^{40} \theta_{mj}^{std} a_m, \qquad M_\theta = \sum_{m=1}^{40} \theta_{mj}^{std} m_m, \qquad D_\theta = \sum_{m=1}^{40} \theta_{mj}^{std} d_m, \tag{1}$$

where j indexes occupations and m technologies. Occupational exposure to, for instance, monitoring technologies is therefore higher when an occupation is more exposed to technologies strongly linked to surveillance and control. Conversely, occupations with limited exposure to technological innovation overall, or exposure to technologies with low monitoring potential, receive lower monitoring scores. The same logic applies to augmentation (reflecting support and complementarity) and displacemnt (capturing labor substitution).

These measures go beyond a small set of illustrative technologies and provide a more comprehensive picture of how digital change affects workplace organization. For comparability across specifications, we standardize each index and construct parallel versions re-scaled to account for cross-country variation in the pace of technological diffusion.

4.2 Empirical Strategy

We study how exposure to specific AI and digital technologies relates to unionization, working conditions, and political attitudes. For each outcome k and each technology $m \in \{$*machine learning*, *additive manufacturing*, *remote monitoring*, *intelligent logistics*, *food ordering*, $\}$, we estimate:

6. Refer to subsubsection A.2.4 for details on the prompt and model and Table A.5 for scores on augmentation, monitoring and displacement.

$$
\begin{aligned}
y_i^{(k)} \;=\; \alpha_k \;+\; \beta_k\, \textit{Technology exposure}_i^{(m)} \;+\; \mathbf{X}_{k,i}\,\boldsymbol{\gamma} \;+\; \lambda_{k,\text{region}(i)} \\
+\; \delta_{k,\text{NACE2d}(i)} \;+\; \phi_{k,\text{c, t}(i)} \;+\; \varepsilon_i^{(k)}
\end{aligned}
\tag{2}
$$

Here $y_i^{(k)}$ is outcome k for ESS respondent i. The vector $\mathbf{X}_i$ includes gender, age, years of education, and firm size. We include fixed effects for two-digit industry (NACE 2), region, and country-year. Standard errors are clustered at the country-year-occupation level.

Our main regressor is the respondents exposure to technology m. Because the same occupation j can, in principle, face different exposure levels depending on a countrys adoption pace and timing, we scale occupational exposure by a proxy for the level of technological diffusion in firms within a given country. Specifically, we use the share of firms in the respondents country-year that use enterprise resource planning (ERP) systems (Eurostat). ERP adoption captures the extent of digital integration across production and back-office processes and provides a consistent, comparable measure across countries and over time.[7] Accordingly, we define exposure to technology m as

$$
\text{Technology exposure}_i^{(m)} = \theta_{j(i)}^{(m)} \times ERP_{\text{c, t}}
$$

where $\theta_{j(i)}^{(m)}$ is the occupational exposure of occupation j to technology m from Prytkova et al. (2025), and $\text{ERP}_{c,t}$ is the country-year share of firms using ERP. Intuitively, exposure varies with both the inherent technology link of the respondents occupation and the country-time intensity of enterprise digitalization. Unless noted otherwise, exposure measures and continuous outcomes are standardized in the presentation of results for comparability.

In addition to the technology-specific estimates in equation (2), we implement a complementary empirical approach that exploits the full set of 40 technologies through the composite measures defined in the previous section. Specifically, we estimate:

$$
\begin{aligned}
y_i^{(k)} \;=\; \alpha_k \;+\; \beta_k^A\, A_i \;+\; \beta_k^M\, M_i \;+\; \beta_k^D\, D_i \\
+\; \mathbf{X}_{k,i}\,\boldsymbol{\gamma} \;+\; \lambda_{k,\text{region}(i)} \;+\; \delta_{k,\text{NACE2d}(i)} \;+\; \phi_{k,\text{c, t}(i)} \;+\; \varepsilon_i^{(k)}
\end{aligned}
\tag{3}
$$

where A_i, M_i, and D_i denote individual-level exposure to augmentation, monitoring, and displacement technologies, respectively.

7. In recent years, when national AI adoption data are available, ERP adoption is strongly correlated with AI adoption (Pearson $r = 0.72$), which supports its use as a country-year proxy and allows the analysis to extend to earlier periods.

This specification captures the joint effects of different dimensions of technological change on unionization and related outcomes. By summarizing exposure along theoretically grounded dimensions, it provides a more structured interpretation of the heterogeneous effects observed across individual technologies. All indices are standardized to facilitate comparability of coefficients across dimensions.

4.3 Exposure to Emerging Digital Technologies and Working Conditions

Table 2 reports the estimated effects of exposure to different types of digital technologies on the probability of being a union member. The results reveal marked heterogeneity across technology families. Exposure to machine learning, additive manufacturing and remote monitoring technologies is positively and significantly associated with union membership. These are technologies that often intensify grievances around autonomy, control, or adjustment while leaving workers inside relatively stable employment relationships and shared organizational settings. These technologies are likely to raise the demand for collective protection without fully destroying the social and organizational conditions necessary for collective organization.

By contrast, exposure to intelligent logistics shows weak or negligible associations, whereas food-ordering technologies display a significant negative effect. This is consistent with our expectation regarding the fragmentation of work. In food delivery and related platform services, algorithmic coordination is paired with individualized workflows, weaker attachment to the firm, and more precarious employment. Even if such technologies generate grievances, they appear less likely to translate into realized unionization because workers are dispersed and the costs of collective action are higher.

Two additional exercises assess the stability of the findings. First, the models are re-estimated using the raw occupational exposure measures, without interacting them with country-year levels of technological diffusion. The results in Table A.7 closely align with the baseline estimates. Second, to address the possibility that unobserved country-industry shocks correlate with the interaction of occupational exposure and country-level technological adoption, a specification with country-industry-year fixed effects is estimated. Table A.8 shows that the coefficients remain substantively unchanged.

While the main results are based on five illustrative technologies, we leverage the full set of 40 technologies to examine heterogeneity in the relationship between technological exposure and unionization more systematically. Figure A.4 displays the full set of technology-specific estimates.

Table 2: The Impact of Emerging Digital Technologies on Unionization

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:			Union member		
Technology exposure	0.006***	0.007***	0.012***	0.001	-0.004***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Technology type	Machine Learning	Additive Manufact.	Remote Monitoring	Intelligent Logistics	Food Ordering
Controls	X	X	X	X	X
Country-Year FE	X	X	X	X	X
Region FE	X	X	X	X	X
Industry FE	X	X	X	X	X
Observations	129,129	129,129	129,129	129,129	129,129
R-squared	0.250	0.250	0.250	0.250	0.250
Std dev. Y	0.363	0.363	0.363	0.363	0.363
Magnitude	0.0168	0.0182	0.0329	0.00272	-0.0105

Note: Standard errors are clustered at the countryyearoccupation level and reported in brackets. All specifications include individual-level controls for age, gender, years of education, and firm size, as well as fixed effects for region, industry, and countryyear. Individual technology exposure is scaled by ERP adoption rates to capture the pace of technological diffusion. The table reports the standard deviation of the dependent variable; the technology exposure variable is standardized (and thus has a standard deviation of approximately one). In addition to the regression coefficients, the table directly reports the magnitude of the relationship between the variables after residualizing with respect to controls and fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The pattern of heterogeneity is striking: 17 technologies display a statistically significant positive association with union membership, 19 display a statistically significant negative one, and the remaining 4 are not statistically different from 0.

To make sense of this wide heterogeneity, we complement the technology-specific estimates with a composite approach that aggregates the full set of 40 technologies into three theoretically motivated indices (augmenting, displacing, and monitoring) and estimates their joint effects on unionization. Table 3 reports the results. Exposure to augmenting and monitoring technologies is positively and significantly associated with union membership, while exposure to displacing technologies is negatively associated with it. This pattern is robust across specifications. Columns (1) and (2) include individual controls alongside region, industry, and country-year fixed effects, and differ only in whether occupational exposure is scaled by country-year ERP adoption rates. Column (3) replaces country-year and industry fixed effects with country-year-industry fixed effects to account for industry-specific shocks varying across countries. These findings reinforce the technology-specific results: the relationship between technological exposure and unionization is not uniform but depends systematically on the nature of the technology.

To unpack this pattern further, we jointly examine how different technologies relate not only to unionization but also to key working conditions. Our framework suggests that collective

Table 3: Unionization and Augmenting, Displacing and Monitoring Technologies

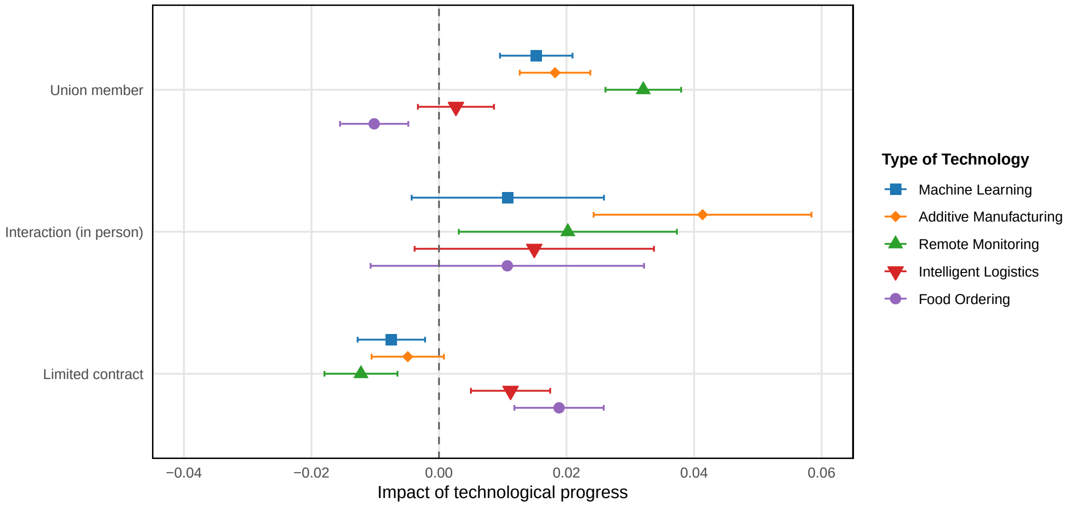
	(1)	(2)	(3)
	Union member		
Expos. to augmenting tech	0.059***	0.041***	0.051***
	[0.010]	[0.010]	[0.009]
Expos. to displacing tech.	-0.105***	-0.091***	-0.096***
	[0.012]	[0.012]	[0.011]
Expos. to monitoring tech.	0.044***	0.049***	0.044***
	[0.011]	[0.011]	[0.010]
Controls	X	X	X
Region FE	X	X	X
Industry FE	X	X	
Country-Year FE	X	X	
Country-Year-Industry FE			X
Occupational Exposure	θ	θ x ERP	θ x ERP
Observations	129,129	129,129	128,698
R-squared	0.250	0.250	0.308

Note: Standard errors, reported in brackets, are clustered at the country-year-occupation level. All models include individual-level controls for age, gender, years of education, and firm size, as well as fixed effects for region, industry, and country-year. Column (3) replaces country-year and industry fixed effects with country-year-industry fixed effects. In columns (2) and (3), individual technology exposures are first scaled by ERP adoption rates to account for the pace of technological diffusion, then weighted by their augmenting, displacing, or monitoring nature, and finally summed across technologies. Column (1) follows the same procedure without the ERP scaling step.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

organization is more likely to emerge when technological change does not erode, and may even reinforce, stable employment relationships and workplace interaction. Figure 1 reports the effects of technological exposure on precarious employment and workplace interaction, alongside the (standardized) effects on union membership for comparison. Technologies associated with higher unionization (i.e., machine learning, additive manufacturing, and remote monitoring) are also linked to more frequent coworker interaction and more stable employment. At the opposite end, exposure to food-ordering technologies is associated with a higher likelihood of precarious employment and lower unionization.

Figure A.5 extends this picture to a broader set of outcomes. Across technologies, exposure is often associated with reduced autonomy, lower perceived influence over workplace decisions, lower job satisfaction, and lower income patterns especially pronounced for intelligent logistics, additive manufacturing, and food-ordering technologies. Yet these adverse effects do not systematically translate into higher unionization. Grievances alone are not sufficient. When workers remain attached to the workplace, technological grievances are more likely to be channeled into collective organization; when exposure is bundled with precarious contracts, the same grievances are less likely to produce union membership.[8]

Figure 1: Effect of technological advance on unionization, precariousness, and interaction across technology types.



Note: The figure reports the estimated effects of different forms of technological exposure on multiple outcomes: union membership, having a limited-time contract, and frequency of interaction with coworkers (in person). All outcomes and exposure measures are standardized to a normal distribution to allow comparability. The models control for gender, education, age, and firm size, and include fixed effects for region, industry, and country-year. Standard errors are clustered by country-year-occupation. Coefficients are shown with 95% confidence intervals.

In sum, the worker-level results support a two-step logic. Many technologies generate grievances by reducing autonomy, influence, and satisfaction, but only some are associated with higher unionization. Technologies embedded in established production settings, such as machine learning, appear to create shared pressures while preserving enough stability and organizational contact for workers to respond collectively. By contrast, technologies prevalent in platform and logistics environments, such as intelligent logistics and food-ordering, are more consistent with a fragmentation pathway. They are associated with more precarious conditions and weaker unionization, suggesting that deteriorating work does not automatically produce organization.

These patterns may also have consequences beyond the workplace. When technological change intensifies insecurity and reduces workers control without generating effective channels of collective voice, resulting grievances may be expressed politically rather than organizationally. Consistent with this interpretation, Appendix A.4 shows that exposure to emerging digital technologies is associated not only with changes in unionization but also with broader shifts in

8. Consistent with the idea that technological change fosters unionization and collective action only when it supports stable employment and workplace organization, we find that declining employment stability is associated with lower unionization. We estimate a model in which technological exposure interacts with fixed-term contract status. As expected, the interaction term is generally negative, indicating that the push toward unionization associated with technological exposure is weakened by precarious employment. Results are shown in Table A.9. These findings, however, should be interpreted with caution as the estimated coefficients are likely affected by post-treatment bias, because employment contracts are themselves endogenous to technological exposure. See (Agnolin, Colantone, and Stanig 2025) for a discussion of the required assumptions.

political attitudes and democratic engagement. In particular, exposure is often linked to greater support for redistribution, but also to lower turnout and lower satisfaction with democracy, especially in settings where collective organization appears weaker.

5 Union Responses to Technology in CBAs

We now turn from individual-level evidence to how unions address technological change in collective bargaining. Our analysis draws on a new corpus of Canadian CBAs spanning 1993-2025. Using bilingual dictionaries, we identify clauses related to training, governance, health and safety, mitigation, and actor language, and we link these topic shares to industry-level exposure to six emerging digital technologies, as well as to a task-based AI measure that distinguishes between augmentation, monitoring, and replacement. After examining the Canadian case, we complement the analysis with a review from other regions and sectors that reveal recurring contractual responses-such as clearer definitions of AI use, information and consultation rights, limits on monitoring, and commitments to training and transition pathways.

Canada offers an especially suitable context for this analysis. It provides extensive and publicly accessible bargaining records, allowing for a fine-grained examination of how unions adapt to technological change. Like the United States, Canada follows a common-law system and features decentralized, firm-level CBAs. These agreements are regulated at the jurisdictional level –typically by province– creating meaningful within-country variation. The countrys labor movement spans a wide range of sectors, from heavy industry and public services to high-tech industries, likely displaying diverse strategies. Moreover, Canada has experienced patterns of labor-market de-routinization similar to those observed in several Western European countries (e.g., Sweden, Great Britain, Norway, Denmark, Finland) and the United States, making it a valuable comparative case (De La Rica and Gortazar 2016).[9][10]

5.1 Data: Collective Bargaining Agreements

We use Canadian CBAs to map how contracts address digital technologies. We built a custom scraper to collect agreements from Employment and Social Development Canadas repository and harvested all available records from 1993–2025. For each agreement we downloaded the

9. Existing political science research has also begun to document how AI exposure shapes individual attitudes (e.g., Magistro et al. 2024; Magistro et al. 2025).

10. See subsection A.5 for additional background on Canada.

PDF and produced machine-readable text (using OCR when needed). The corpus contains more than 40,000 agreements in English and French.[11] We retain ESDC metadata (employer, union, location, NAICS industry, sector, employees, and signing/effective/expiry dates), which permits measures of duration and timing. We remove exact and near-duplicate files. The unit of analysis is the agreement document. Our aim is to quantify how unions regulate emerging digital technologies by counting governance, protection, and adjustment clauses, rather than tallying generic technology terms.

5.2 Measuring Dependent Variables: Topics in CBAs

The dependent variables are shares of text devoted to specific contract themes.[12] All texts are lowercased, and tokenization uses a word-character regular expression that removes punctuation. We remove stopwords and compute document length as the number of non-stopword tokens. Dictionary matching proceeds on the normalized token stream under two rules. We rely on a dictionary approach as it is a tool that is scalable and can be used with recognizable bilingual terminology. For single tokens and ordered multiword phrases (e.g., "artificial intelligence"), matches are literal with phrase boundaries enforced. For unordered multiword sets (e.g., {notice, date, change}), we apply a conservative co-occurrence rule: a hit requires that every keyword appears in the document, and the count equals the minimum per-keyword frequency. Counts for auxiliary categories such as modal verbs and negations come from the full token counts before stopword removal so that items like *not* or *may* are not dropped. Denominators for share measures use the non-stopword length.

The categories align with expected union responses to technological change: capability building (*Training and Retraining*); governance and information rights (*Notice and Content Requirements*, *Joint Committee*, *Union Notice*); protection of conditions and health (*Working Conditions and Protection*, *Health, Safety, and Well-Being*); and mitigation and adjustment (*Remedies and Mitigation*, *Displacement Rights and Bumping*, *Retirement Allowance*), with *Exceptions and Limits* marking carve-outs. Language-of-rights measures distinguish active (*receive*, *gain*, *earn*) from passive (*entitle*, *give*, *offer*, *provide*, *compensate*). Agency terms (*Union as Agent*, *Worker as Agent*, *Firm as Agent*) track which actor is named. For additional details on how the topics were constructed, see Appendix A.7.

11. See subsection A.6 for dataset details.

12. Constructed as $\mathrm{DV}_{dc} = \frac{\mathrm{hits}_{dc}}{N_d^{\mathrm{nonstop}}}$, where hits_{dc} is the dictionary count for category c in document d, and N_d^{nonstop} is the document length after stopword removal.

As an illustration, Figure 2 plots the 12-month moving-average share of words tied to monitoring and surveillance in technology-related clauses. Levels are small through the 1990s, rise in the 2000s, and step up again in the mid-2010s. The most pronounced increase occurs after 2020, with a sharp jump beginning in 2023. By 2024–2025 the average share is roughly five times its early-1990s level, indicating growing contractual attention to electronic monitoring, data collection, and supervisory tools.

