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

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October 28, 2025

Abstract

This study examines how emerging digital technologies reshape working conditions, preferences, and collective organization. While production automation is often seen as weakening organized labor, we ask whether different kinds of technological exposure can also spur renewed unionization and prompt adaptive union strategies. We combine European survey data (2012–2024), a novel occupational technology exposure index, and text analysis of 40,000 Canadian collective bargaining agreements (1993–2025) to assess how digital tools, including machine learning, gig platforms, and remote monitoring, affect union membership, job quality, and political attitudes. We find heterogeneous effects: some skill-enhancing or production-integrated technologies can support unions, whereas platform-based tools weaken them, reduce worker autonomy, and increase political alienation. Union responses also vary by exposure type: with AI augmentation, unions negotiate training and co-governance; under pervasive monitoring, they demand privacy safeguards; where displacement risk is high, they are less successful at securing such protections. Overall, technology does not uniformly weaken organized labor. Its consequences depend on the type of technology and are actively contested at the bargaining table.

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—especially trade unions—remain underexplored. Much research examines how automation affects jobs and wages, but far less is known about how these forces 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 2024b). 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, union membership, and political preferences? Second, how are trade unions responding to these developments through collective bargaining?

Our core argument is that technology's impact on labor is heterogeneous, not uniform. Technologies reconfigure work in distinct ways, with varying consequences for worker autonomy, solidarity, and collective action. Much of the literature treats "automation" chiefly as a displacement threat, but in practice digital tools also augment some tasks and monitor or reorganize others, leading to uneven effects across occupations. Algorithmic management and surveillance systems can isolate workers, reduce their discretion, and erode informal coworker contact—dampening trust and collective agency. Gig delivery platforms illustrate this dynamic: individualized workflows on impersonal apps fragment the workforce, making solidarity more difficult, thereby undercutting the foundations of union power. By contrast, other innovations expand skill requirements or facilitate collaboration, potentially augmenting workers' roles. When new tools enhance employees' discretion or require teamwork (for instance, advanced manufacturing systems that workers jointly manage), they may empower workers and even foster collective demands. These differences condition whether unions are weakened or, under certain conditions, revitalized by technological change. Rather than causing an across-the-board decline in organized labor, emerging technologies create distinct organizational challenges and opportunities that can either undermine worker solidarity or generate new incentives for it.

These varied impacts of technology may also shape how unions respond. Facing the uncertainty of AI-driven change, unions adjust their strategies based on the type of technological exposure. Where augmentation dominates, unions can negotiate around training, upskilling, and joint implementation of new tools. Where monitoring is pervasive, they may push for governance mechanisms—advance notice of technological changes, information sharing, and limits on surveillance. And where displacement threats loom, unions may focus on job security and mitigation (e.g. redeployment and retraining), though diminished bargaining power can blunt these efforts. In sum, technological change will likely not produce a uniform decline of organized labor.

To investigate these questions, we combine micro-level survey analysis with textual analysis of union contracts. First, focusing on Western Europe survey data (2012–2024), we construct a fine-grained index of exposure to six categories of workplace technology (e.g. machine learning, embedded systems, remote monitoring, food ordering). This measure moves beyond one-dimensional "automation risk" scores to capture the diverse ways technology permeates jobs. We also complement this individual-level indicator of risk with regional exposure, as risk may not be realized if technology is not available in the region. We find that exposure to emerging technologies has heterogeneous effects on workers' attitudes. For example, app-based gig workers (such as food-delivery couriers) are significantly less likely to be union members and report lower job satisfaction and political trust, reflecting the isolating nature of platform work. In contrast, workers in more skill-intensive tech environments (for instance, those using advanced manufacturing or IoT systems) exhibit higher union membership, suggesting that when technology implementation requires training or teamwork, workers' leverage can persist or even increase. We also find that even cutting-edge AI tools (like machine-learning decision aids) often coincide with reduced perceived autonomy and lower job satisfaction. Moreover, we find that across all technologies, exposure is associated with a tendency toward greater political alienation.