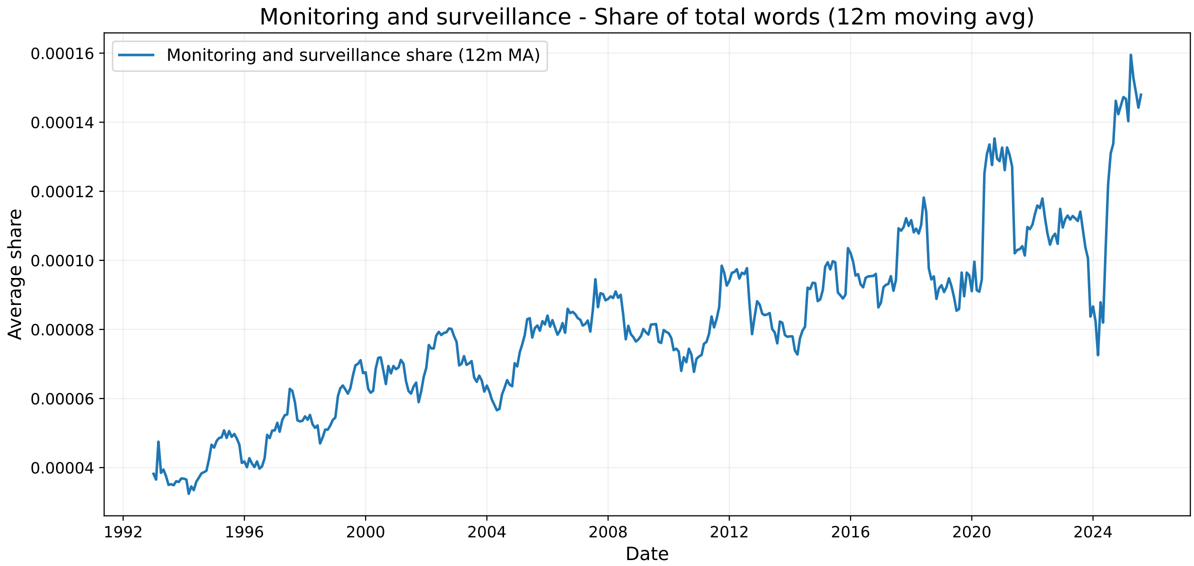


Figure 2: Salience of Monitoring and Surveillance in CBAs, Canada 1993–2025.
Note: 12-month moving average across agreements with technology-related clauses.

5.3 Measuring Independent Variables: Exposure to Emerging Digital and AI Technologies

Our main exposure measures are drawn from the *TechXposure* database (Prytkova et al. 2025), which scores industry exposure to emerging digital technologies. We first examine the full analysis period using measures covering emerging digital technologies, as discussed in Section 4.1.2. As a second, more AI-specific approach, we construct an AI exposure score at the industry–occupation level. A prompt-based LLM scores task-level exposure along three pathways: augmentation, replacement, and monitoring. More specifically, it generates four 1–10 component scores (AI capability, replacement, augmentation, and monitoring), corresponding 1–10 certainty scores, and four binary exposure flags. We then construct certainty-weighted components and indices. Unlike our earlier proxy for augmentation, monitoring, and displacement, this measure is explicitly tailored to AI and LLMs, whereas the TechXposure-based measure captures exposure to a broader set of digital technologies. Full details on the construction of the index and the prompt are provided in Appendix A.8, and descriptive statistics are reported in Appendix A.8.3.

5.4 Model Estimation

We estimate OLS models at the agreement level that relate the share of contract text on topic k to a single exposure measure m. For each outcome k and exposure m, we run a separate regression with a linear time trend (year), firm size (employees), and fixed effects for two-digit industry (NAICS 2) and location. Inference uses standard errors clustered at the employer level.

$$
\begin{aligned}
y_i^{(k)} \;&=\; \alpha_k \;+\; \beta_{km}\,\text{Technology Exposure}_i^{(m)} \;+\; \rho_k\,\text{year}_i \;+\; \theta_k\,\text{employees}_i \\
&\quad +\; \delta_{k,\text{NAICS2}(i)} \;+\; \lambda_{k,\text{location}(i)} \;+\; \varepsilon_i^{(k)}.
\end{aligned}
\tag{4}
$$

Here, $y_i^{(k)}$ is the share of non-stopword tokens in agreement i assigned to topic k, Technology Exposure$_i^{(m)}$ is the standardized exposure m, and $\delta_{k,\text{NAICS2}(i)}$ and $\lambda_{k,\text{location}(i)}$ denote two-digit NAICS industry and location fixed effects, respectively. The coefficient of interest, β_{km}, measures the change in the outcome share (on a 0-1 scale) associated with an increase in exposure m.

5.5 Exposure to Emerging Digital Technologies and CBAs

Figure 3 provides the clearest test of our argument that technological change enters collective bargaining through distinct pathways rather than as a single automation shock. Exposure to monitoring-intensive technologies is associated with larger shares of agreement text devoted to training and retraining, joint committees, monitoring and surveillance, exceptions or limits, and working-conditions protection. Substantively, these are provisions aimed at governing technological change inside continuing employment relationships. This is the pattern our theory anticipates when new technologies increase managerial visibility and control without necessarily removing workers from the workplace: unions respond by seeking to structure implementation, constrain employer discretion, and make the use of data and surveillance contestable. Notably, monitoring exposure is not associated with a parallel expansion of notice or compensation-oriented clauses. In these agreements, monitoring appears less as a trigger for downstream adjustment than as an ongoing workplace-governance problem.

A different bargaining repertoire emerges for displacement exposure. Agreements in more displacement-exposed industries devote more language to union notice, remedies and mitigation, bumping or displacement rights, and retirement allowances, while showing little corresponding increase in training and retraining or joint-committee provisions. This is a defensive contractual response. Where the central threat is substitution or job loss, bargaining shifts away from co-governing implementation and toward securing advance warning, managing exits, and redistributing the costs of workforce adjustment. By contrast, augmentation does not display a similarly broad positive profile once monitoring and displacement are held constant.

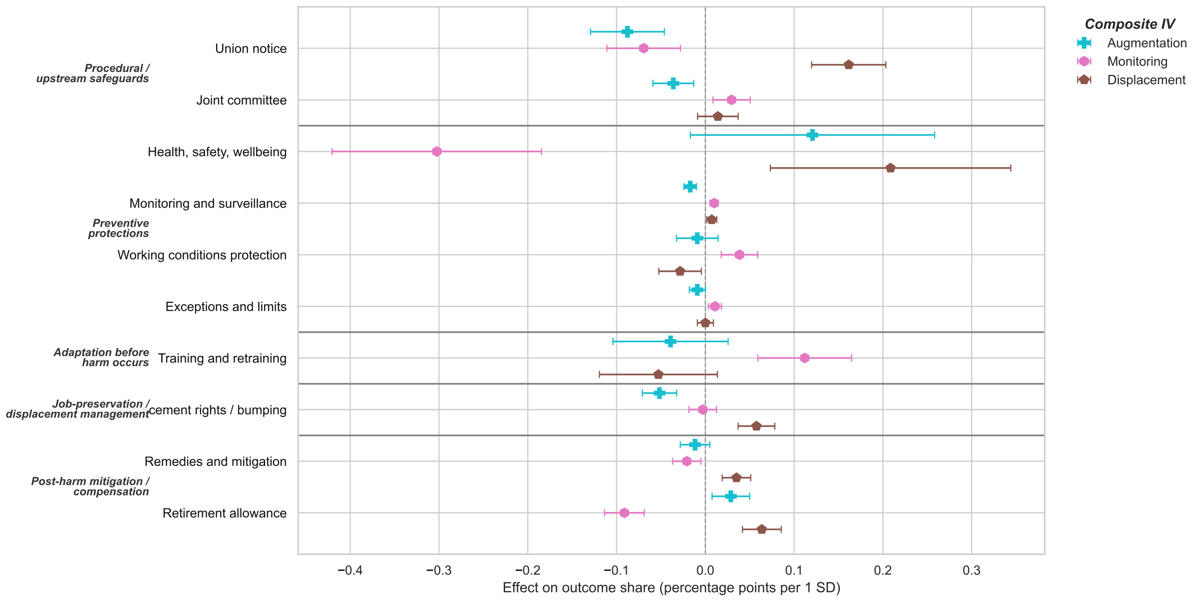
Appendix Figure A.14 shows that this pathway-based interpretation is not an artifact of aggregation. The technology-specific estimates map onto the same theoretical logic. *Additive manufacturing* is associated with more training and retraining, displacement-management clauses, and remedies or mitigation, consistent with a production setting in which workers remain in place but must bargain over adaptation to consequential reorganization. *Remote monitoring* is associated with more training and more exceptions or limits, while *intelligent logistics* is associated with more joint-committee language, training, and remedies. In both cases, unions appear to bargain over the governance of implementation under intensified oversight. By contrast, *food ordering* is associated mainly with union notice and exceptions or limits, a narrower and more defensive pattern that fits the theorys expectation for technologies combining control with fissuring in fragmented service settings. *Machine learning*, finally, is associated primarily with health, safety, and well-being language, suggesting that in these agreements it is experienced less as a standardized retraining problem than as a source of uncertainty, pressure, and worker-protection concerns.[13] Taken together, the composite and technology-specific results support the same conclusion: unions do not respond to technology in the abstract. They respond to the particular way new tools reorganize managerial control, job security, and the scope for collective governance.

Regarding other explanatory variables, Figure A.18 in the Appendix shows that more recent years are associated with a higher likelihood of including clauses on health, safety, wellbeing, training and re-training, and notice provisions. Likewise, unions representing a larger number of employees-an indicator of union strength-are more likely to include terms related to notice requirements, training, co-governance, and remedies or mitigation, while being less likely to rely on passive rights.

Overall, these results reinforce a central point of our argument: bargaining responses depend not only on whether technology threatens workers, but on how it does so and in what employment

13. Refer to Figure A.15 for a heatmap showing the relationship between CBA content shares and exposure to 40 technologies.

Figure 3: CBA Key Content and Composite Augmentation, Monitoring, and Displacement Exposure



Notes: The figure reports coefficient estimates from regressions of topic-specific collective bargaining agreement (CBA) content shares on three composite exposure measures: augmentation, monitoring, and displacement. Each composite measure is constructed as a weighted sum of standardized technology exposures across the 40 technologies, where the weights come from the technology-specific augmentation, monitoring, and displacement scores, and is then standardized. The figure reports the estimated effects of different forms of technological exposure on the share of each topic in the CBAs. The dependent variable, shown on the y-axis, represents the share of words in each topic relative to the total document length (average length: 13,239 words). In this case, topics refer to the inclusion of clauses related to health and well-being, training, notice, union participation, etc. The independent variables capture exposure to emerging technologies, measured using related patent data at the four-digit NAICS level. Coefficients are interpreted as percentage-point changes in the outcome share associated with a one-standard-deviation increase in the corresponding composite exposure measure. All models control for the number of employees and include fixed effects for year and location. The sample of CBAs covers all agreements signed between 1993 and 2025 (N = 40,742). Standard errors are clustered at the employer level. Each panel displays coefficient estimates with 95% confidence intervals.

setting. Technological change thus enters collective bargaining most strongly when workers can still organize around how new tools are introduced, monitored, and contested.

5.6 Exposure to LLMs, AI, and Collective Wage Bargaining

The previous subsection examined bargaining responses to a broad set of emerging digital technologies using composite exposure measures constructed over that wider technological universe. This subsection turns to a different empirical object: a post-2021, AI-specific measure of occupational-industry vulnerability to AI and LLMs, derived from LLM-based coding and described in Section 5.3. Although this measure is organized around the same conceptual pathways—augmentation, monitoring, and displacement—it should not be read as the earlier digital-technology composites re-estimated on a shorter sample. Rather, it is designed to isolate vulnerability to the current AI wave. We therefore restrict attention to agreements signed between 2022 and 2025 and examine whether AI-specific exposure is associated with a distinct contractual profile.

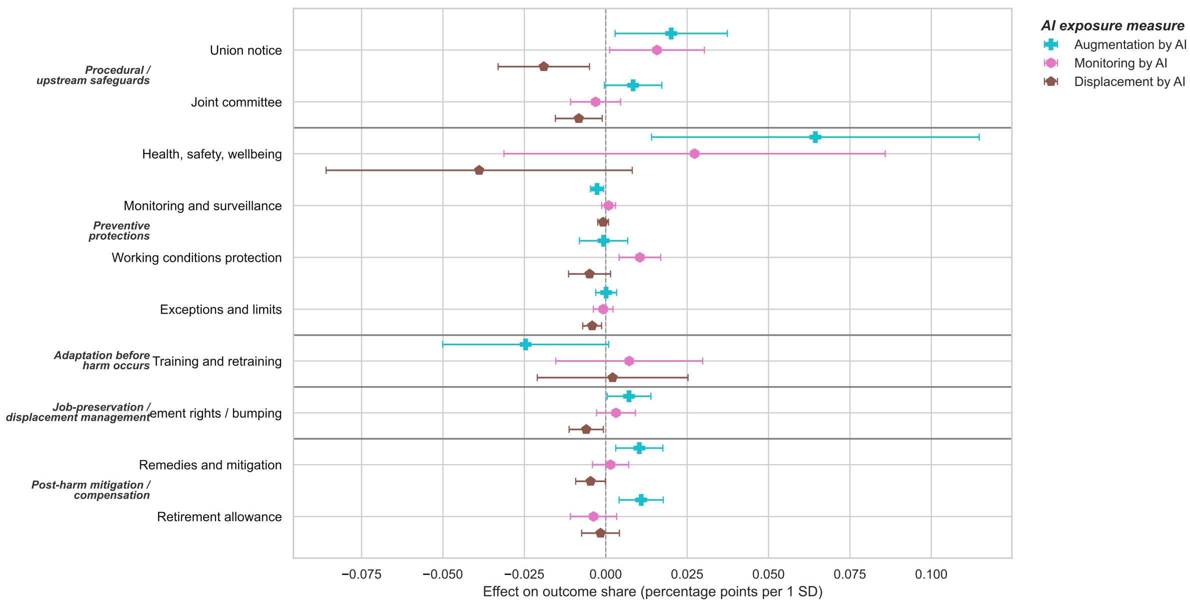
Figure 4 indicates that the three AI pathways are associated with different contractual responses. The most expansive positive pattern appears for *augmentation*. Agreements in more augmentation-exposed settings devote more language to health, safety, and well-being, notice-content requirements, remedies and mitigation, retirement allowances, and union notices. Read substantively, these coefficients suggest that AI-related augmentation is bargained less as a simple productivity gain than as a problem of governed implementation. Where AI tools complement ongoing work rather than eliminate it outright, workers remain sufficiently central to the labor process to press for safeguards, participation, and adjustment.

A more targeted pattern emerges for *monitoring*. The strongest positive associations here are with notice-content requirements, union notices, and working-conditions protection. This is substantively important. In the AI setting, monitoring raises questions about disclosure, data use, evaluation, and the conditions under which employers can deploy algorithmic oversight. The bargaining response is therefore narrower than under augmentation but still recognizably procedural: unions seek information, formal notice, and a foothold from which the use of AI systems can be reviewed and contested. Monitoring-intensive AI thus enters collective bargaining primarily as a problem of transparency and managerial accountability.

By contrast, *displacement* exposure is associated with weaker worker-protective content. In more replacement-exposed settings, agreements devote less language to union notices, joint committees, and remedies and mitigation, with similarly negative patterns across several other protective topics. Notably, we do not observe an offsetting rise in training or other forward-looking adjustment clauses. This is a different pattern from the broader digital-technology analysis above and should be interpreted cautiously: in the contemporary AI case, heightened replacement risk appears to compress rather than expand the space for proactive bargaining. One plausible implication is that where AI makes workers more readily substitutable, unions face a more adverse bargaining environment and secure fewer ex ante protections.

Overall, the post-2021 AI results sharpen our broader argument by showing that the form of technological vulnerability matters as much as exposure itself. AI-related augmentation is associated with a thicker contractual repertoire of protection, notice, and governed implementation; AI-related monitoring shifts bargaining toward disclosure and procedural oversight; and AI-related replacement is associated with a thinner protective response. The broader digital-technology results and the AI-specific results thus speak to the same theoretical claim, but they do so using different measures and different empirical windows: the former captures exposure to emerging digital technologies in general, whereas this subsection isolates a distinct, LLM-coded measure of vulnerability to the current AI wave.

Figure 4: CBA Key Content and Post-2021 AI Exposure Measures



Note: The figure reports the estimated effects of different forms of technological exposure on the share of each topic in the CBAs. The dependent variable, shown on the y-axis, represents the share of words devoted to each topic relative to the total document length (average length: 13,239 words). In this case, topics capture the inclusion of clauses related to health and well-being, training, notice requirements, union participation, and similar areas. The independent variables measure exposure to LLMs and AI, using an LLM-based classifier that categorizes technologies into three types: augmentation, displacement, and monitoring. Exposure is computed for each industry-occupation pair in the sample. All models control for the number of employees and include fixed effects for year and location. The sample of CBAs is limited to the years 2022-2025 (N = 788). Standard errors are clustered at the employer level. Each panel displays coefficient estimates with 95 percent confidence intervals.

5.7 CBAs Across the Globe

The Canadian results point to a common toolkit: early notice, information sharing, and training pathways. To examine how far these patterns generalize, and to illustrate concrete clause language, we present examples from other settings. For instance, a recent survey of European union officials and delegates directly involved in bargaining reports that about 20% of unions have a collective agreement addressing AI, while 42% are in discussions or negotiations (Brunnerová et al. 2024, 3). Where provisions exist, they most often cover training on new AI tools (75%), employee or union involvement when new technologies are introduced (62%), and the impact of AI or algorithmic management systems on working time and the right to disconnect (48%) (Brunnerová et al. 2024, 2). The recurring elements most commonly covered in CBAs are as follows. Broadly, these examples indicate that unions are bargaining for clear definitions of technological change, early notice and information sharing, structured implementation processes, limits on monitoring, and training provisions that keep new technology-related work within the bargaining unit.

Defining the scope of technological change. Agreements first clarify what constitutes "technological change," which anchors employer obligations toward employees. For instance, one contract states: "Technological change includes, but is not limited to, the use of machines (including, by way of example only, computers, robots, handheld devices, and tablets), automation software, systems, programs, applications, or other scientific advancements to replace or substitute for, improve, alter, increase or decrease, or evolve the type or manner of work performed by employees in the Employers workplace" (Bally's Las Vegas).[14] The extensive parameters defined by the aforementioned contract highlight the crucial role that definitions play in the bargaining process. "Technological change' can be interpreted in numerous ways, thus explicitly characterizing the scope of the term is necessary for effective bargaining.

CBAs also add technology-specific definitions, especially for AI. One agreement notes, "The parties acknowledge that 'Artificial Intelligence' and 'AI' have become catchall names that generally refer to the ability of a machine-based system to apply analysis and logic-based techniques to solve problems or perform tasks, and to improve as it analyzes more data" (IATSE).[15] AI is an important consideration given its increased incorporation into various occupational fields and work platforms. The inclusion of specific definitions for AI reflect the evolving technological landscape and its influence on labor.

Agreements further emphasize the importance of maintaining a human-in-the-loop role. For example, one states:"The parties acknowledge the importance of human contributions in motion pictures and the need to address the potential impact of the use of AI systems on employment under the Basic Agreement, the Videotape Electronics Supplemental Basic Agreement, and the West Coast Studio Local Agreements" (IATSE).[16] With the rise of automated processes and AI, outlining the role that human involvement plays is a key strategy for bargainers. Without emphasizing the importance of a human-in-loop role, bargainers risk overlooking an increasingly important determinant of working conditions.

14. Bally's Las Vegas Manager, LLC and Local Joint Executive Board of Las Vegas 2019, 64

15. Alliance of Motion Picture and Television Producers and International Alliance of Theatrical Stage Employees, Moving Picture Technicians, Artists and Allied Crafts of the United States, its Territories and Canada 2024, 13

16. Alliance of Motion Picture and Television Producers and International Alliance of Theatrical Stage Employees, Moving Picture Technicians, Artists and Allied Crafts of the United States, its Territories and Canada 2024, 13

Baseline governance rights: notice, information, bargaining, and jurisdiction. Consistent with the Canadian case, many agreements require advance notice so unions can assess job impacts and bargain over implementation. For instance: “The State shall endeavor to notify the Union one hundred eighty (180) days, but no less than sixty (60) days, prior to implementation of automation or technological changes that will result in a significant impact on bargaining unit employees. Upon request of the Union within thirty (30) days of such notification, the State shall negotiate with the Union on the impact of such changes” (SEIU Local 1000).[17] Notice is paired with information rights that specify what the employer must provide, including the proposed implementation date, who is affected, how duties will change, whether the change replaces existing practice, the rationale, and the implementation plan (AFGE).[18] Similar rules appear in Norways 2018-2021 NHO-LO basic agreement, which requires companies to inform employees via shop stewards about planned control measures and, before acting, to explain the purpose, practical consequences, implementation steps, and expected duration (Brunnerová et al. 2024, 20).

Algorithmic management (AM) and digital rights. Telefónica, Spains leading telecommunications company, provides an example of an agreement addressing AM through a national accord on the right to disconnect, negotiated with the trade unions representing its employees (Brunnerová et al. 2024, 7). Spain also adopted Law 12/2021 on algorithmic management, which grants unions the right to request information about how AI is implemented and how it affects hiring and working conditions, recognizing AIs growing influence on human decision-making (Brunnerová et al. 2024, 7). In a separate case, an agreement between Spanish unions and JUST EAT in 2021 established a right to digital and work disconnection, stating that “the company is not to communicate with workers outside their working hours unless exceptional circumstances arise that justify such, and/or to communicate the weekly work schedule to the delivery group” (Brunnerová et al. 2024, 21). This safeguard is especially relevant amid reports of increasing after-hours work (e.g, Smith 2025).

Electronic monitoring and surveillance. Across countries, CBAs establish safeguards on data collection and use, addressing the “dual-use” problem whereby tools introduced for logistics,

17. State of California and Service Employees International Union (SEIU) Local 1000 2023–26.

18. National Science Foundation and American Federation of Government Employees (AFGE) Local 3403, AFLCIO 2022, 154.

customer service, or safety purposes can later be repurposed for surveillance or discipline.[19] Many CBAs narrow permissible uses of monitoring technologies and reinforce due-process protections. For instance, one agreement states that "the surveillance system is not intended for use as a means to track employees time and attendance" (NAIL)[20], while another specifies that "security camera data will not be used for routine monitoring of bargaining-unit employees conduct, performance, behavior, or time and attendance" (AFGE)[21]. Similarly, the NTEU agreement clarifies that "the intent of the cameras is to maintain the safety and internal security of government property and not to monitor day-to-day employee performance or conduct."[22] Some agreements go further, explicitly prohibiting targeted surveillance: "No recording shall be used by any manager against any employee for the purpose of finding misconduct or issuing discipline The company will not randomly review audio, video, or other electronic monitoring data, nor review it for the purpose of discovering policy violations in the absence of an observation or incident" (ATU)[23]. In Italy, an agreement signed by the unions FILCAMS-CGIL and FISASCAT-CISL covering an application that checks drivers regulatory compliance and safety requires prior union approval and limits the tool strictly to its stated purposes (Brunnerová et al. 2024, 6). The listed examples provide evidence of intentional efforts by bargaining groups to establish protections against increased monitoring and data collection. While monitoring and data collection systems might be introduced as tools to aid in logistical processes, they can be altered to surveil workers. Consequently, including explicit clauses about the use of employee data can act as a preemptive measure to protect the interests of those bargaining.

Bargaining-unit integrity and training pathways. When technology creates new tasks or reshapes existing ones, CBAs aim to keep that work in the unit and to equip current workers for those roles. Examples include: "If a technological change creates new work that replaces, enhances or modifies bargaining unit work, bargaining unit employees will perform that new or modified work" (IBT)[24] and "The Employer shall not use technological changes for the sole purpose of converting jobs from bargaining unit status to non-bargaining unit

19. Examples of monitoring systems refer to tools like CCTV, Entry Control Video (ECV), and Intrusion Detection Systems (IDS).

20. Seymour Johnson Air Force Base, North Carolina and National Association of Independent Labor (NAIL) Local 7 2022, 102

21. American Federation of Government Employees (AFGE) Local 0446 and U.S. Department of Agriculture, Forest Service 2019, 66

22. National Park Service Headquarters and National Treasury Employees Union (NTEU) Chapter 296 2017, 166

23. First Transit, Inc., Mesa and Tempe Division and Amalgamated Transit Union (ATU) Local 1433 2016–21, 8

24. United Parcel Service, Inc. and International Brotherhood of Teamsters 2023–28, 18.

status" (IAMAW).[25] Training and internal mobility rules then operationalize this aim: "present employees shall be given first consideration for any new or changed position... In the event training is necessary... the employer will provide adequate training to all affected employees at the time the technology is implemented" (OPEIU).[26] CBAs provide workers with a framework to navigate the evolving occupational landscape. The terminology used throughout numerous CBAs hint towards the rising relevance of technological innovation and its potential effects on various occupational groups.

6 Conclusion

We have shown that digital technologies affect organized labor through a two-step process. First, they reshape the labor process by altering autonomy, pace, monitoring, and employment stability. Second, these grievances are likely to translate into collective organization only when workers remain in settings that preserve social contact, stable employment, and channels of voice. This framework helps explain why exposure to machine learning, or remote monitoring, is associated with higher unionization, whereas exposure to food-ordering platforms is not. Deteriorating work does not automatically produce organization; it does so only when the conditions for collective action remain intact.

The bargaining evidence reinforces the same logic. Unions do not respond to all technologies in the same way. In our analysis of collective bargaining agreements, technologies that directly restructure workflow or intensify monitoring are associated with more training provisions, notice requirements, joint committees, and health and safety language. In the post-GenAI period, the contrast becomes especially sharp: augmentation is associated with stronger worker protections and joint governance, monitoring shifts bargaining toward oversight and disclosure, and replacement is associated with weaker proactive safeguards. Unions appear strongest where technology reorganizes work but leaves workers in place, and weakest where technology makes workers more replaceable.

These findings move beyond both robot-centered accounts of technological change and density-centered accounts of labor power. Technological change does not uniformly weaken unions. Its consequences depend on how technologies reorganize work and on whether workers remain able

25. Adams County Circuit Clerk, Deputy Clerks and District No. 9, International Association of Machinists and Aerospace Workers (IAMAW), AFLCIO 2021–24, 11.

26. Office and Professional Employees International Union (OPEIU) Local 537, AFLCIO and American Federation of Musicians Local 325 2019–24, 6.

to transform shared grievances into collective organization and bargaining. Automation, in this sense, is not only a labor demand shock but also a workplace-governance shock, reshaping how work is organized, monitored, and contested. More broadly, the politics of AI and digitalization will depend on whether workers retain the institutional capacity to respond collectively.

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A Appendix

Contents

A.1 Descriptive ESS Variables

Table A.1: Description of ESS Variables

Variable	**Description**	**Coding**	**ESS**
Union member	Member of trade union or similar organisation	0 = No (or yes previously), 1 = Yes	6–11
Influence on decisions	Allowed to influence policy decisions about activities of organisation	10-point scale: 1 = no influence, 10 = complete control	6–11
Decide daily work	Allowed to decide how daily work is organised	10-point scale: 1 = no influence, 10 = complete control	6–11
Satisfaction job	How satisfied with job	10-point scale: 1 = Extremely dissatisfied, 10 = Extremely satisfied	6
Limited contract	Employment contract: unlimited or limited	0 = unlimited, 1 = limited	6–11
Interaction (in person)	Speak with colleagues in person, how often	7-point scale: Never, Less often, Once a month, Several times a month, Several times a week, Once a day, Several times a day	10
Income	Household's total net income, all sources	10 income deciles	6–11
Redistribution	Government should reduce differences in income levels	5-point scale: Disagree strongly, Disagree, Neither agree nor disagree, Agree, Agree strongly	6–11
Voted	Voted last national election	0 = Not voted, 1 = Voted	6–11
Satisfaction dem.	How satisfied with the way democracy works in country	10-point scale: 1 = Extremely dissatisfied, 10 = Extremely satisfied	6–11

A.2 Types of Technologies and descriptives

A.2.1 Types of Technology

Table A.2: Types of Technology and Descriptions (Part A)

Type of Technology	Description
Machine Learning & Neural Networks	Machine learning training techniques, model architectures, and data processing for computer vision applications.
Additive Manufacturing	Digitally guided fabrication and production technologies that build or shape components layer by layer, including industrial 3D printing and related automated manufacturing processes.
Remote Monitoring & Control Systems	Real-time remote monitoring and management technologies for factories, building management, warehouses, intelligent homes, disaster management, and network security.
Intelligent Logistics	Monitoring, remote control, data acquisition, and mobile robot technologies for logistics and delivery applications, including supply chain management, warehouse operations, package tracking, and courier services.
Food Ordering & Vending Systems	Wireless infrastructures, encryption, monitoring, and remote control technologies for food order management, such as automatic vending, self-service ordering, meal preparation, and delivery.
3D Printer Hardware	Three-dimensional printers and their components, such as printing heads, pens, nozzles, platforms, and devices for printing, extruding, cleaning, recycling, heating, and cooling.
3D Printing	Printing systems for creating three-dimensional objects using a variety of materials and techniques, like photocuring and powder spreading.
Smart Agriculture & Water Management	Various Internet of Things (IoT) technologies for intelligent and remote management in agriculture, and water and sewage systems.
Internet of Things (IoT)	Systems and devices interconnected via IoT for data collection, remote control, and real-time monitoring in diverse applications, including agriculture, home automation, and environmental monitoring.
Predictive Energy Management and Distribution	A combination of network, data management, and AI technologies for monitoring, distribution, and efficient use of electrical power and energy, including renewable energy sources, and for consumption prediction in intelligent power management.
Industrial Automation & Robot Control	Industrial process automation, including robots, programmable logic controllers, and related control apparatuses such as remote control and fault diagnosis.
Smart Home & Intelligent Household Control	Various IoT technologies for the intelligent control of homes and buildings, including household appliances, home environments, and smart home integrations, often utilizing wireless communication and monitoring.
Autonomous Vehicles & UAVs	Developments in unmanned aerial vehicles (UAVs), drones, and autonomous driving technologies, with an emphasis on vehicle control, navigation, and sensor integration.
Parking & Vehicle Space Management	Networking technologies for parking management, including systems for monitoring available spaces and intelligent parking solutions.
Vehicle Telematics & Electric Vehicle Management	Technologies for intra-vehicle information management, especially in electric vehicles, including aspects of real-time monitoring, traffic information, and vehicle diagnostics.
Passenger Transportation	Technologies for ride-sharing, taxi hailing, and public transportation reservations using real-time information, electronic ticketing, and route optimization.
Digital Advertising	Automated tracing and tagging, and AI technologies for digital advertisements, including targeted delivery on mobile devices.
Electronic Trading and Auctions	Online trading platforms, financial instrument exchanges, and auction mechanisms, focusing on real-time bidding, trading, and market data.
Online Shopping Platforms	Wireless technologies (e.g., RFID and mobile terminals), encryption (e.g., blockchain), and AI technologies for e-commerce transactions, and digital tools related to the purchase, sale, and display of product information, including recommendation systems.
E-Coupons & Promotion Management	Data management platforms for electronic coupon distribution, management, redemption, and associated loyalty programs.

Note: Descriptions are sourced from Prytkova et al. 2025.

Table A.3: Types of Technology and Descriptions (Part B)

Type of Technology	**Description**
Electronic Payments & Financial Transactions	A combination of wireless (e.g., mobile) and encryption (e.g., blockchain) technologies for processing electronic payments (e.g., credit card transactions) and interfacing with financial institutions.
Mobile Payments	A combination of mobile technologies for processing electronic payments.
Gaming & Wagering Systems	A combination of user interface and data management technologies for gaming, both online and physical, including gambling and gaming machines.
Digital Authentication	Encryption and robotic processing technologies for verifying user identities, securing transactions, and safeguarding data through various authentication mechanisms, such as biometrics and cryptographic methods.
E-Learning	A combination of AI and data management technologies for digital platforms and systems in education, including teaching, learning, and classroom management.
Location-Based Services & Tracking	Technologies that provide location-based content and services, often relying on global positioning and navigation systems and related communication technology.
Voice Communication	Technologies focusing on voice communication, including communication protocols and user interfaces.
Electronic Messaging	Digital communication methods, infrastructure, and user interfaces for services such as email and conferences.
Workflow Management	A combination of AI and network technologies for management applications, including workflow automation, recruitment, event scheduling, and building and property management.
Cloud Storage & Data Security	Cloud-based data storage, distributed data management, encryption, and backup, often integrated with blockchain technology.
Information Processing	Systems for managing, processing, and delivering data and information across various domains, potentially including content generation, transmission, and verification.
Cloud Computing	Cloud computing and virtual machines, focusing on cloud platforms and resource allocation in cloud environments.
Recommender Systems	Algorithms and systems for providing recommendations and personalized content delivery based on user behavior, search queries, and similarity metrics.
Social Networking & Media Platforms	User interfaces for online social networking services, content sharing, and recommendation systems.
Digital Media Content	Tools and platforms for digital media content creation, management, distribution, and access.
Augmented and Virtual Reality (AR/VR)	Augmented reality (AR) and virtual reality (VR) models, devices, interfaces, and experiences, including head-mounted displays and interactions in virtual environments.
Medical Imaging & Image Processing	Diverse applications for acquiring and analyzing medical images from various modalities, such as computed tomography (CT), ultrasound, magnetic resonance imaging (MRI), and virtual reality (VR), for purposes including diagnosis, surgical planning, and the design of prostheses.
Health Monitoring	Wearable and implantable devices and systems for real-time health monitoring that track vital signs such as blood pressure, heart rate, and temperature, coupled with comprehensive medical data management.
Medical Information	A combination of data sharing, encryption, and Natural Language Processing (NLP) technologies for the storage, retrieval, and management of medical and patient information, encompassing electronic medical records, prescription management, and remote healthcare services.
E-Healthcare	An integration of data sharing, wireless communication, monitoring, and user interface technologies for healthcare and health management systems, including those used in hospitals and cloud-based platforms.

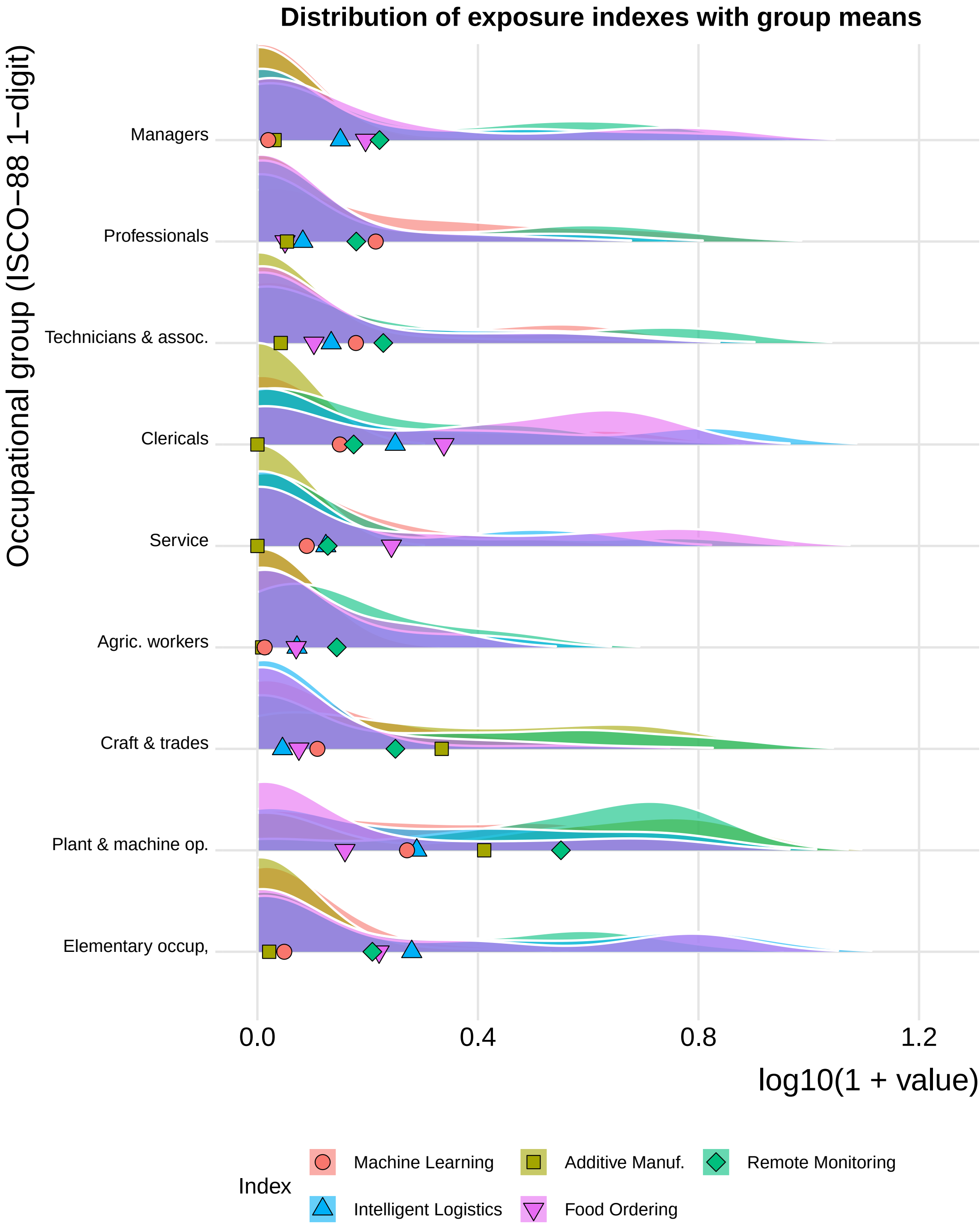
Note: Descriptions are sourced from Prytkova et al. 2025.

A.2.2 Exposure to types of technology by occupation

Table A.4: Top five most exposed occupations to each technology.