Second, we analyze how unions are responding to these trends by examining more than 40,000 collective bargaining agreements (CBAs) from Canada spanning 1993–2025. Using text analysis, we identify technology-related clauses in these contracts and link each agreement to measures of technological exposure in its sector. We also introduce a novel AI exposure index, built with large language model (LLM) tools, to assess whether generative AI in an occupation is likely to augment, displace, or monitor workers. We find that unions are beginning to negotiate over AI and algorithmic monitoring, though such provisions remain uneven across agreements. Contracts in sectors exposed to smart mobility, remote monitoring, and food ordering technologies are more likely to include safeguards focused on safety and well-being, training, and union notification. In the post–generative AI period, we observe a sharp contrast between exposure to augmentation and exposure to displacement. When technologies are expected to assist workers, agreements devote more attention to worker-oriented provisions—such as training and upskilling programs and joint committees to manage implementation. Where displacement risks dominate, new safeguards are fewer, and commitments beyond traditional job-security language are limited. Finally, to situate these findings in a broader context, we review examples of agreements from the United States and Europe. These illustrate how forward-looking unions are pressing for protective rules and joint governance of AI—demanding advance consultation on AI rollout, safeguards for worker privacy, and commitments to retraining. Together, our results highlight both the possibilities and limits of union influence: while some unions are crafting innovative responses to AI, the adoption of such measures remains uneven across countries and sectors.

This study makes several contributions to the political economy of labor and technology. First, it enriches the debate on union decline under automation by uncovering substantial heterogeneity in outcomes (Agnolin et al. 2025; Balcazar 2022; Leduc and Liu 2024; Gonzalez-Rostani 2024b; 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 context – thus extending recent theories that the consequences of automation "need not be uniform." Our results complement and build upon work by (Becher and Stegmueller 2025), who posit that under certain conditions (e.g. when automation involves large, immobile capital investments) workers' leverage can actually increase. We provide empirical evidence for such conditional scenarios: some technologies can erode worker power, but others may reinvigorate unionization instead. We thus disentangle which technological progress matters, extending previous work focusing beyond robotization.

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 and an original AI exposure index. This 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 our measure with indicators of the pace of technological adoption. Finally, using an LLM-based classification of tasks, we distinguish whether AI is likely to augment or replace a given occupation, or subject it to heightened monitoring. Capturing these multidimensional exposures allows us to provide a more detailed account of how technological change shapes workers' daily experiences and concerns.

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 negotiate the terms of technological change. Our analysis shows that unions can secure concrete protections (e.g., training programs and limits on surveillance) alongside new technologies, supporting arguments that worker representation can facilitate adaptation to innovation rather than simply resist it (Belloc, Burdin, and Landini 2022). Together, these contributions deepen our understanding of the nexus 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 Technology, Work and Unionization

2.1 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 2024a) and left-wing in the Global South (Boix, Gonzalez-Rostani, and Owen 2025), and exhibit signs of political disengagement (Gonzalez-Rostani 2024b). 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 2024c).

Most of this literature treats "automation" as a single risk, often framed as displacement. Yet, technologies also augment tasks, restructure monitoring and coordination, and shape day-to-day interactions at work. The result is uneven exposure across occupations and within workplaces, with distinct implications for autonomy, coworker ties, and job satisfaction. Some tools may isolate workers, reduce informal contact, and dampen collective action, while others expand discretion or improve matching. Our contribution is to open this "black box" by differentiating technology families and mapping how different types of technologies affect workers' working conditions and attitudes. We study not only policy preferences linked to employment risk, but also outcomes on life and job satisfaction, autonomy, and social interaction, thereby connecting political attitudes to concrete changes in working conditions. By distinguishing augmentation from displacement and monitoring, we show which elements of technological change are more tightly linked to preferences and which have been overlooked.

2.2 Measuring Exposure to Emerging Digital Technologies

A central challenge in the literature is measuring how much any given worker is exposed to technological change. Most studies adopt a single, aggregate "automation risk" index. Objective versions of this index rely on proxies such as regional robot density (e.g., Acemoglu and Restrepo 2020a), an occupation's routine task intensity (Goos, Manning, and Salomons 2014; Frey and Osborne 2017; Arntz, Gregory, and Zierahn 2017), or the share of tasks classified as cognitive (e.g., Autor, Levy, and Murnane 2003). These indicators are informative, yet they primarily capture displacement and are tuned to robots and routineness rather than the growing set of digital technologies that nowadays structure work. Scholars also use survey items on perceived automation risk, typically workers' worries about technology-driven job loss; those perceptions correlate with voting and policy preferences (Borwein et al. 2025; Busemeyer et al. 2023; Gallego et al. 2022; Kurer and Häusermann 2022; Gonzalez-Rostani and Tober 2025). These subjective measures, however, again emphasize job loss and pay less attention to other channels, such as monitoring, performance evaluation, work intensification, or task-level productivity gains.

We argue that exposure to emerging technologies is multidimensional and that its effects extend to working conditions. Different technologies alter autonomy, pace, evaluation, and pay in distinct ways and can therefore prompt different forms of collective action and unionization. Algorithmic management and workplace surveillance, for example, implicate labor relations differently than classic automation or AI decision aids. Remote monitoring tools can reduce workers' discretion, enable punitive control, and degrade the social climate. Telematics and GPS-based tracking of drivers may intensify oversight and increase dissatisfaction. Smart-mobility systems can narrow route choice. Food-ordering platforms built around standardized, non-personalized interfaces reduce face-to-face contact and make mutual recognition among workers harder, with consequences for identity, solidarity, and organization.