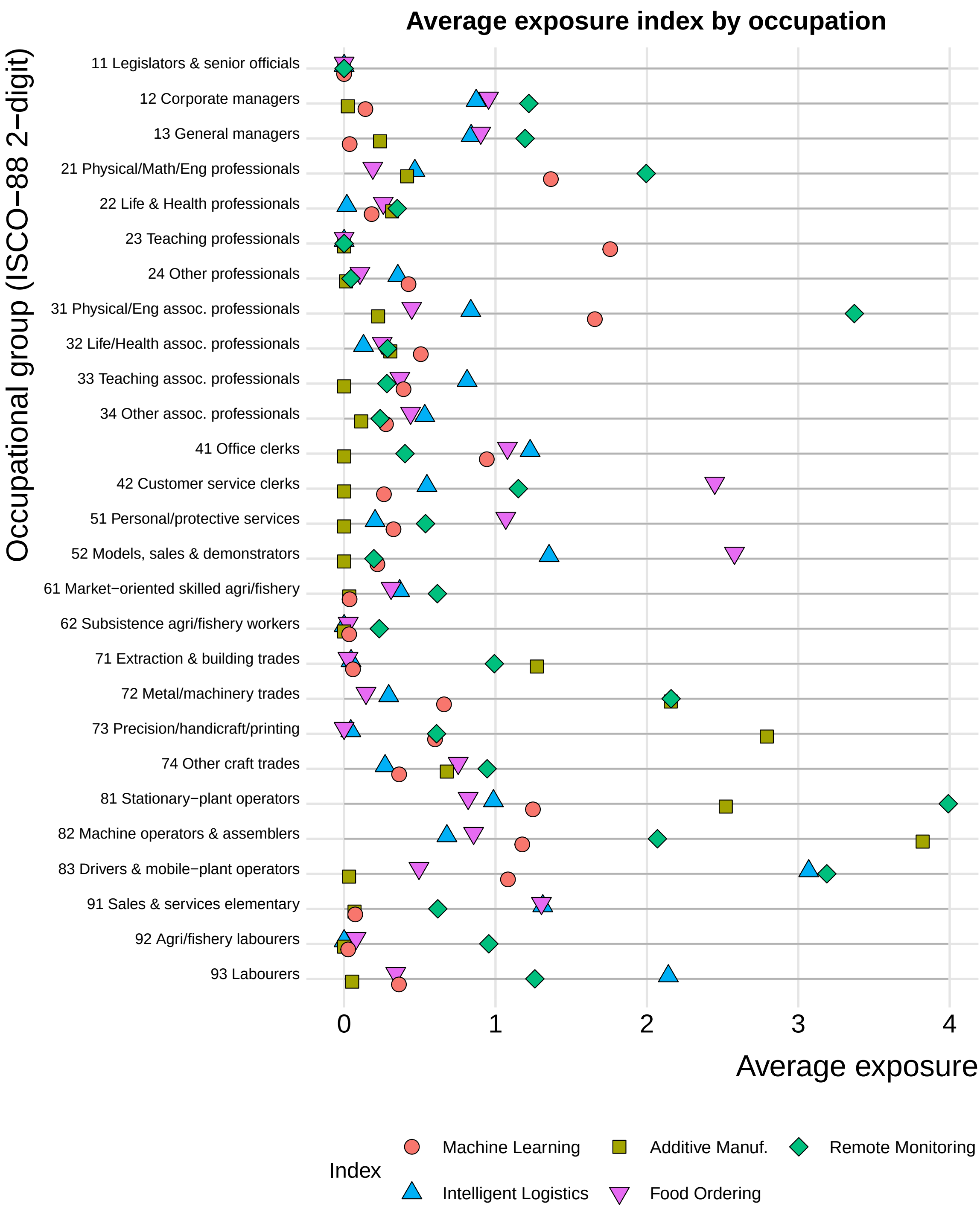
Technology	ISCO-08 Occupation	4-digit code
Machine learning	Photographic products machine operators	8132
	Electronics engineers	2152
	Information technology trainers	2356
	Telecommunications engineers	2153
	Chemical and photographic products plant and machine operators	8130
Additive Manufacturing	Plastic products machine operators	8142
	Metal moulders and coremakers	7211
	Rubber products machine operators	8141
	Rubber, plastic and paper products machine operators	8140
	Metal working machine tool setters and operators	7223
Remote monitoring	Chemical processing plant controllers	3133
	ICT installers and servicers	7422
	Computer network professionals	2523
	Computer network and systems technicians	3513
	Electronics and telecommunications installers and repairers	7420
Intelligent logistics	Messengers, package deliverers and luggage porters	9621
	Freight handlers	9333
	Supply, distribution and related managers	1324
	Transport clerks	4323
	Mail carriers and sorting clerks	4412
Food ordering	Food service counter attendants	5246
	Fast food preparers	9411
	Restaurant managers	1412
	Food preparation assistants	9410
	Food preparation assistants	9400

Figure A.1: Exposure to Types of Technology by Occupational Group



Note: The figure shows the distribution of exposure to the five technological types across ISCO-08 4-digit occupations. For each ISCO-88 1-digit major occupational group, kernel density ridges summarise how exposure values are distributed. Values are trimmed at 0 given that 0 is the minimum exposure. Exposure is expressed as $\log_{10}(1 + \text{value})$ to reduce skewness and improve readability. The colored markers overlaid on each ridge indicate the average exposure of the occupations within that major group for each technology.

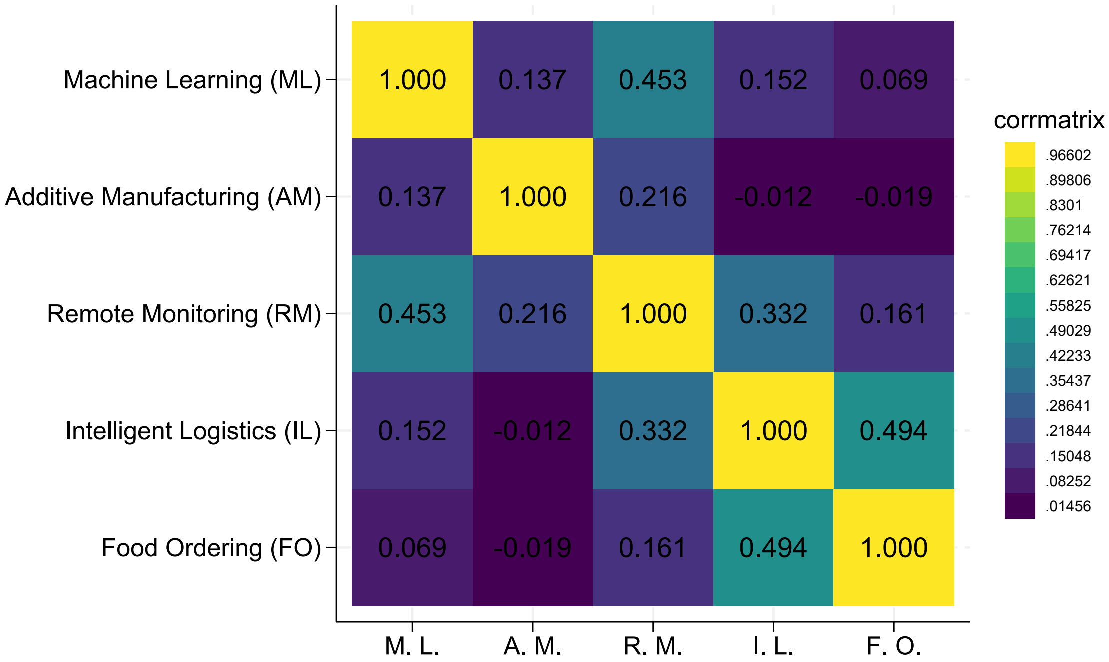
Figure A.2: Average Exposure to Types of Technology by Occupation



Note: The figure reports the average exposure to the various technological types across ISCO-88 2-digit occupational groups. For each group, the exposure value corresponds to the mean of the underlying ISCO-08 4-digit occupations classified within that category. Coloured markers denote the average exposure for each technology.

A.2.3 Correlation between Exposure Indexes

Figure A.3: Correlation Matrix of Exposure Indexes



A.2.4 Prompt-based coding of augmentation, monitoring, and displacement on technology families

To characterize the 40 technologies in the TechXposure taxonomy along the three conceptual pathways used in the paper, we conducted a prompt-based coding exercise at the technology level. The unit of analysis was the technology itself as typically deployed in current-to-near-term workplaces. For each technology, the model received the technology label together with the corresponding description.

The coding was produced on April 24, 2026 using OpenAI's `gpt-5.4-mini` through the Codex environment. Rather than asking the model to score all dimensions jointly, we ran three separate prompt passes, one for augmentation, one for monitoring, and one for displacement. This separation was deliberate: it reduced cross-dimension anchoring and produced more variation than a single omnibus prompt. Each prompt asked for a 1–10 integer score for all 40 technologies and returned a structured table with `tech40_id`, the requested score, and a short justification.

The three prompts shared the same core framing. First, they instructed the model to score typical workplace deployment in practice. Second, they defined the pathway-specific concept. Augmentation was defined as the extent to which a technology helps workers do their jobs better, faster, safer, or at higher quality while keeping humans substantively in the loop. Monitoring was defined as the extent to which a technology enables employers or systems to observe, record, track, evaluate, or discipline worker behavior, output, location, pace, or compliance. Displacement was defined as the extent to which a technology can reduce labor demand by automating tasks, compressing staffing needs, or removing the need for some roles or hours. Third, the prompts supplied common anchors: low values corresponded to little or no connection to the pathway, middle values to partial or task-specific relevance, and high values to technologies for which the pathway is a central and realistic consequence of adoption.

In condensed form, the augmentation prompt stated: "Score augmentation for the following 40 technologies. Unit of analysis is the technology itself as typically deployed in current-to-near-term workplaces, not a specific occupation and not the most futuristic version. Augmentation means the degree to which the technology helps workers do their jobs better, faster, safer, or at higher quality while keeping humans substantively in the loop." The monitoring and displacement prompts used the same structure but substituted the relevant pathway definitions and scoring anchors.

Once the technology-level scores were fixed, we converted them into observation-level pathway indices by weighting each technology score by the corresponding standardized TechXposure intensity. Let a_i, m_i, and d_i denote the augmentation, monitoring, and displacement scores for technology $i \in \{1, \ldots, 40\}$; let x_{oi}^{std} denote the standardized exposure of observation o to technology i; and let Δx_{oi}^{std} denote the standardized shock version of the same exposure measure. We then constructed the level indices as

$$A_o = \sum_{i=1}^{40} x_{oi}^{std} a_i, \qquad M_o = \sum_{i=1}^{40} x_{oi}^{std} m_i, \qquad D_o = \sum_{i=1}^{40} x_{oi}^{std} d_i, \tag{5}$$

and the shock indices as

$$A_o^{\Delta} = \sum_{i=1}^{40} \Delta x_{oi}^{std} a_i, \qquad M_o^{\Delta} = \sum_{i=1}^{40} \Delta x_{oi}^{std} m_i, \qquad D_o^{\Delta} = \sum_{i=1}^{40} \Delta x_{oi}^{std} d_i. \tag{6}$$

Within each estimation sample, we then standardized each composite index to mean zero and standard deviation one before using it in the regressions. The final empirical specifications therefore use standardized pathway summaries rather than the 40 technology-specific scores directly.

Table A.5: Technology scores and rankings: Augmentation, Monitoring, and Displacement

Technology	**Aug.**	**Aug. Rank**	**Monit.**	**Monit. Rank**	**Displ.**	**Displ. Rank**
3D Printer Hardware	4	31	2	31	1	37
3D Printing	6	20	4	16	5	13
Additive Manufacturing	7	11	5	11	6	7
Smart Agriculture & Water	7	12	4	17	4	20
Internet of Things (IoT)	5	26	5	12	2	30
Predictive Energy Mgmt	7	13	3	25	4	21
Industrial Automation	8	2	6	6	8	1
Remote Monitoring	7	14	8	1	4	22
Smart Home	2	38	1	38	1	38
Intelligent Logistics	8	3	8	2	7	2
Autonomous Vehicles/UAVs	6	21	4	18	7	3
Parking/Vehicle Space	3	34	2	32	3	26
Vehicle Telematics/EV	5	27	7	4	2	31
Passenger Transport	4	32	6	7	3	27
Food Ordering/Vending	3	35	4	19	6	8
Digital Advertising	3	36	3	26	5	14
Electronic Trading/Auctions	5	28	6	8	7	4
Online Shopping Platforms	4	33	4	20	5	15
E-Coupons & Promotion	2	39	2	33	3	28
Electronic Payments	6	22	3	27	5	16
Mobile Payments	5	29	2	34	4	23
Gaming & Wagering	1	40	6	9	4	24
Digital Authentication	8	4	5	13	5	17
E-Learning	6	23	6	10	6	9
Location-Based Services	6	24	8	3	2	32
Voice Communication	7	15	2	35	1	39
Electronic Messaging	8	5	4	21	1	40
Workflow Management	8	6	7	5	7	5
Cloud Storage/Security	7	16	3	28	2	33
Information Processing	7	17	2	36	6	10
Cloud Computing	8	7	2	37	2	34
Recommender Systems	5	30	1	39	4	25
Social Networking/Media	3	37	4	22	2	35
Digital Media Content	7	18	3	29	6	11
AR/VR	6	25	4	23	2	36
Machine Learning	8	8	5	14	7	6
Medical Imaging	9	1	1	40	6	12
Health Monitoring	7	19	4	24	3	29
Medical Information	8	9	3	30	5	18
E-Healthcare	8	10	5	15	5	19

A.3 Additional Results: The Impact of Emerging Digital Technologies on Working Conditions and Unionization

Table A.6: Precariousness, workplace interaction, and unionization

Panel A Precariousness		**Panel B** Workplace interaction	
Dep. Var.	Union member	Dep. Var.	Union member
	(1)		(2)
Limited contract	-0.050***	Interaction (Colleagues)	0.024***
	[0.005]		[0.004]
Controls	X	Controls	X
Country-Year FE	X	Country-Year FE	X
Region FE	X	Region FE	X
Industry FE	X	Industry FE	X
Observations	103,347	Observations	12,838

Notes: The dependent variable is a dummy variable for union membership. Panel A reports the association between precarious employment (defined as holding a fixed-term contract) and unionization. Panel B reports the association between workplace interaction (a standardized measure of interactions with colleagues) and unionization. All specifications include controls for gender, education, age, and firm size, as well as countryyear, region, and industry fixed effects. The smaller sample in Panel B reflects the fact that the workplace interaction question was administered only in wave 10 of the European Social Survey. Standard errors are clustered at the countrywave level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.7: The Impact of Technology on Unionization (unadjusted measure)

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:	Union member				
Technology exposure: θ	0.007***	0.007***	0.013***	-0.000	-0.006***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Technology type	Machine Learning	Additive Manufact.	Remote Monitoring	Intelligent Logistics	Food Ordering
Controls	X	X	X	X	X
Country-Year FE	X	X	X	X	X
Region FE	X	X	X	X	X
Industry FE	X	X	X	X	X
Observations	129,129	129,129	129,129	129,129	129,129
R-squared	0.250	0.250	0.250	0.250	0.250

Note: Standard errors are clustered at the country-year-occupation level and reported in brackets. All specifications include individual-level controls for age, gender, years of education, and firm size, as well as fixed effects for region, industry, and country-year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: The Impact of Technology on Unionization (robust to industry shocks)

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:			Union member		
Technology exposure	0.006***	0.006***	0.011***	0.000	-0.005***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Technology type	Machine Learning	Additive Manuf.	Remote Monitoring	Intelligent Logistics	Food Ordering
Controls	X	X	X	X	X
Country-Industry-Year FE	X	X	X	X	X
Region FE	X	X	X	X	X
Observations	128,698	128,698	128,698	128,698	128,698
128,698					
R-squared	0.307	0.307	0.308	0.307	0.307

Note: Standard errors are clustered at the country-year-occupation level and reported in brackets. Individual technology exposure is scaled by ERP adoption rates to capture the pace of technological diffusion. Limited contract is defined as a binary indicator. All specifications include individual-level controls for age, gender, years of education, and firm size, as well as fixed effects for region and country-industry-year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: The Impact of Technology and Limited Contract on Unionization

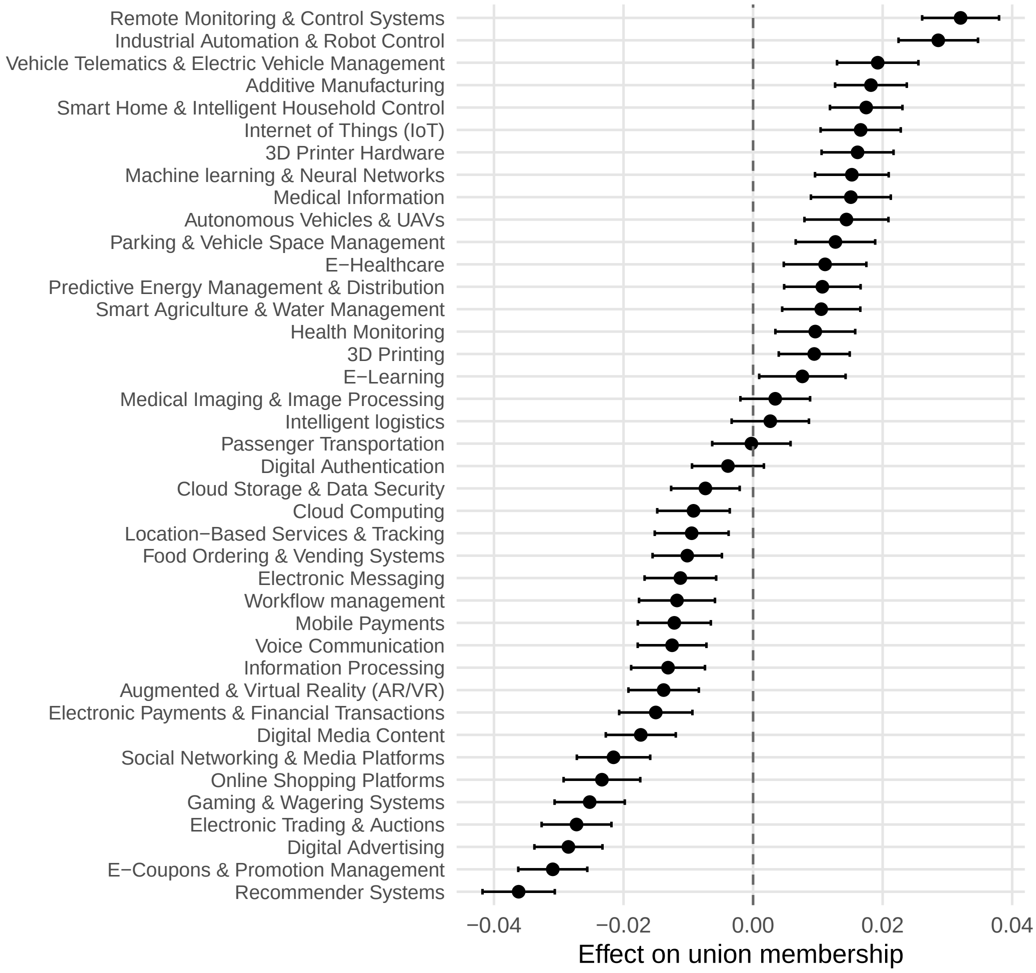
	(1)	(2)	(3)	(4)	(5)
Dep. Var.:			Union member		
Technology exposure	0.007***	0.009***	0.015***	0.003*	-0.003*
	[0.002]	[0.001]	[0.002]	[0.002]	[0.002]
Limited Contract	-0.049***	-0.050***	-0.049***	-0.049***	-0.049***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Tech exposure X Limited	-0.004	-0.002	-0.007**	-0.007***	-0.004
Contract	[0.003]	[0.003]	[0.003]	[0.003]	[0.002]
Technology type	Machine Learning	Additive Manufact.	Remote Monitoring	Intelligent Logistics	Food Ordering
Controls	X	X	X	X	X
Country-Year FE	X	X	X	X	X
Region FE	X	X	X	X	X
Industry FE	X	X	X	X	X
Observations	103,347	103,347	103,347	103,347	103,347
R-squared	0.262	0.262	0.263	0.262	0.262

Note: Standard errors are clustered at the country-year-occupation level and reported in brackets. Individual technology exposure is scaled by ERP adoption rates to capture the pace of technological diffusion. All specifications include individual-level controls for age, gender, years of education, and firm size, as well as fixed effects for region, industry and country-year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.4 Additional results: Exposure to Emerging Digital Technologies and Politics

We next examine whether changes in working conditions are mirrored in political responses. Figure A.6 presents estimates for political preferences and engagement. Exposure to most

Figure A.4: Effect of technological advance on union membership across technology types



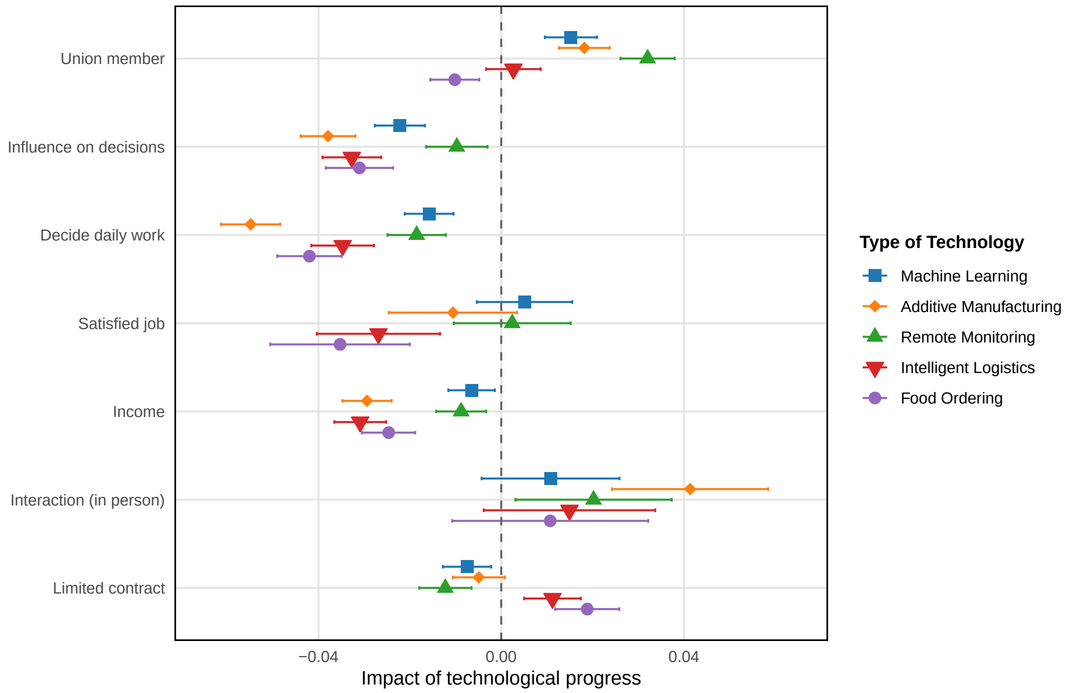
Note: The figure reports the estimated effects of different forms of technological exposure on union membership. The models control for gender, education, age, and firm size, and include fixed effects for region, industry, and country-year. Standard errors are clustered by country-year-occupation. Coefficients are shown with 95% confidence intervals.

technologies is associated with a shift toward more left-leaning positions on the ideological scale and with stronger support for redistribution, except in the case of intelligent logistics and food-ordering technologies. These patterns are consistent with higher demands for compensation among affected workers.