In this paper we make two contributions in this regard. First, we separate exposure by technology type and link each type to potential changes in working conditions. Empirically, we implement a fine-grained measurement strategy that treats exposure as a vector rather than a single score. We use a recent method that maps occupations to relevant technologies using text embeddings applied to occupational descriptions and patent records (Prytkova et al. 2025). We distinguish six categories of emerging workplace technologies: Machine Learning, Embedded Systems, Remote Monitoring, Smart Mobility, Intelligent Logistics, and Food Ordering Platforms. This disaggregated approach avoids mixing very different influences; for instance, a delivery driver may be highly exposed to Smart Mobility innovations (route optimization and autonomous driving) but not to Embedded Systems or to Machine Learning in the same way as a software engineer.

Second, we introduce a new measure of exposure to the latest wave of AI and LLMs. Using AI-assisted analysis of occupational tasks, we estimate the degree to which current generative models can perform the tasks associated with each occupation. This LLM-based metric, developed by the authors, captures the potential for substitution or complementarity at the task level and is sensitive to very recent advances that patent-based linkages may miss. These measures allow us to trace distinct channels of technological exposure and to examine how they map onto political attitudes and collective behavior.

2.3 The Role of Unions and CBAs

Existing work documents the central role of trade unions in shaping economic and political outcomes (Ahlquist 2017; Becher and Stegmueller 2021). Politically, unions mobilize workers, increase participation, and organize latent workplace demands (Iversen and Soskice 2015; Becher and Stegmueller 2019; Frymer and Grumbach 2021). Economically, they influence wage-setting and working conditions through collective bargaining (Freeman and Medoff 1984; Farber et al. 2021), reducing inequality and setting standards not only for their members but often across the broader workforce (Western and Rosenfeld 2011; Rosenfeld 2014; Ahlquist and Levi 2013). In short, unions organize workers' demands in both economic and political domains, shaping distributive conflict and democratic representation.

Despite their importance, comparatively little is known about how AI and digital technologies (among the most consequential forces transforming work) affect labor-market institutions, particularly the organization, agency, and strength of unions. Most existing research examines the effects of automation and robotics on employment and wages; far less considers their implications for labor-market institutions and collective representation.

A few exceptions exist. In the United States, Balcazar (2022) provides causal evidence that local exposure to industrial robots, instrumented following Acemoglu and Restrepo (2020b), is associated with weaker union presence. Similarly, higher local robot adoption has been linked to lower representation of working-class candidates in local elections (Agnolin 2025). Relatedly, unions act as buffers against political disengagement, with recent evidence showing that regions with higher union density experience a weaker impact of automation shocks (Gonzalez-Rostani 2024b).

In Europe, research has been limited by a scarcity of consistent subnational data on unionization. Agnolin et al. (2025) address this limitation by constructing a novel dataset on regional and sectoral union density and show that robotization contributes to declining unionization rates. The effect operates mainly through the reallocation of employment from highly unionized sectors toward less organized ones, while within-sector effects remain ambiguous. Extending the framework of Acemoglu and Restrepo (2020b), Leduc and Liu (2024) incorporate search frictions and wage bargaining, arguing that automation erodes workers' bargaining power and may discourage unionization. Taken together, the evidence points to a general weakening of unions in response to automation. Less is known about when technological exposure might instead spur unionization and shape union strategies.

Recent theory suggests effects need not be uniform (Becher and Stegmueller 2025). In an open-economy model of strategic mobilization and bargaining, automation involving large fixed-capital investments can anchor production domestically, raising workers' bargaining power and incentives to unionize. Their quantile-IV results show heterogeneous effects of robot exposure across U.S. labor markets. Evidence from European establishments likewise indicates that employee representation can support the adoption of advanced technologies through involvement in training, work organization, and process innovation (Belloc, Burdin, and Landini 2022).

Building on this work, we study how technological innovation beyond industrial robots shapes labor-market institutions. We focus on AI and other emerging digital technologies and their impact on working conditions, unionization, and unions' responses through collective bargaining. These technologies pose distinct organizational and distributive challenges that, under some conditions, may revive unionization.

Importantly, we move beyond union density and analyze the content of collective bargaining agreements, tracing how unions respond by negotiating provisions on training, monitoring, and worker participation. CBAs reveal not only membership changes but also unions' ability to set rules and influence workplace conditions. Prior work in comparative political economy and industrial relations shows that union strength cannot be inferred from membership alone; the structure, coverage, and content of CBAs are central to shaping labor-market outcomes and distributive conflict (e.g., Traxler, Blaschke, and Kittel 2001; Baccaro and Howell 2017; Visser 2016; Freeman and Medoff 1984; Cazes, Garnero, Martin, et al. 2019).

Qualitative evidence shows growing engagement with technological issues. The Berkeley Labor Center identifies roughly 500 U.S. collective bargaining agreements (CBAs) that address emerging technologies (Kresge 2025). Labor law and labor studies also document cases featuring provisions on AI and algorithmic management (Montreuil and Foucher 2023; Rainone 2025; Borelli et al. 2025). Moreover, a 2023 survey of UNI Europa affiliates indicates that AI-related CBAs remain limited in number and are concentrated in service sectors (Brunnerová et al. 2024). While this literature offers rich qualitative insights, it lacks large-scale, longitudinal analysis of CBAs across industries and time. This gap is particularly salient for working conditions, which economic studies often overlook, even though CBAs contain detailed provisions beyond wages (Arold et al. 2025). Our contribution is to provide a systematic, text-based analysis of CBAs, examining how unions respond to technological exposure by negotiating provisions related to training, monitoring, autonomy, and worker participation.

3 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 AI and related tools as heterogeneous, as they reshape tasks and workplace relations in distinct ways that can alter both grievances and incentives 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 4 then shifts to the collective and institutional level, exploring whether and how trade unions address these emerging issues in CBAs.

3.1 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.

3.1.1 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 workplace power and autonomy, we consider two additional measures: the extent to which respondents can influence firm-policy decisions about organizational activities (*influence on decisions*) and the degree to which they can decide how their daily work is organized (*decide daily work*).

We also include self-reported job satisfaction and life satisfaction (*satisfaction job* and *satisfaction life*). Contractual stability is measured with an indicator for limited-term employment (*limited contract*), distinguishing temporary from permanent contracts. To assess the social context of work, we use the frequency of interactions with colleagues in person and by phone (*interaction in person* and *interaction by phone*). These variables inform us about changing opportunities for social interaction at the workplace, factors that may influence the capacity for collective organization. Finally, we include household income in deciles (*income*).

Political outcomes include self-placement on the left–right scale (*left-right*) and *redistribution* as the agreement that "the government should reduce differences in income levels". Political engagement is measured by self-reported turnout in the last national election (*voted*) and *interest in politics*. Satisfaction with the way democracy works in the respondent's country (*satisfaction dem.*) serves as an indicator of system support.

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

3.1.2 Measuring Independent Variables: Exposure to Emerging Digital Technologies

Our 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 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.

Departing from Prytkova et al. (2025), who primarily rely on an overall exposure index, we focus on six technology areas that are particularly relevant for workplace dynamics.[2] The first is *Machine Learning*, encompassing training techniques, model architectures, and data processing for computer-vision applications. We next construct a composite index for *Embedded Systems*—the unweighted mean of exposure to technologies 4–9 in Prytkova et al.—which includes Smart Agriculture, the Internet of Things, Predictive Energy, Industrial Automation, Remote Monitoring and Control, and Smart Home. We also include exposure to *Remote Monitoring and Control*, referring to real-time supervision and management in factories, building systems, warehouses, intelligent homes, disaster management, and network security. An index for *Smart Mobility* (averaging technologies 10–14) captures Intelligent Logistics, Autonomous Vehicles, Parking Management, Vehicle Telematics, and Passenger Transportation. We further consider *Intelligent Logistics*, which covers remote control, data acquisition, and mobile-robot technologies for logistics and delivery, including supply chain management, warehouse operations, and package tracking. Finally, we include exposure to *Food Ordering* technologies, encompassing wireless infrastructure, encryption, monitoring, and remote control for food order management, such as vending, self-service ordering, and delivery.[3]

Each dimension speaks to distinct job-quality risks and opportunities. For example, *Remote Monitoring* relates to pace control and surveillance; *Intelligent Logistics* restructures task allocation and skill demand; *Food Ordering* changes service workflows and scheduling; *Machine Learning* affects evaluation and algorithmic decision-making; *Embedded Systems* alter safety and maintenance routines; and *Smart Mobility* reshapes routes and shifts.

Because the same occupation can face different exposure levels depending on a country's

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

3. The *Embedded Systems* and *Smart Mobility* indices are unweighted means of their components; the other four measures are kept separate to preserve conceptual specificity.

adoption pace and timing, we scale occupational exposure by the share of firms in the respondent's 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. 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.