At the same time, technological exposure is also linked to political alienation. Self-reported turnout declines, particularly for embedded systems, intelligent logistics, and food-ordering technologies, while interest in politics falls across technology types, consistent with the alienation pattern documented by Gonzalez-Rostani 2024. Satisfaction with democracy also declines for nearly all exposures. Together, these findings point to a complex political response: technological change can simultaneously increase demands for protection and weaken democratic engagement.

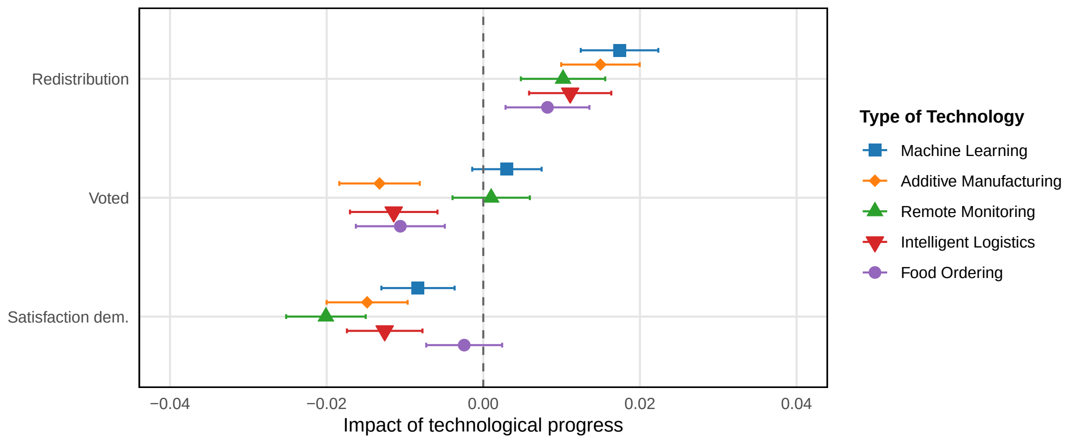
When technological change reduces workers control without generating effective collective organization, its effects extend beyond the workplace. In those settings, grievances appear less likely to be channeled through collective voice and more likely to spill over into broader disengagement from political and democratic institutions. This combination of material demands and democratic alienation is also consistent with prior evidence linking technological disruption to populist backlash (Anelli, Colantone, and Stanig 2021; Gonzalez-Rostani 2026; Kurer 2020).

Figure A.5: Effect of technological advance on working conditions across technology types



Note: The figure reports the estimated effects of different forms of technological exposure on multiple outcomes: union membership, influence on policy decisions within the organization, autonomy over daily work organization, job satisfaction, income decile, frequency of interaction with coworkers (in person), and having a limited-time contract. All outcomes and exposure measures are standardized to a normal distribution to allow comparability. The models control for gender, education, age, and firm size, and include fixed effects for region, industry, and country-year. Standard errors are clustered by country-year-occupation. Coefficients are shown with 95% confidence intervals.

Figure A.6: Effect of technological advance on political outcomes across technology types.



Note: The figure reports the estimated effects of different forms of technological exposure on political outcomes: support for redistribution, having voted in the last election and satisfaction with how democracy works. All outcomes and exposure measures are standardized to a normal distribution to allow comparability. The models control for gender, education, age, and firm size, and include fixed effects for region, industry, and country-year. Standard errors are clustered by country-year-occupation. Coefficients are shown with 95% confidence intervals.

A.5 Canadian Labor Relations and Technological Change Background

A.5.1 Collective Bargaining Structure in Canada

Canadian collective bargaining is characterized by a decentralized, enterprise-level system of industrial relations. The majority of labor relations fall under provincial jurisdiction, with each province (and territory) administering its own labor relations legislation and board. In practice, this means rules and procedures can vary across Canadas sub-national units, although all adhere to the general Wagner Act model of union recognition and collective bargaining rights. Bargaining typically occurs at the level of the individual employer or bargaining unit, rather than through national or sector-wide agreements. Unlike many European countries, Canada has no legal provision for extending a single collective agreement to an entire industry, and multi-employer or sectoral contracts are the exception rather than the norm. One consequence of this structure is that outcomes and union strategies may differ by sector and region, making Canada an insightful laboratory of diverse industrial relations practices within one country.

A.5.2 Union Density and Coverage Rates

Canadas unionization rate is relatively high for a developed economy without national-level bargaining, though it has declined from its peak in the 1980s. As of 2023, just over 30% of Canadian employees (approximately 5.3 million workers) were covered by a collective agreement.[27] This overall coverage rate has fallen from about 37% in 1981 to 30.4% in 2023, reflecting changes in the economy and labor laws over time. Crucially, union density in Canada is highly bifurcated by sector. The public sector is heavily unionized, with around 76-77% of public-sector employees covered by collective agreements, a rate nearly five times that of the private sector. In contrast, the private-sector union coverage has dropped to roughly 15.5% in recent years. This gap has widened over time: private unionization declined sharply after the 1990s (e.g. manufacturing unions suffered losses due to industrial restructuring), even as public-sector unions maintained or grew their presence.

A.5.3 Recent Developments in AI and Digital Technologies in Canadian Workplaces

In recent years, Canada has experienced a rapid uptick in the adoption of AI and digital technologies across industries, prompting responses from policymakers and labor organizations. According to the latest Statistics Canada data, AI use by businesses has been growing quickly. In the second quarter of 2025, about 12.2% of Canadian businesses reported using AI in their operations (for producing goods or delivering services), double the share that had adopted AI just one year earlier (6.1% in Q2 2024).[28] These applications range from data analytics and chatbots to machine-learning-driven process automation. Certain sectors are leading the way: information and cultural industries, professional and technical services, and finance have the highest AI uptake, whereas industries like agriculture and hospitality report minimal AI use so far. Parallel research has estimated that three in five Canadian workers are employed in occupations with a high potential exposure to AI technologies, underscoring the broad relevance of AI to the workforce.

27. https://www.statcan.gc.ca/o1/en/plus/7416-state-unions-canada.
28. https://www150.statcan.gc.ca/n1/pub/11-621-m/11-621-m2025008-eng.htm.

Table A.10: Use of AI among businesses in producing goods or delivering services over the last 12 months, second quarter of 2024 and 2025

	2nd quarter of 2025	**2nd quarter of 2024**
AI used in producing goods or delivering services	12.2	6.1
Text analytics using AI	35.7	27.0
Data analytics using AI	26.4	25.0
Virtual agents or chat bots	24.8	26.5
Natural language processing	23.1	28.9
Marketing automation using AI	23.1	15.2
Speech or voice recognition using AI	20.0	18.1
Large language models	19.1	21.9
Machine learning	18.6	20.1
Recommendation systems using AI	14.0	12.3
Image or pattern recognition	11.4	21.8
Deep learning	6.6	1.9
Decision making systems based on AI	5.7	6.1
Robotics process automation	3.8	2.6
Augmented reality	3.2	2.6
Biometrics	3.2	1.0
Machine or computer vision	3.1	4.7
Neural networks	2.5	4.4
Other type	6.1	6.7

Notes: The results in this table are based on the survey that was in collection from April 1 to May 5, 2025, and from April 2 to May 6, 2024. Respondents were asked what the business or organization experienced in the last 12-month period. As a result, those 12 months could range from April 1, 2024, to May 5, 2025, and from April 2, 2023, to May 6, 2024, depending on when the business responded.
Source: Canadian Survey on Business Conditions, second quarter of 2025 (Table 33-10-1004-01) and second quarter of 2024 (Table 33-10-0825-01).

Against this backdrop, unions and labor stakeholders in Canada have become increasingly engaged with the implications of AI and digitalization. Major unions have started to proactively address AI in collective bargaining and policy forums. For example, the Canadian Union of Public Employees (CUPE), Canadas largest public-sector union, released guidance in 2025 for bargaining strong collective agreements for the digital age.[29] This guide emphasizes that there is no single AI clause - instead, unions must review and update many parts of their agreements to meet the challenges of AI. It outlines how contract provisions can ensure consultation and negotiation before new tech is introduced, protect workers data and privacy, guard against discriminatory or unsafe technology, and secure jobs and wages as work is transformed. Likewise, Unifor (the countrys largest private-sector union) has highlighted its efforts in bargaining over new technology.[30] Unifor reports that it has negotiated contract language to give workers a say in technology implementation - guaranteeing advance notice of automation, the right for workers to participate in deploying new systems, and just transition supports for those displaced. These negotiated provisions aim to ensure that technological changes are made with workers rather than to workers, reflecting a strategy of adaptation and influence instead of resistance. Canadian union federations and professional associations are also weighing in. The Canadian Labour Congress (CLC) and various sectoral unions have been advocating for a national strategy on AI that includes worker protections. For instance, unions in knowledge-based sectors (like university faculty associations under CAUT, or federal public service professionals under PIPSC)

29. https://cupe.ca/sites/default/files/bargaining_ca_digital_age_en.pdf.
30. https://www.unifor.org/sites/default/files/legacy/documents/document/1173-future_of_work_eng_no_bleed.pdf.

have called for frameworks to manage AIs effects on jobs, emphasizing retraining and skills development, ethical use of AI, and job protection as key priorities.[31]

On the policy side, the Canadian government and research institutes have begun addressing the future of work in the AI era. Federal initiatives, like the Future Skills Centre,[32] have funded research on AI-related skill needs, and think tanks have proposed strategies for inclusive AI adoption. A notable theme in recent policy discourse is the call for worker engagement in AI rollout. Analysts argue that Canada should avoid a purely technocratic implementation of AI and instead involve employees and their unions in designing how AI is integrated into workplaces. A Macdonald-Laurier Institute report (2023)[33] echoes a Brookings Institution finding that enhancing worker voice through unions or other means during AI adoption leads to better outcomes, ensuring that productivity gains translate into shared benefits:

> Policy should encourage companies to bring workers (and their unions, where applicable) into the AI design and implementation process. This could be achieved through formal structures - for example, work councils or joint management-labour committees focused on technology - or through requirements for consultation when government funding is involved.

For example, recent collective bargaining in sectors like warehousing and transportation has touched on algorithmic scheduling and monitoring - unions have pushed back against unilateral use of AI-driven performance management tools, citing privacy and fairness concerns. In 2023, a high-profile strike in the federal public service (PSAC strike) prominently featured remote work and the handling of new digital work arrangements as key issues, illustrating how technology is becoming a core subject of labor relations.

A.6 Data CBAs

31. https://www.caut.ca/bulletin/commentary-is-your-union-strategizing-about-ai-and-automation/.
32. https://fsc-ccf.ca/wp-content/uploads/2025/09/canadas-workforce-in-transition_sept2025.pdf.
33. https://macdonaldlaurier.ca/unleashing-ai-canadas-blueprint-for-productivity-innovation-and-workforce-integration/.

Table A.11: Total Count for CBAs by NAICS2 (1993–2025)

NAICS-2 Digit	**Count**
11	141
21	484
22	687
23	1,845
33	7,191
41	423
45	821
48	7,174
51	2,125
52	295
53	50
54	367
56	630
61	7,296
62	5,117
71	456
72	741
81	208
91	4,721
Total	**40,742**

A.6.1 Descriptives CBAs

Figure A.7 plots the monthly count of agreements. The series declines over time. Counts are high in the mid-1990s (several months above 500), trend downward through the 2000s and 2010s, and fall below 100 per month by the late 2010s, with low flows in 2024-2025. Much of the decline occurs in manufacturing (NAICS 31-33). Because contract length and bargaining-unit consolidation can change, we interpret the series as agreement *flow* in our corpus, not as coverage or bargaining intensity.

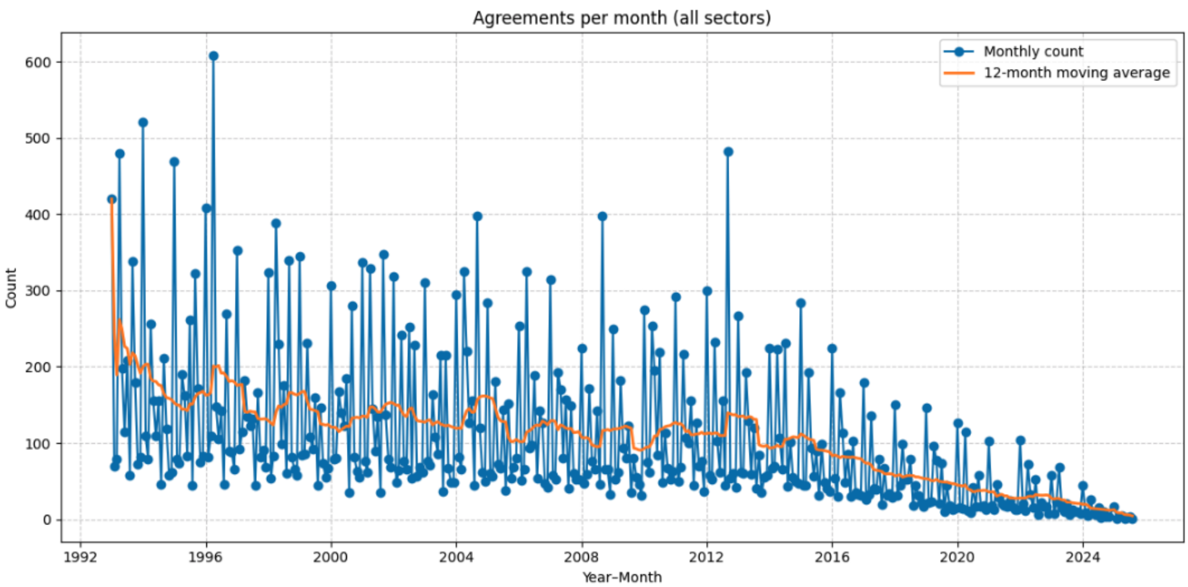


Figure A.7: Monthly Canadian collective bargaining agreements, 1993–2025

Table A.12: Total # of Unique Elements:

metric	value
CBA	40772
Employers	9611
Unions	597
Industries 6 digits	673
Jurisdictions	21
Location	854
Years	33