3.2 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 $m \in \{$*embedded systems*, *food ordering*, *intelligent logistics*, *machine learning*, *remote monitoring*, *smart mobility*$\}$, we estimate:

$$\begin{aligned} y_i^{(k)} \;&=\; \alpha_k \;+\; \beta_k \, \mathit{Technology\ exposure}_i^{(m)} \;+\; \mathbf{X}_{k,i}\,\boldsymbol{\gamma} \;+\; \lambda_{k,\mathrm{region}(i)} \\ &\quad +\; \delta_{k,\mathrm{NACE2d}(i)} \;+\; \phi_{k,\mathrm{c,\ t}(i)} \;+\; \varepsilon_i^{(k)} \end{aligned} \tag{1}$$

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 level. Our main regressor is the respondent's exposure to technology m,

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

where $\theta_{j(i)}^{(m)}$ is the occupational exposure of occupation j to technology m from Prytkova et al. (2025), and $\mathrm{ERP}_{c,t}$ is the country-year share of firms using ERP. Intuitively, exposure varies with both the inherent technology link of the respondent's 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.

3.3 Exposure to Emerging Digital Technologies and Working Conditions

Table 1 reports the estimated effects of exposure to different types of AI and digital technologies on the probability of being a union member. The results reveal marked heterogeneity across technology families. Exposure to machine learning, embedded systems, remote monitoring, and smart mobility technologies is positively and significantly associated with union membership, suggesting that workers in occupations more affected by these tools are more likely to join unions. These technologies are often integrated into production and decision-making processes in ways that reshape task structures and monitoring, potentially raising concerns about job security or autonomy and prompting collective organization.

By contrast, exposure to intelligent logistics shows weak or negligible associations, while food-ordering technologies display a negative and significant effect. The latter likely reflects the platform-based, individualized, and often precarious nature of work in food delivery and related services, where algorithmic coordination and fragmented employment relationships hinder union formation and collective action.

Table 1: The Impact of Emerging Digital Technologies on Unionization

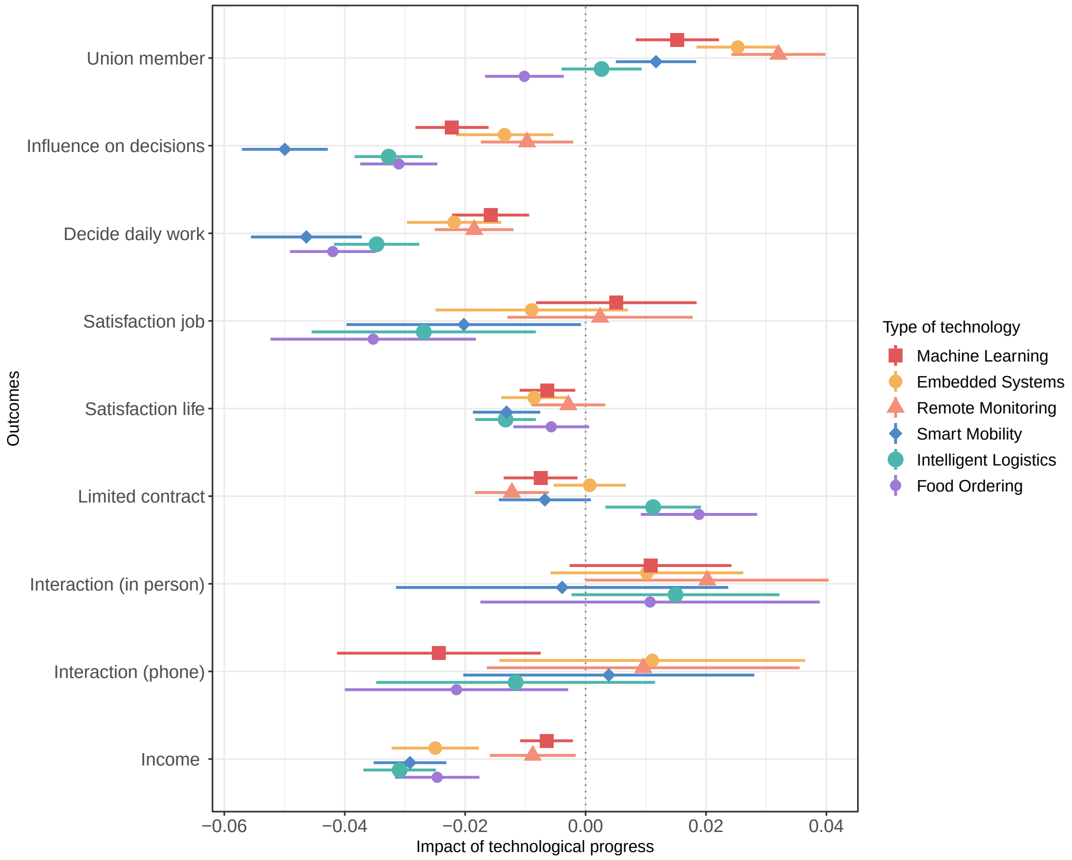
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Union member					
Technology exposure	0.006***	0.010***	0.012***	0.004***	0.001	-0.004***
	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]	[0.001]
Technology type	Machine Learning	Embedded Systems	Remote Monitoring	Smart Mobility	Intelligent Logistics	Food Ordering
Controls	X	X	X	X	X	X
Country-Year FE	X	X	X	X	X	X
Region FE	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X
Observations	129,129	129,129	129,129	129,129	129,129	129,129
R-squared	0.250	0.250	0.250	0.250	0.250	0.250
Std dev. Y	0.363	0.363	0.363	0.363	0.363	0.363
Magnitude	0.0168	0.0261	0.0329	0.0114	0.00272	-0.0105