Figure A.8: Number of CBA by Industry

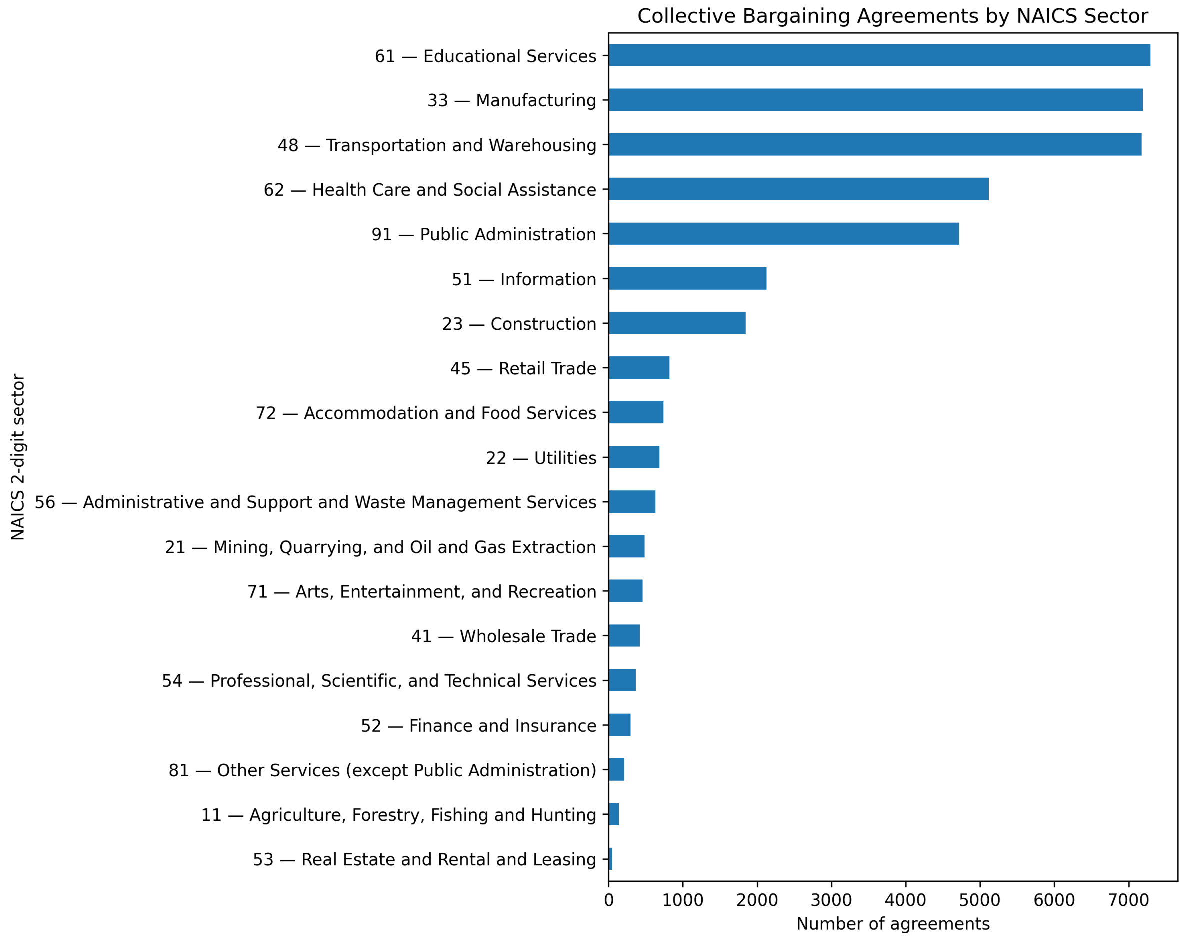


Figure A.9: Number of CBA by Jurisdiction

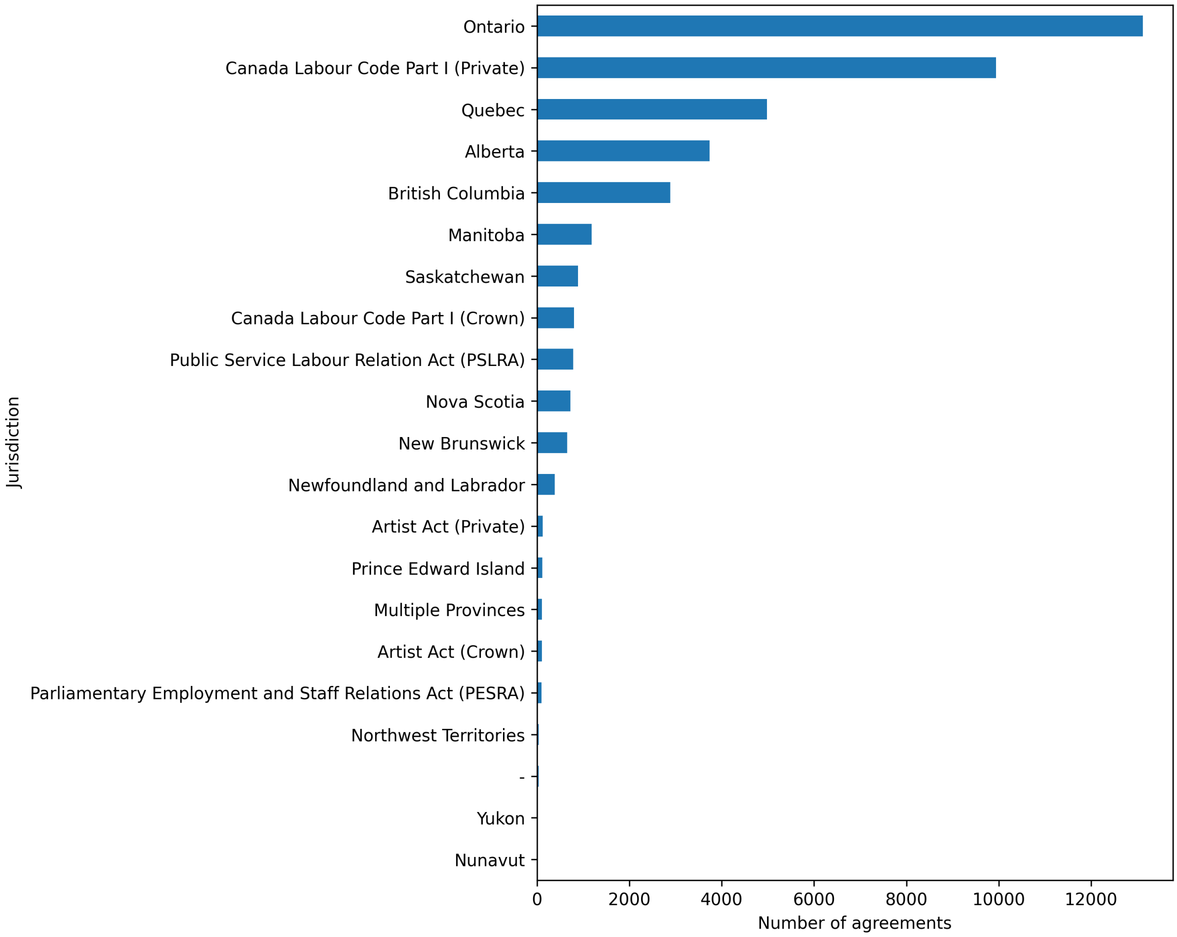
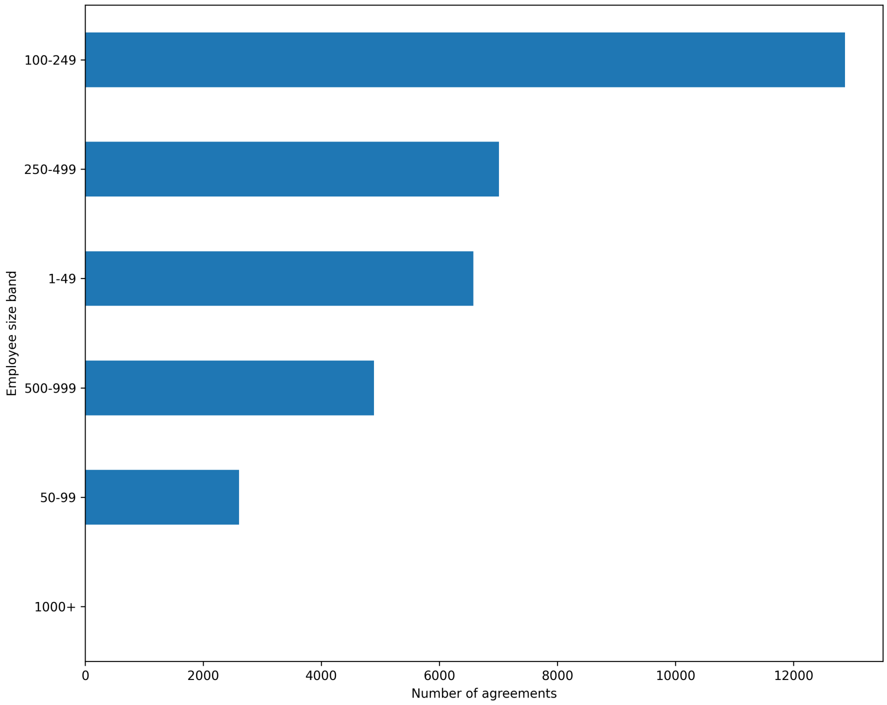


Figure A.10: Number of CBA by Employer Size



A.7 Measuring Topics in CBAs

The dependent variables used in the analysis are constructed with a dictionary-based text-as-data approach. For each agreement, the text is lowercased, tokenized, and English and French stopwords are removed. For each provision category, we define a bilingual dictionary consisting of single-word and ordered multi-word expressions. For a given contract and category, the dictionary count is the number of occurrences of any of these expressions in the text (multi-word expressions must appear in the specified order). The final measure is a share: the dictionary count divided by the total number of non-stop words in the agreement. In the main text we report results for the following provision categories; below we list the English components of each dictionary (parallel French terms are also included in the implementation but omitted here for brevity).

Health Safety Wellbeing *work intensification*, *workload*, *psychosocial risks*, *mental health*, *right disconnect*, *remote work*, *privacy*, *working conditions*, *conditions of work*, *hours*, *shift*, *overtime*, *night shift*, *telework*, *hybrid*, *flexible schedule*, *breaks*, *rest period*, *paid break*, *heat stress*, *cold exposure*, *noise*, *vibration*, *dust*, *fumes*, *chemical exposure*, *ppe*, *personal protective equipment*, *hearing protection*, *respirator*, *gloves*, *safety boots*, *ergonomic*, *musculoskeletal*, *repetitive motion*, *manual handling*, *lifting*, *conveyor*, *assembly line*, *line speed*, *machine guarding*, *lockout tagout*, *loto*, *safeguard*, *incident reporting*, *near miss*, *first aid*, *joint health and safety committee*, *jhsc*.

Training & Retraining *training*, *retraining*, *upskilling*, *reskilling*, *instruction*, *orientation*, *education*, *no loss pay*, *during working hours*, *at employer expense*, *training plan*, *onboarding*, *apprenticeship*, *journeyperson*, *red seal*, *trade certification*, *ticket*, *license*, *licence*, *skills*, *competence*, *competency*, *competencies*, *skill upgrade*, *professional development*, *in-house training*, *on the job training*, *ojt*, *safety training*, *lockout training*, *forklift training*, *first aid training*, *whmis*, *hazcom*, *standard operating procedure*, *sop*, *work instruction*.

Notice Content Requirements *notice state nature change*, *effective date change*, *anticipated impacts*, *employees affected*, *classifications affected*, *locations affected*, *training plan*, *timelines*, *mitigation measures.*

Joint Committee *union management committee*, *joint committee*, *technological change committee*, *bilateral committee.*

Rights Active *receive*, *gain*, *earn.*

Rights Passive *entitle*, *give*, *offer*, *reimburse*, *pay*, *grant*, *provide*, *compensate*, *guarantee*, *hire*, *train*, *supply*, *protect*, *allow*, *cover*, *inform*, *notify*, *select*, *award.*

Working Conditions Protection *no reduction pay*, *no loss wages*, *no reduction hours*, *no loss benefits*, *classification protection*, *wage protection*, *maintain employment status.*

Remedies Mitigation *mitigation measures*, *transition plan*, *adjustment plan*, *impact review*, *employment security plan*, *job security plan*, *avoid layoff*, *minimize adverse effects*, *placement services.*

Union Notice *advance notice*, *written notice*, *notice union*, *effective date*, *number employees affected*, *classifications affected.*

Displacement Rights Bumping *displacement*, *bumping*, *redeployment*, *seniority rights*, *layoff avoidance*, *surplus employee.*

Exceptions Limits *de minimis changes*, *minor modifications*, *routine maintenance*, *like for like replacement*, *pilot project*, *trial basis*, *emergency change.*

Agent Union *union*, *unions*, *representative*, *representatives*, *steward*, *stewards*, *local.*

Agent Worker *employee*, *employees*, *worker*, *workers*, *nurse*, *nurses*, *teacher*, *teachers*, *member*, *members*, *operator*, *operators*, *driver*, *drivers*, *mechanic*, *mechanics*, *clerk*, *clerks*, *labourer*, *laborer*, *labourers*, *laborers*, *steward*, *stewards.*

Agent Firm *employer*, *employers*, *company*, *companies*, *board*, *management*, *firm*, *firms.*

Retirement Allowance *early retirement*, *retirement allowance*, *voluntary retirement*, *severance pay*, *bridging retirement.*

In all cases, the dependent variable measures reported in the paper are defined as the share of non-stop words in the agreement that belong to the corresponding dictionary.

Table A.13: Descriptive Statistics of Collective Bargaining Agreement Topics

Topics	mean	sd	min	max
Health Safety Wellbeing	0.010	0.007	0.000	0.075
Training & Retraining	0.005	0.003	0.000	0.062
Notice Content Requirements	0.002	0.001	0.000	0.015
Joint Committee	0.001	0.001	0.000	0.018
Rights Active	0.001	0.001	0.000	0.019
Rights Passive	0.009	0.006	0.000	0.065
Working Conditions Protection	0.001	0.001	0.000	0.029
Remedies Mitigation	0.001	0.001	0.000	0.013
Union Notice	0.004	0.003	0.000	0.022
Displacement Rights Bumping	0.001	0.001	0.000	0.009
Exceptions Limits	0.000	0.000	0.000	0.004
Agent Union	0.010	0.011	0.000	0.182
Agent Worker	0.029	0.018	0.000	0.154
Agent Firm	0.013	0.010	0.000	0.100
Retirement Allowance	0.001	0.001	0.000	0.017

A.8 Measuring Exposure to AI

A.8.1 Definition

Unit of observation A unique *industry-occupation* pair.

Output schema (one CSV row; 15 fields, exact order)

```
Industry,Occupation,E0,E1,E2,E3,AI_capability,AI_capability_certainty,
Replacement,Replacement_certainty,Augmentation,Augmentation_certainty,
Monitoring,Monitoring_certainty,Rationale
```

Meaning of fields

- `Industry`, `Occupation`: strings containing codes and labels.
- `E0`–`E3`: binary flags (0/1). These are not mutually exclusive. Mark 1 if a non-trivial share of core tasks fits the category; else 0.
  - `E0`: no exposure to LLMs.
  - `E1`: direct exposure; an LLM alone can reduce task time by ≥50% with no quality loss.
  - `E2`: exposure via LLM-powered software; ≥50% time saving when software is added on top of an LLM.
  - `E3`: exposure with image capabilities; ≥50% time saving when an LLM is paired with systems that read/create/interpret images.
- `AI_capability`, `Replacement`, `Augmentation`, `Monitoring`: 1–10 scores.
- `AI_capability_certainty`, `Replacement_certainty`, `Augmentation_certainty`, `Monitoring_certain`
  1–10 certainties aligned to each score.
- `Rationale`: short free-text justification (1–2 sentences). *Do not use commas; use semi-colons.*

Derived components (certainty-weighted) Let s_j be the 1–10 score and c_j the 1–10 certainty for $j \in \{\text{Aug}, \text{Mon}, \text{Cap}, \text{Rep}\}$. Define:

$$\text{augmentation\_ex} = s_{\text{Aug}} \cdot \frac{c_{\text{Aug}}}{10}, \quad \text{monitoring\_ex} = s_{\text{Mon}} \cdot \frac{c_{\text{Mon}}}{10},$$
$$\text{ai\_capability\_ex} = s_{\text{Cap}} \cdot \frac{c_{\text{Cap}}}{10}, \quad \text{replacement\_ex} = s_{\text{Rep}} \cdot \frac{c_{\text{Rep}}}{10}.$$

Indices

$$\text{ai\_exposure\_index} = \text{mean}\,\{\text{augmentation\_ex, monitoring\_ex, ai\_capability\_ex, replacement\_ex}\}$$

$$\text{ai\_exposure\_negative} = \text{mean}\,\{\text{monitoring\_ex, ai\_capability\_ex, replacement\_ex}\}$$

For the category flags, apply weights $\texttt{E1} = 1$, $\texttt{E2} = 0.5$, $\texttt{E0} = 0$, $\texttt{E3} = 0$:

$$\text{E\_exposure\_index} = 1 \cdot E1 + 0.5 \cdot E2 + 0 \cdot E0 + 0 \cdot E3.$$

Normalize when any flag is 1:

$$\text{E\_exposure\_index\_0\_1} = \frac{\text{E\_exposure\_index}}{E0 + E1 + E2 + E3}, \qquad \text{E\_exposure\_index\_0\_10} = 10 \cdot \text{E\_exposure\_index\_0\_}$$

For sensitivity, keep raw (unweighted-by-certainty) versions:
`ai_exposure_index_raw`, `ai_exposure_negative_raw`.

A.8.2 Implementation

Data inputs De-duplicated industry-occupation pairs; optional admin records to enrich with scores.

OpenAI model and call Model: `gpt-4o-mini`. Low temperature (0.1) to reduce variance. Keys are read from the environment.

```
from openai import OpenAI
import os
client = OpenAI(api_key=os.environ["OPENAI_API_KEY"])

resp = client.responses.create(
    model="gpt-4o-mini",
    input=prompt_string,
    temperature=0
)
text = resp.output_text
```

Prompt (exact string from the notebook) The scoring prompt was stored as `FEW_SHOT_PROMPT`. Below is the verbatim content (ellipses appear in the notebook examples):

```
You are an expert in labor economics and AI task analysis.
I will give you an industry (NAICS code + description) and an occupation
(NOC code + description).

Task:
1) Classify the core tasks into exposure categories. Indicate each category with 0/1:
   - E0: No exposure to LLMs.
```

```
   - E1: Direct exposure to LLMs; an LLM alone can reduce task time by 50% without
   quality loss.
   - E2: Exposure via LLM-powered applications; cuts time by 50% when software
   is added on top of an LLM.
   - E3: Exposure with image capabilities; cuts time by 50% whe... LLM is
   combined with systems that read/create/interpret images.
   Rule for 1 vs 0: mark 1 if a non-trivial portion of core tasks falls in that
   category; else 0. Never leave blanks.

2) Provide four 1-10 scores + a 1-10 certainty for each:
   - AI_capability (automation potential)
   - Replacement (displacement likelihood)
   - Augmentation (complementarity likelihood)
...

Output:
722511 - Full-service restaurants,65200 - Food and beverage serv...
and POS enable monitoring; Replacement low; Augmentation modest

Input:
Industry: 622110 - General medical and surgical hospitals
Occupation: 31301 - Registered nurses

Output:
622110 - General medical and surgical hospitals,31301 - Register...
Replacement low; Augmentation high; Monitoring very high via EHR

--- End of examples ---

Now produce one CSV row for the following pair.
```

Output hygiene and validation

1. Sanitize to a single line: strip code fences/backticks, collapse newlines.
2. Enforce 15 fields: if extra commas appear, overflow text is glued into `Rationale`.
3. Coerce `E0`–`E3` to {0,1}, accepting variants like `true`/`True` as 1.
4. Replace any commas in `Rationale` with semicolons so the CSV stays parseable.
5. Retry on transient errors up to 5 times with exponential backoff and small jitter.

Two-pass match back to the user data

1. *Exact code join*: extract numeric prefixes via regex, e.g., `industry_code = ^(\d+)`, `occupation_code = ^(\d+)`. Join on the code pair.
2. *Fuzzy rescue*: build `pair_text = Industry || Occupation`. Use RapidFuzz `token_set_ratio` and accept only if similarity ≥ 80. Record `match_type` $\in$ {`perfect_code`, `imperfect_pair`, `unmatched`} and `match_score`.

Feature engineering

- Cast `E0`–`E3` to numeric.

- Compute certainty-weighted components and indices defined in Section A1.
- Keep raw counterparts for sensitivity checks.
- Optional roll-ups: derive `naics2` from the first two digits of `industry_code` and summarize by sector.

Reproducibility and security Fix seeds when sampling; keep `temperature=0.1`; save the exact prompt used; avoid hard-coded keys; version the prompt, scored CSV, and post-processing scripts; pin library versions (`pandas`, `rapidfuzz`, `openai`).

Practical interpretation `ai_exposure_index` blends capability, replacement risk, augmentation, and monitoring, each scaled by certainty. `ai_exposure_negative` removes augmentation for a risk-tilted view. `E_*` indices summarize the binary exposure flags.

Variable map (as used in code)

- Inputs: `Industry`, `Occupation`
- Flags: `E0`, `E1`, `E2`, `E3`
- Scores: `AI_capability`, `Replacement`, `Augmentation`, `Monitoring`
- Certainties: `AI_capability_certainty`, `Replacement_certainty`, `Augmentation_certainty`, `Monitoring_certainty`
- Weighted components: `ai_capability_ex`, `replacement_ex`, `augmentation_ex`, `monitoring_ex`
- Indices: `ai_exposure_index`, `ai_exposure_index_raw`,

  `ai_exposure_negative`, `ai_exposure_negative_raw`, `E_exposure_index`, `E_exposure_index_0_1`, `E_exposure_index_0_10`

A.8.3 Descriptives Measuring AI exposure

In this section you will find descriptives about our main measure of exposure to AI and LLM.

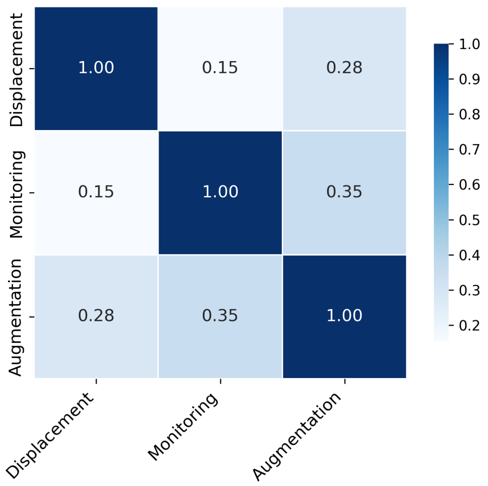
- Figure A.11 displays the pairwise correlations among the three AIexposure measures used in the analysis: displacement, monitoring, and augmentation. The matrix shows that the measures are positively related but not strongly collinear, indicating that each captures a distinct dimension of AI-related task transformation. Displacement correlates moderately with augmentation and weakly with monitoring, while monitoring and augmentation show a slightly stronger association. These patterns support treating the three indices as complementary rather than interchangeable measures of AI exposure in collective bargaining agreements.

- Figure A.12 shows the distribution of the three AI-exposure measures across all collective bargaining agreements in the dataset. Displacement exposure is concentrated at relatively low values, reflecting limited substitutability of human labor for most covered occupations. In contrast, monitoring and augmentation exhibit wider variation, with clear clusters at moderate and higher levels of exposure. These distributions highlight meaningful heterogeneity across agreements and sectors, underscoring that different AI-related task transformations vary in relevance and intensity across occupations.

- Figure A.13 reports average exposure levels by NAICS 2-digit industry for the three AI-related measures. Displacement exposure varies comparatively little across sectors, with most industries clustered at low to moderate values. Monitoring and augmentation show wider dispersion, with professional services, finance, transportation, and information exhibiting some of the highest levels, while sectors such as agriculture, mining, and administrative support show lower exposure. These patterns indicate that the relevance of different AI task transformations is uneven across industries, reflecting variation in occupational mixes and workplace processes.