Standard errors are clustered at the country-year level and are reported in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 1 extends the analysis to a broader set of outcomes related to working conditions. All outcomes are standardized to facilitate comparison. Across technologies, exposure is associated with lower perceived influence over workplace decisions and reduced autonomy in organizing daily work, with particularly large negative effects for smart mobility, intelligent logistics, and food-ordering technologies. These technologies are also associated with lower job and life satisfaction, as well as lower income levels.

Exposure to machine learning and remote monitoring is associated with greater employment stability. In contrast, the likelihood of holding a fixed-term contract increases with exposure

Figure 1: 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 and life satisfaction, having a limited-time contract, frequency of interaction with coworkers (in person or by phone), and income decile. 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. Coefficients are shown with 95% confidence intervals.

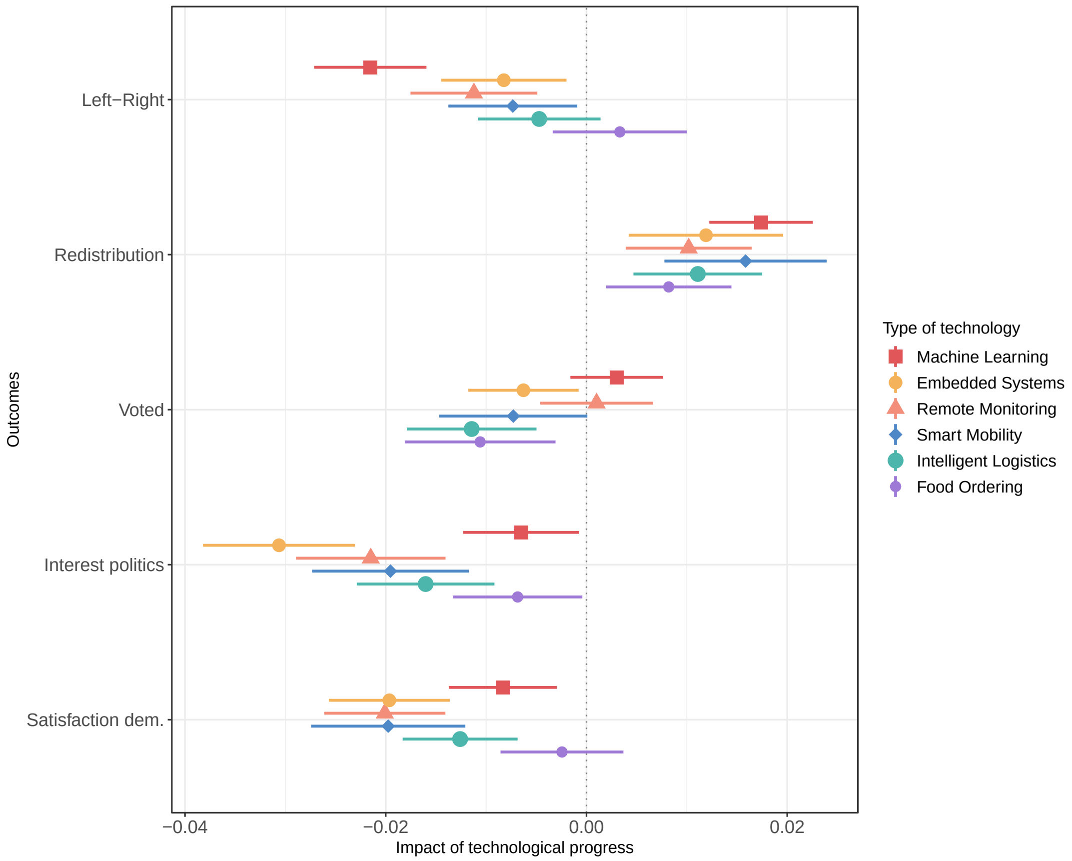
to intelligent logistics and food-ordering technologies—the same technologies showing weak or negative links to unionization. Furthermore, we find little evidence that exposure affects workplace interaction, although both machine-learning and food-ordering exposure are correlated with fewer phone contacts among colleagues.

In sum, the results show that technological change has divergent relationships with labor organization and working conditions. Technologies embedded in established production settings, such as machine learning and embedded systems, are associated with stronger collective organization even as workers report declining influence and autonomy. In contrast, technologies prevalent in platform and logistics environments, such as intelligent logistics and food-ordering, correlate with more precarious conditions and weaker unionization, consistent with fragmented employment relations and reduced opportunities for collective representation.

3.4 Exposure to Emerging Digital Technologies and Politics

We next examine whether changes in working conditions are mirrored in political responses. Figure 2 presents the estimates for political preferences and engagement. Exposure to most technologies corresponds with a shift toward more left-leaning positions on the ideological scale, except for intelligent logistics and food-ordering technologies. Consistent with higher compensation demands among affected workers, support for redistribution also increases with exposure. At the same time, political engagement declines: self-reported turnout falls—particularly for embedded systems, intelligent logistics, and food-ordering—and interest in politics decreases across technology types. Satisfaction with democracy similarly drops for nearly all exposures.

Figure 2: 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, self-placement on the left–right ideological scale, having voted in the last election, interest in politics, 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. Coefficients are shown with 95% confidence intervals.

These results suggest a complex political response to technological change. While workers affected by most technologies express greater support for redistribution and lean more leftward, they also exhibit signs of disengagement and alienation, especially when technologies are associated with precarious work and reduced workplace autonomy. This pattern points to a dual effect of technological exposure: shaping both political preferences and the willingness or ability to participate in democratic processes.

4 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 country's 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).[4][5]

4.1 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 Canada's repository and harvested all available records from 1993–2025. For each agreement we downloaded the

4. 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).

5. See subsection A.3 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.[6] 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.

Figure 3 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.

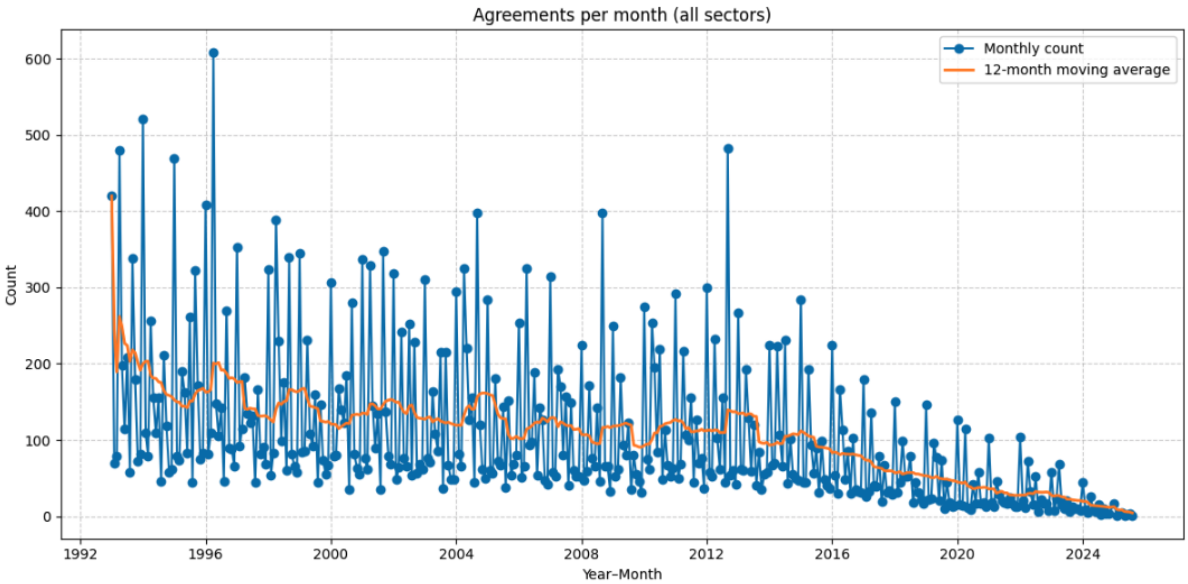


Figure 3: Monthly Canadian collective bargaining agreements, 1993–2025

4.2 Measuring Dependent Variables: Topics in CBAs

The dependent variables are shares of text devoted to specific contract themes.[7] 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.

6. See subsection A.4 for dataset details.

7. 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.

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.

As an illustration, Figure 4 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.