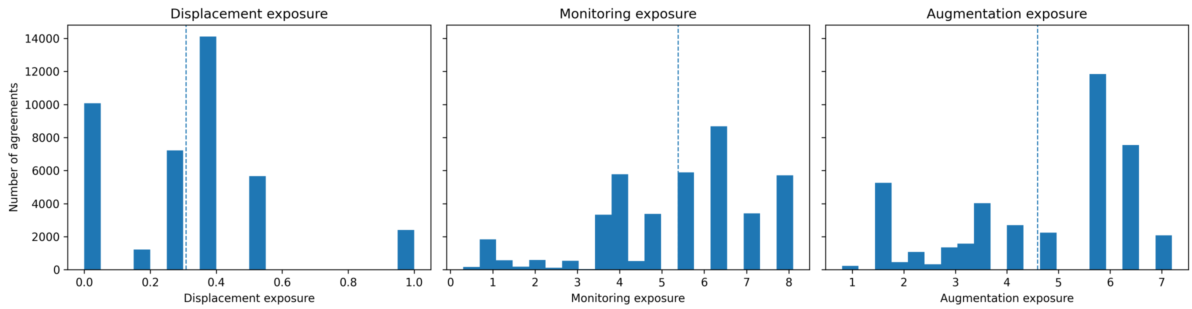
- Tables A.13 to A.17 summarize patterns of AI exposure across major dimensions of the collective bargaining agreement dataset. Table A.17 reports average exposure scores for agreements signed by the twenty largest unions, showing substantial variation in displacement, monitoring, and augmentation across organizations. Table A.16 presents average exposure by jurisdiction, reflecting differences across states and federal categories. Table A.14 shows exposure levels by NAICS sector, while Table A.15 breaks out the same measures by employer size. Together, these tables highlight meaningful heterogeneity in AI-related task exposure across unions, industries, jurisdictions, and firm sizes, underscoring the diverse contexts in which collective bargaining agreements operate.

Figure A.11: Correlation Matrix of Exposure Measures in CBA using LLMs



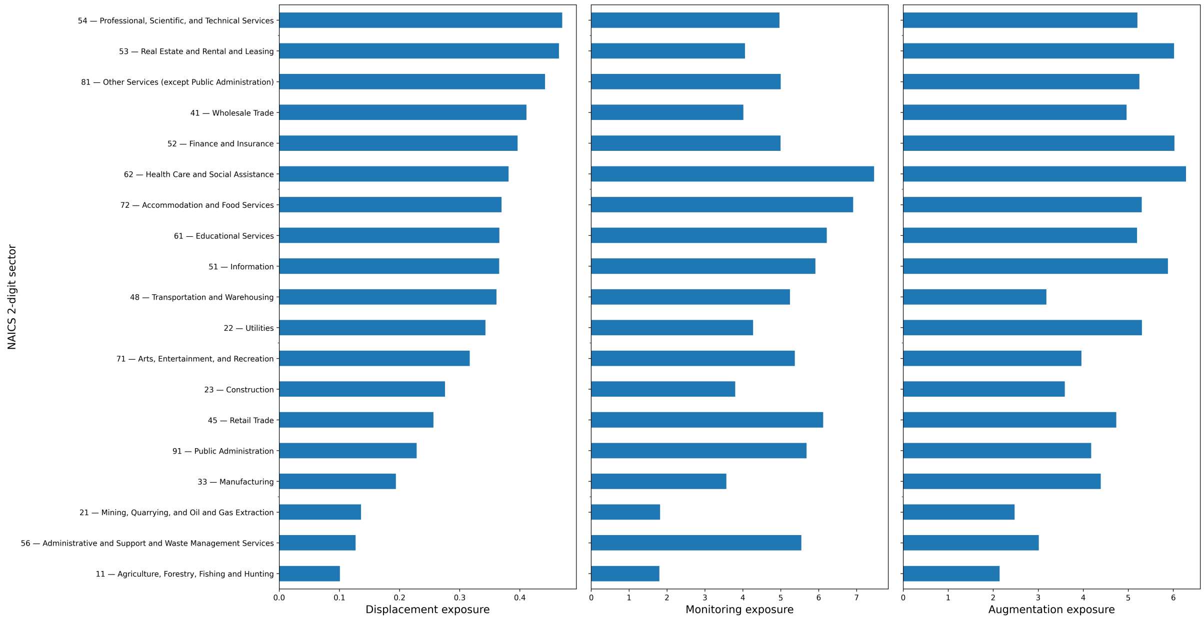
Note: The displacement measures range from 0 to 1. Monitoring and augmentation range from 0 to 10. Higher values indicate stronger exposure of the occupation to each type of AI-related task transformation. Displacement reflects the extent to which AI can substitute for human labor; monitoring captures the potential for AI to oversee or evaluate tasks; and augmentation measures how much AI can enhance worker productivity. These scores were estimated using LLMs. Employee counts represent the average firm size in each sector.

Figure A.12: Frequency of Exposure in CBA



Note: The displacement measures range from 0 to 1. Monitoring and augmentation range from 0 to 10. Higher values indicate stronger exposure of the occupation to each type of AI-related task transformation. Displacement reflects the extent to which AI can substitute for human labor; monitoring captures the potential for AI to oversee or evaluate tasks; and augmentation measures how much AI can enhance worker productivity. These scores were estimated using LLMs. Employee counts represent the average firm size in each sector.

Figure A.13: Frequency of Exposure in CBA by Industry



Note: The displacement measures range from 0 to 1. Monitoring and augmentation range from 0 to 10. Higher values indicate stronger exposure of the occupation to each type of AI-related task transformation. Displacement reflects the extent to which AI can substitute for human labor; monitoring captures the potential for AI to oversee or evaluate tasks; and augmentation measures how much AI can enhance worker productivity. These scores were estimated using LLMs. Employee counts represent the average firm size in each sector.

Table A.14: Collective Bargaining Agreements by NAICS Sector

Industry	NAICS	CBAs	Share (%)	Displacement av	Displacement sd	Monitoring av	Monitoring sd	Augmentation av	Augmentation sd	Employees av	Employees sd
Educational Services	61	7296	17.9	0.37	0.13	6.21	1.46	5.2	1.39	362.87	237.21
Manufacturing	33	7191	17.6	0.19	0.18	3.57	1.6	4.39	1.64	244.85	186.47
Transportation and Warehousing	48	7174	17.6	0.36	0.37	5.24	1.69	3.18	1.79	106.11	159.13
Health Care and Social Assistance	62	5117	12.6	0.38	0.06	7.46	1.01	6.29	0.93	259.25	200.01
Public Administration	91	4721	11.6	0.23	0.25	5.68	0.93	4.18	1.44	243.71	230.76
Information	51	2125	5.2	0.37	0.09	5.91	1.47	5.88	0.83	146.75	184.76
Construction	23	1845	4.5	0.28	0.39	3.8	1.91	3.59	1.15	328.13	239.31
Retail Trade	45	821	2	0.26	0.14	6.12	0.87	4.74	0.84	300.64	244.17
Accommodation and Food Services	72	741	1.8	0.37	0.08	6.91	0.72	5.3	0.85	272.79	181.6
Utilities	22	687	1.7	0.34	0.19	4.27	0.94	5.3	1.18	371.06	264.47
Administrative and Support and Waste Management Services	56	630	1.5	0.13	0.23	5.54	1.5	3.01	1.66	184.12	213.8
Mining, Quarrying, and Oil and Gas Extraction	21	484	1.2	0.14	0.29	1.82	1.6	2.48	1.48	312.99	226.9
Arts, Entertainment, and Recreation	71	456	1.1	0.32	0.24	5.37	1.14	3.96	1.38	229.14	207.04
Wholesale Trade	41	423	1	0.41	0.2	4.02	1.35	4.96	1.55	210.24	192.59
Professional, Scientific, and Technical Services	54	367	0.9	0.47	0.23	4.97	1.02	5.2	1.81	205.8	202.27
Finance and Insurance	52	295	0.7	0.4	0.09	5	1.15	6.03	0.69	187.37	229.12
Other Services (except Public Administration)	81	208	0.5	0.44	0.22	5	0.88	5.25	1.3	214.39	170.21
Agriculture, Forestry, Fishing and Hunting	11	141	0.3	0.1	0.24	1.8	2	2.15	1.57	156.62	146.6
Real Estate and Rental and Leasing	53	50	0.1	0.47	0.22	4.06	0.48	6.02	0.89	218.52	269.84

Note: The displacement measures range from 0 to 1. Monitoring and augmentation range from 0 to 10. Higher values indicate stronger exposure of the occupation to each type of AI-related task transformation. Displacement reflects the extent to which AI can substitute for human labor; monitoring captures the potential for AI to oversee or evaluate tasks; and augmentation measures how much AI can enhance worker productivity. These scores were estimated using LLMs. Employee counts represent the average firm size in each sector.

Table A.15: Collective Bargaining Agreements by Employer Size

Size band	CBAs	Share (%)	Displacement av	Displacement sd	Monitoring av	Monitoring sd	Augmentation av	Augmentation sd	Employees av	Employees sd
1-49	6574	16.1	0.335	0.303	5.148	1.767	4.015	1.86	20.275	12.763
50-99	2605	6.4	0.33	0.331	5.336	1.782	3.878	1.917	69.672	14.201
100-249	12870	31.6	0.282	0.229	5.243	1.946	4.551	1.652	157.511	41.8
250-499	7011	17.2	0.293	0.221	5.276	1.978	4.647	1.66	344.627	70.554
500-999	4894	12	0.307	0.223	5.295	1.882	4.71	1.648	683.357	137.421

Note: The displacement measures range from 0 to 1. Monitoring and augmentation range from 0 to 10. Higher values indicate stronger exposure of the occupation to each type of AI-related task transformation. Displacement reflects the extent to which AI can substitute for human labor; monitoring captures the potential for AI to oversee or evaluate tasks; and augmentation measures how much AI can enhance worker productivity. These scores were estimated using LLMs. Employee counts represent the average firm size in each sector.

Table A.16: Collective Bargaining Agreements by Jurisdiction

Jurisdiction	CBAs	Share (%)	Displacement av	Displacement sd	Monitoring av	Monitoring sd	Augmentation av	Augmentation sd	Employees av	Employees sd
-	38	0.1	0.359	0.24	5.584	1.527	4.842	1.945	384.111	319.063
Alberta	3740	9.2	0.334	0.242	5.543	2.063	4.793	1.526	298.485	211.209
Artist Act (Crown)	109	0.3	0.369	0.122	6.15	1.381	5.77	1.181	74.5	13.472
Artist Act (Private)	127	0.3	0.418	0.144	5.637	1.333	5.429	1.205	256	214.745
British Columbia	2887	7.1	0.272	0.235	5.096	1.792	4.405	1.635	327.854	218.511
Canada Labour Code Part I (Crown)	804	2	0.312	0.211	5.029	1.526	4.415	1.654	157.545	205.393
Canada Labour Code Part I (Private)	9945	24.4	0.323	0.32	5.258	1.79	3.83	1.931	86.049	137.887
Manitoba	1186	2.9	0.345	0.226	5.93	1.932	4.97	1.442	331.057	241.657
Multiple Provinces	109	0.3	0.327	0.341	4.558	1.904	3.969	1.755	299.967	232.409
New Brunswick	654	1.6	0.229	0.237	4.493	2.223	4.163	1.69	302.158	203.523
Newfoundland and Labrador	387	0.9	0.269	0.191	4.976	2.227	4.484	1.818	346.786	244.616
Northwest Territories	39	0.1	0.343	0.2	5.708	2.617	5.044	1.671	242.704	210.81
Nova Scotia	721	1.8	0.306	0.217	5.423	2.157	4.762	1.633	362.25	239.602
Nunavut	18	0	0.667	0.243	5.3	2.173	4.433	1.698	419.417	265.957
Ontario	13116	32.2	0.294	0.188	5.749	1.944	5.021	1.686	306.518	218.798
Parliamentary Employment and Staff Relations Act (PESRA)	100	0.2	0.291	0.198	5.377	1.206	5.266	1.209	111.46	93.219
Prince Edward Island	116	0.3	0.317	0.141	6.715	1.5	5.116	1.461	434.013	272.235
Public Service Labour Relation Act (PSLRA)	784	1.9	0.534	0.277	5.191	1.08	5.326	1.425	199.968	225.928
Quebec	4978	12.2	0.278	0.2	4.678	1.823	4.717	1.584	274.081	203.534
Saskatchewan	892	2.2	0.325	0.223	5.998	2.06	4.738	1.581	326.858	225.079
Yukon	22	0.1	0.5	0	6.85	1.279	4.9	0.716	702.273	117.587

Note: The displacement measures range from 0 to 1. Monitoring and augmentation range from 0 to 10. Higher values indicate stronger exposure of the occupation to each type of AI-related task transformation. Displacement reflects the extent to which AI can substitute for human labor; monitoring captures the potential for AI to oversee or evaluate tasks; and augmentation measures how much AI can enhance worker productivity. These scores were estimated using LLMs. Employee counts represent the average firm size in each sector.

Table A.17: Collective Bargaining Agreements by Top 20 Unions

Union	CBAs	Share (%)	Displacement av	Displacement sd	Monitoring av	Monitoring sd	Augmentation av	Augmentation sd	Employees av	Employees sd
Unifor, Independent-national	958	2.3	0.301	0.259	5.103	1.978	4.394	1.871	215.4	219.471
Alberta Teachers' Association, Independent-national	632	1.6	0.5	0	8.084	0.198	5.595	0.063	321.619	178.921
Canadian Merchant Service Guild, Independent-national	448	1.1	0.735	0.279	3.625	1.582	3.686	1.139	40.924	114.726
Christian Labour Association of Canada, Independent-national	394	1	0.33	0.392	5.107	1.914	3.845	1.626	214.332	212.559
Alberta Union of Provincial Employees, Independent-national	356	0.9	0.381	0.148	5.844	1.607	5.444	1.366	297.622	211.669
Manitoba Teachers' Society, Independent-national	329	0.8	0.491	0.04	7.921	0.692	5.581	0.501	285.408	220.976
Saskatchewan Teachers' Federation, Independent-national	246	0.6	0.499	0.008	8.093	0.108	5.6	0	284.292	225.768
Ontario Secondary School Teachers' Federation, Independent-national	167	0.4	0.328	0.068	6.772	0.718	4.719	1.501	198.013	188.756
Association des enseignantes et des enseignants franco-ontariens, Independent-national	124	0.3	0.387	0.101	7.135	0.923	5.081	1.548	383.595	215.005
Federation of Women Teachers' Associations of Ontario, Independent-national	106	0.3	0.375	0	5.6	0	7.2	0	497.707	245.045
Nova Scotia Teachers Union, Independent-national	95	0.2	0.5	0	7.689	1.203	5.642	0.18	403.778	230.332
Ontario Public School Teachers' Federation, Independent-national	76	0.2	0.301	0.062	6.591	0.796	4.584	2.166	317.621	194.165
Ontario English Catholic Teachers' Association, Independent-national	69	0.2	0.408	0.079	6.865	1.047	5.78	1.236	318.661	218.014
Fédération des syndicats du secteur aluminium, Independent-national	65	0.2	0.323	0.174	4.754	1.778	4.403	1.678	249.035	197.873
Elementary Teachers' Federation of Ontario, Independent-national	59	0.1	0.32	0.063	6.305	0.801	5.261	2.203	446.389	204.453
Research Council Employees' Association, Independent-national	56	0.1	0.467	0.256	4.361	0.679	5.368	1.846	231.694	213.658
L'Association des employés de Malo Transport (1971) inc., Independent-local	43	0.1	0.116	0.126	3.609	2.15	3.74	1.649	229.051	171.581
Ontario Professional Fire Fighters Association, Independent-national	40	0.1	0.044	0.096	6.4	0	2.345	0.539	236.55	173.676
Toronto Police Association, Independent-local	40	0.1	0.412	0.058	5.89	1.191	5.6	0	323.846	358.297
Syndicat de professionnelles et professionnels du Gouvernement du Québec, Independent-national	32	0.1	0.355	0.072	4.625	0.773	5.45	1.675	354.143	222.024

Note: The displacement measures range from 0 to 1. Monitoring and augmentation range from 0 to 10. Higher values indicate stronger exposure of the occupation to each type of AI-related task transformation. Displacement reflects the extent to which AI can substitute for human labor; monitoring captures the potential for AI to oversee or evaluate tasks; and augmentation measures how much AI can enhance worker productivity. These scores were estimated using LLMs. Employee counts represent the average firm size in each sector.

A.8.4 Implementing AI Measure on ISCO 08

In addition to the industry–occupation measures described earlier, we extended the approach to the international ISCO-08 classification at the four-digit unit-group level. For each occupation, the model received the full ISCO entry exactly as published, including the ISCO level, the ISCO 08 code, the occupation title, definition, tasks (usually presented as a lettered list), examples of roles included in that unit group, and any accompanying notes. The model was instructed to use only that information to generate the same set of AI exposure indicators and certainty scores, following the exact instructions already described in the previous subsection.

To illustrate the type of input the model processed, consider the ISCO entry for *Legislators*, which includes structured information such as the code, definition, and detailed task list:

> Level 4, ISCO 08 Code 1111, Title Legislators, Definition: Legislators determine, formulate, and direct policies of national, state, regional or local governments and international governmental agencies, and make, ratify, amend or repeal laws, public rules and regulations. They include elected and non-elected members of parliaments, councils and governments., Tasks: Tasks include – (a) presiding over or participating in the proceedings of legislative bodies and administrative councils of national, state, regional or local governments or legislative assemblies; (b) determining, formulating and directing policies of national, state, regional or local governments; (c) making, ratifying, amending or repealing laws, public rules and regulations within a statutory or constitutional framework; (d) serving on government administrative boards or official committees; (e) investigating matters of concern to the public and promoting the interests of the constituencies which they represent; (f) attending community functions and meetings to provide service to the community, understand public opinion and provide information on government plans; (g) negotiating with other legislators and representatives of interest groups in order to reconcile differing interests, and to create policies and agreements; (h) as members of the government, directing senior administrators and officials of government departments and agencies in the interpretation and implementation of government policies., Occupations: Examples of the occupations classified here: – City councillor – Government minister – Mayor – Member of parliament – President (government) – Secretary of State – Senator – State governor, Notes:

Entries such as this were processed one-by-one by the model. For each occupation, it returned a single comma-separated row containing the occupation identifier, the exposure categories, the exposure and certainty scores, and a brief rationale, following the same instructions used for CBAs' analysis. These outputs were then compiled and merged with the ISCO structure to create the final dataset of AI exposure scores at the four-digit occupation level.

A.8.5 Descriptives AI Measure on ISCO 08

Table A.18: Top 10 ISCO-08 Level 4 Occupations by Augmentation Exposure

ISCO 08 Code	Title EN	Augmentation
2166	Graphic and Multimedia Designers	8.1
4132	Data Entry Clerks	8.1
2642	Journalists	8.1
2413	Financial Analysts	8.1
2511	Systems Analysts	8.1
2431	Advertising and Marketing Professionals	8.1
2310	University and Higher Education Teachers	8.1
2513	Web and Multimedia Developers	8.1
2641	Authors and Related Writers	8.1
4120	Secretaries (general)	8.1

Table A.19: Top 10 ISCO-08 Level 4 Occupations by Monitoring Exposure

ISCO 08 Code	Title EN	Monitoring
1114	Senior Officials of Special-interest Organizations	8.1
3212	Medical and Pathology Laboratory Technicians	8.1
3251	Dental Assistants and Therapists	8.1
4131	Typists and Word Processing Operators	8.1
2267	Optometrists and Ophthalmic Opticians	8.1
4321	Stock Clerks	8.1
4313	Payroll Clerks	8.1
4414	Scribes and Related Workers	8.1
4416	Personnel Clerks	8.1
5329	Personal Care Workers in Health Services Not Elsewhere Classified	8.1

Table A.20: Top 10 ISCO-08 Level 4 Occupations by AI Capability Exposure

ISCO 08 Code	Title EN	AI Capability
4131	Typists and Word Processing Operators	8.1
2512	Software Developers	7.2
2631	Economists	7.2
2641	Authors and Related Writers	7.2
2514	Applications Programmers	7.2
2431	Advertising and Marketing Professionals	6.4
2513	Web and Multimedia Developers	6.4
2511	Systems Analysts	6.4
2413	Financial Analysts	6.4
2642	Journalists	6.4

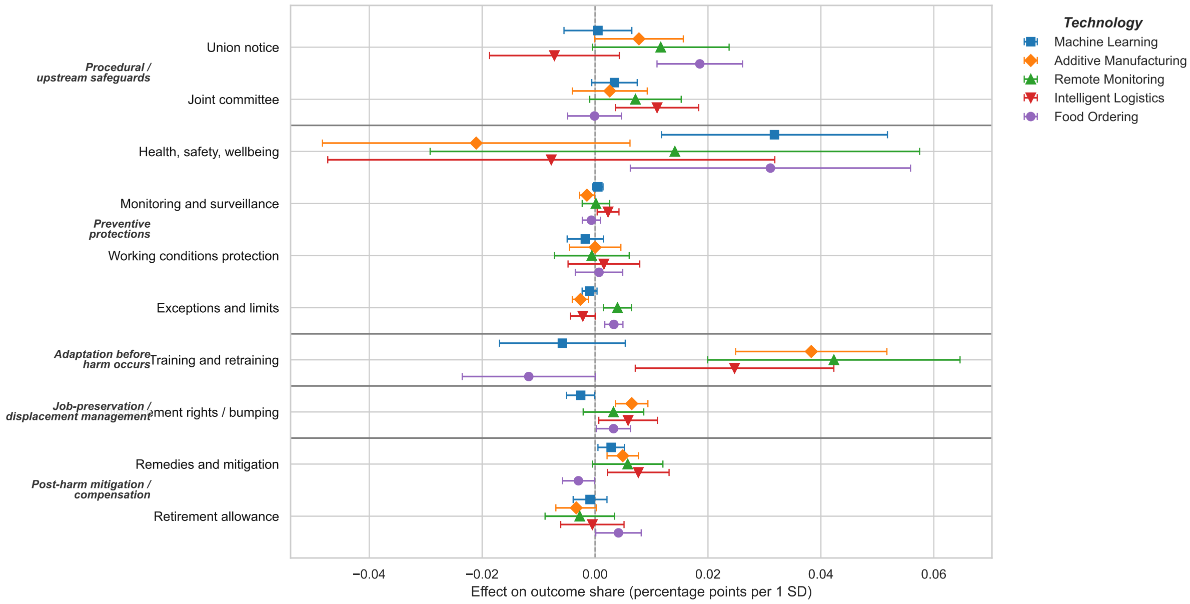
A.9 Additional Results CBAs

[34]

Figure A.16 turns to who is named in the agreements. Exposure to *smart mobility* increases references to unions and workers while reducing references to firms, pointing to a more collective

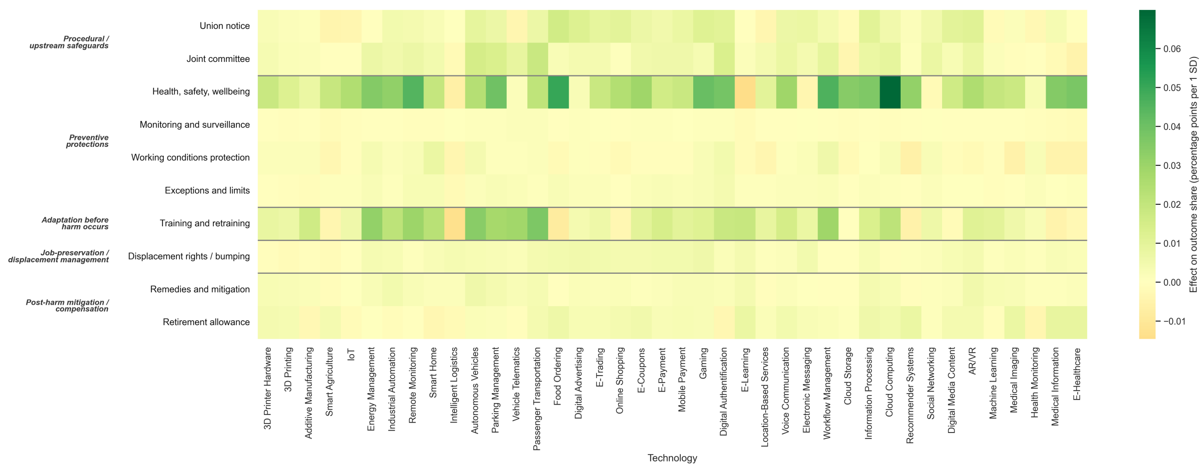
34. Refer to Figure A.15 for the results a heatmap of CBAs content share and exposure to 40 technologies.

Figure A.14: CBA Key Content and Exposure to Selected Technologies



Notes: The figure reports the estimated effects of different forms of technological exposure on the share of each topic in the CBAs. The dependent variable, shown on the y-axis, represents the share of words in each topic relative to the total document length (average length: 13,239 words). In this case, topics refer to the inclusion of clauses related to health and well-being, training, notice, union participation, etc. The independent variables capture exposure to emerging technologies, measured using related patent data at the four-digit NAICS level. All models control for the number of employees and include fixed effects for year and location. The sample of CBAs covers all agreements signed between 1993 and 2025 (N = 40,742). Standard errors are clustered at the employer level. Each panel displays coefficient estimates with 95% confidence intervals.

Figure A.15: CBA Key Content and Exposure to 40 Technologies



Notes: The figure reports coefficient estimates from separate regressions of topic-specific collective bargaining agreement (CBA) content shares on standardized exposure to each of the 40 technologies in the Tech40 classification. Outcomes are clause-text shares in the agreement. Each cell shows the estimated effect on the outcome share, in percentage points, associated with a one-standard-deviation increase in the corresponding technology exposure. Warmer colors indicate lower coefficients and greener colors indicate higher coefficients. The estimation sample uses the full non-missing Tech40 CBA sample. All specifications include controls for year, number of employees, two-digit NAICS fixed effects, and location fixed effects; standard errors are clustered at the employer level. The heatmap excludes agent outcomes and rights outcomes, which are shown separately.

Table A.21: Top 10 ISCO-08 Level 4 Occupations by Replacement Exposure

ISCO 08 Code	Title EN	Replacement
2131	Biologists, Botanists, Zoologists and Related Professionals	5.6
2120	Mathematicians, Actuaries and Statisticians	4.0
2643	Translators, Interpreters and Other Linguists	4.0
4312	Statistical, Finance and Insurance Clerks	4.0
5223	Shop Sales Assistants	3.5
5244	Contact Centre Salespersons	3.5
5230	Cashiers and Ticket Clerks	3.5
3311	Securities and Finance Dealers and Brokers	3.5
3513	Computer Network and Systems Technicians	3.5
3512	Information and Communications Technology User Support Technicians	3.5

Table A.22: Top 10 ISCO-08 Level 4 Occupations by Displacement Exposure

ISCO 08 Code	Title EN	Displacen
8312	Railway Brake, Signal and Switch Operators	
8122	Metal Finishing, Plating and Coating Machine Operators	
9621	Messengers, Package Deliverers and Luggage Porters	
7512	Bakers, Pastry-cooks and Confectionery Makers	
8159	Textile, Fur and Leather Products Machine Operators Not Elsewhere Classified	
8151	Fibre Preparing, Spinning and Winding Machine Operators	
7511	Butchers, Fishmongers and Related Food Preparers	
8183	Packing, Bottling and Labelling Machine Operators	
8322	Car, Taxi and Van Drivers	
7114	Concrete Placers, Concrete Finishers and Related Workers	

framing of implementation. *Food ordering* modestly raises worker-oriented language. Meanwhile, exposure to *Embedded systems* technologies tend to reduce mentions of workers and unions and shift focus toward firms.

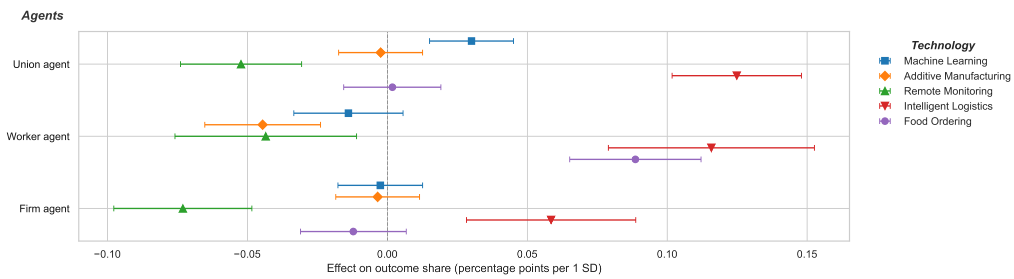


Figure A.16: Exposure to Emerging Digital Technologies and CBAs (1993-2025)
Note: The figure reports the estimated effects of different forms of technological exposure on the share of each topic in the CBAs. The dependent variable, shown on the y-axis, represents the share of words devoted to each topic relative to the total document length (average length: 13,239 words). In this case, topics refer to the actor emphasized in the agreement-whether it is the worker, the union, or the firm. The independent variables capture exposure to emerging technologies, measured using related patent data at the four-digit NAICS level. All models control for the number of employees and include fixed effects for year and location. The sample of CBAs covers all agreements signed between 1993 and 2025 (N = 40,742). Standard errors are clustered at the employer level. Each panel displays coefficient estimates with 95% confidence intervals.

Actor language exhibits a similar pattern (Figure A.17). Under *augmentation*, references to the *worker* become more frequent, and mentions of the *firm* also rise. With *monitoring*, both actors appear more often, reflecting shared oversight and newly formalized responsibilities. By contrast, under *replacement*, mentions of the *worker* and the *union* decline. In short, when AI is framed as augmenting rather than substituting labor, unions appear to emphasize coordinated responses that involve both workers and firms.

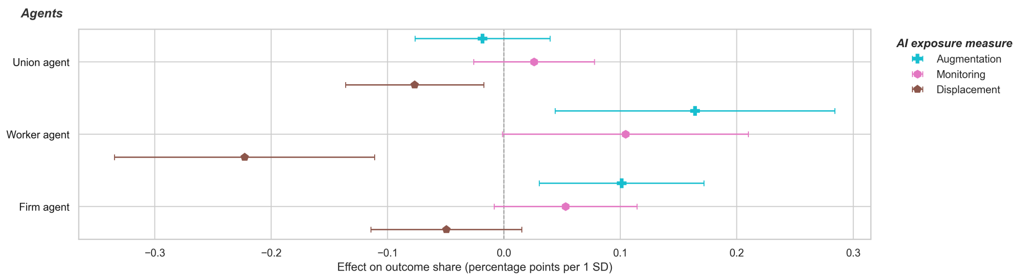
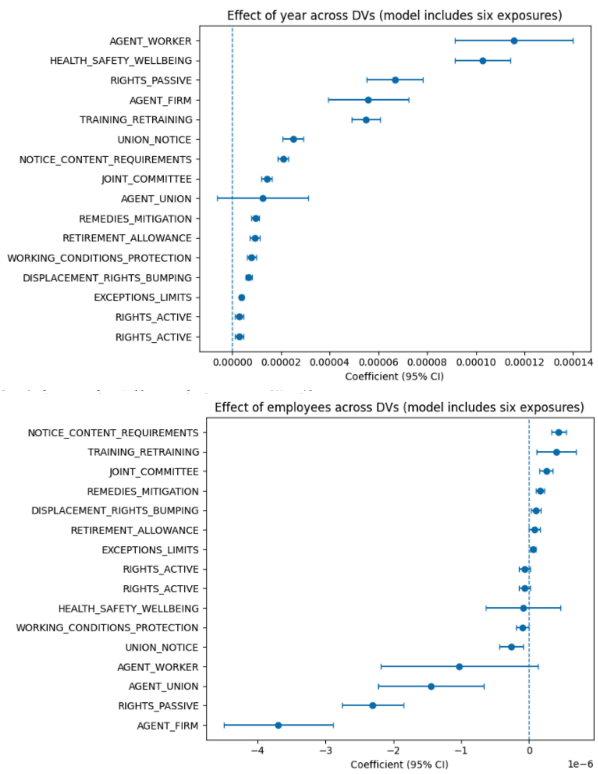


Figure A.17: Predominant Actors Mentioned in AI- and LLM-Exposed Agreements (2022-2025)
Note: The figure reports the estimated effects of different forms of technological exposure on the share of each topic in the CBAs. The dependent variable, shown on the y-axis, represents the share of words devoted to each topic relative to the total document length (average length: 13,239 words). In this case, topics refer to the actor emphasized in the agreement-whether it is the worker, the union, or the firm. The independent variables measure exposure to LLMs and AI, using an LLM-based classifier that categorizes technologies into three types: augmentation, displacement, and monitoring. Exposure is computed for each industry-occupation pair in the sample. All models control for the number of employees and include fixed effects for year and location. The sample of CBAs is limited to the years 2022-2025 (N = 788). Standard errors are clustered at the employer level. Each panel displays coefficient estimates with 95% confidence intervals.

Figure A.18: Exposure to Emerging Digital Technologies and CBAs



Note: Each panel reports coefficient estimates with 95% confidence intervals.

A.10 ETUI

This section provides additional descriptive evidence on the link between working conditions and unionization. Our ETUI analysis uses a dataset delivered by the European Trade Union Institute (ETUI). Importantly, this is not an individual-level microdataset. Instead, it is a weighted cell-level dataset in which each observation summarizes the distribution of responses within a particular occupation or industry cell. The ETUI dataset is organized in four related ways: by 2-digit ISCO occupation, by 2-digit ISCO occupation and country, by aggregated industry, and by industry and country. In addition to the main response shares, the dataset contains a small set of descriptive variables for each cell, including the share of women, average age, the share aged 34 or younger, the share aged 50 and above, and the share living in a large city.

In the analysis reported in the paper, we focus on the occupation-side ETUI data because the technology-exposure measures are matched at the occupation level. Occupations are coded at the ISCO 2-digit level, and the main technology merge is therefore performed using 2-digit ISCO occupation codes. In practice, this means that each ETUI occupation cell is linked to a common technology-exposure profile shared by workers in that occupational category.

The substantive questions we examine from the ETUI data center on unions, worker voice, and employment security. In particular, we use the ETUI response-share variables for current union membership, whether the workplace has a union, whether non-members would be willing to join a union in the future, whether respondents think unions do not improve working conditions, whether workers discuss work issues online with other workers, and whether workers are on temporary contracts. Conceptually, these measures allow us to study whether occupations with greater exposure to particular technologies also tend to be more unionized, more union-friendly, more communication-intensive, or more precarious in terms of employment arrangements.

To connect the ETUI data to technology, we merge the occupation cells to external exposure measures from the TechXposure project. These measures assign each 2-digit ISCO occupation a value for each of 40 technology categories, which can also be grouped into broader technology families. The ETUI results reported in the figures should therefore be interpreted as occupation-level associations between the intensity of exposure to specific technologies and the union- and work-related outcomes summarized by ETUI.

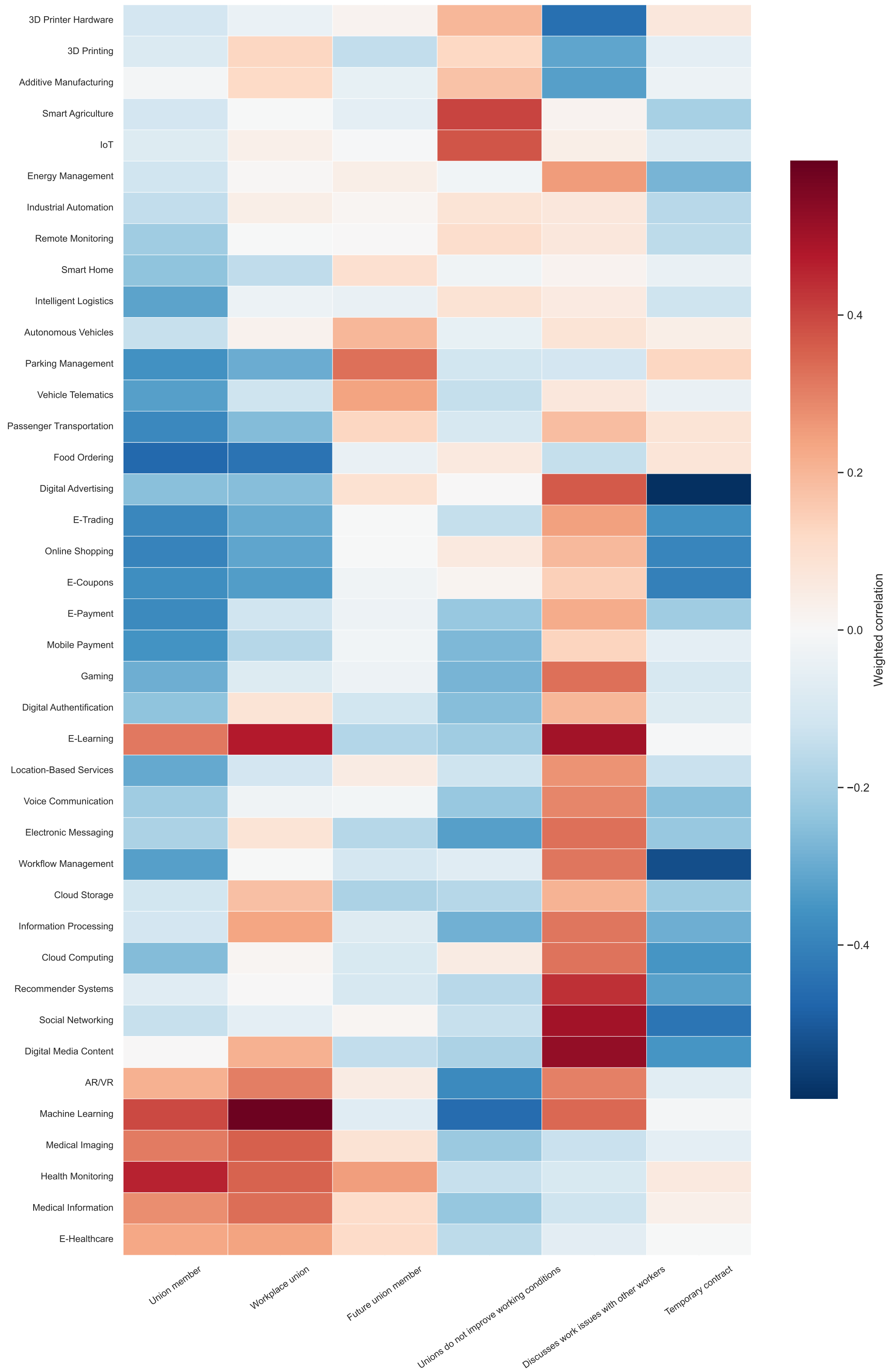


Figure A.19: Technology-level heatmap of union, worker-discussion, and contract outcomes.

Notes: The figure uses the ETUI IPWS occupation-level dataset, specifically the matched pooled occupation rows (`country = all`) after merging the ETUI occupation cells to the full set of 40 occupation-level technology exposure measures. The unit of observation is the ISCO 2-digit occupation cell rather than the individual worker, and all correlations are weighted by the ETUI cell weight `N_cell`. Each row corresponds to one of the 40 technologies in the exposure catalog. The columns report the weighted correlation between technology exposure and six ETUI outcomes: union membership, workplace union presence, willingness to join a union in the future, the share saying unions do not improve working conditions, the share discussing work issues with other workers, and the share on temporary contracts. The color scale is centered at zero, so positive correlations indicate that occupations with higher exposure to that technology tend to have higher values of the corresponding outcome, while negative correlations indicate the opposite. Because the columns are shown in their original direction, positive values for union-related and workplace-discussion measures are substantively different from positive values for adverse outcomes such as unions not improving working conditions or temporary contracts. The figure is descriptive and should not be interpreted as identifying causal effects of technology exposure on unionization, worker attitudes, or job quality.