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

Our main exposure measures come from the *TechXposure* database (Prytkova et al. 2025), which scores industry exposure to emerging digital technologies (refer to Section 3.1.2).[8] We focus on six areas: *embedded systems*, *smart mobility*, *remote monitoring*, *intelligent logistics*, *food ordering*, and *machine learning*.

As a second approach, we construct an AI exposure score at the industry–occupation level.

8. We rely on 4-digit industry-level indicators.

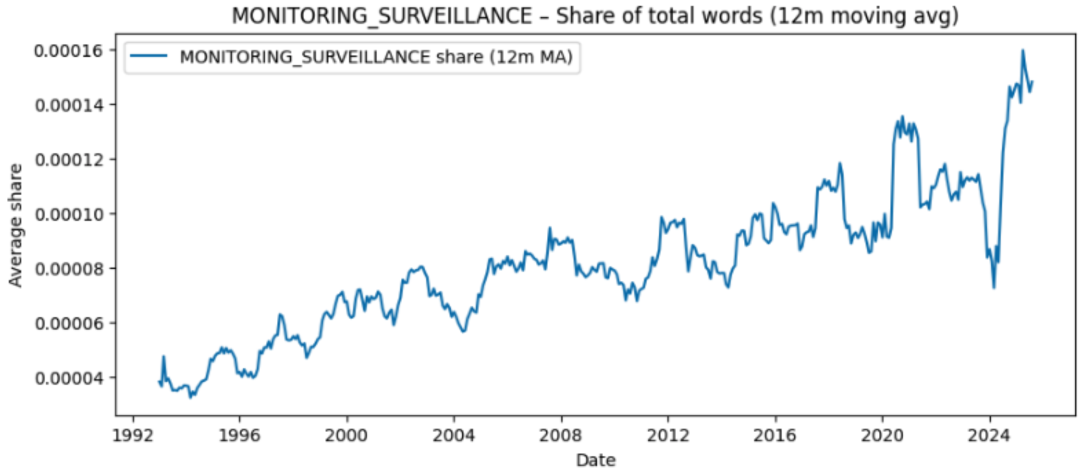


Figure 4: Salience of Monitoring and Surveillance in CBAs, Canada 1993–2025.
Note: 12-month moving average across agreements with technology-related clauses.

A large language model scores task-level exposure along three pathways—augmentation, replacement, and monitoring—with four 1–10 components (AI capability, replacement, augmentation, monitoring) and corresponding 1–10 certainty scores, plus four binary exposure flags (E0–E3). We form certainty-weighted components and indices (e.g., `ai_exposure_index` as the mean of the four weighted components; a "negative" version excluding augmentation) and summarize the E-flags into an index. Full details about the index and prompt used are described in subsection A.5. This measure complements TechXposure by distinguishing replacement, augmentation, and monitoring channels, and is specific to AI and LLMs.

4.4 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 $m \in \{$*embedded systems*, *remote monitoring*, *smart mobility*, *intelligent logistics*, *food ordering*, *machine learning*$\}$, 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.

$$\begin{aligned} y_i^{(k)} \;&=\; \alpha_k \;+\; \beta_{km}\,\text{Technology Exposure}_i^{(m)} \;+\; \rho_k\,\text{year}_i \;+\; \theta_k\,\text{employees}_i \\ &\quad+\; \delta_{k,\text{NAICS2}(i)} \;+\; \lambda_{k,\text{location}(i)} \;+\; \varepsilon_i^{(k)}. \end{aligned} \tag{2}$$

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.

4.5 Exposure to Emerging Digital Technologies and CBAs

Figure 5 summarizes how industry exposure to six digital technologies relates to the content of CBAs. The figure shows that exposure to *machine learning*, *smart mobility*, and *food ordering* technologies is associated with a greater emphasis on health, safety, and well-being provisions. These results suggest that as monitoring and mobility technologies become more salient, agreements devote more space to clauses aimed at preventing risks and ensuring workplace safety. Similarly, exposure to *smart mobility* and *remote monitoring* is linked to increases in training and retraining language, indicating that unions are incorporating skill-adjustment provisions to prepare workers for technological transitions. Exposure to these technologies—particularly *remote monitoring*, *smart mobility*, and *food ordering*—also coincides with increases in procedural safeguards, including more frequent references to joint committees and notice requirements, and to a lesser extent, with positive (though more uncertain) associations with remedies and mitigation. This pattern suggests that when technological change directly affects day-to-day work, unions tend to formalize mechanisms for information exchange and joint oversight. Overall, the structure of agreements in these contexts appears to evolve from ex post compensation (e.g., early-retirement clauses) to ex ante regulation, emphasizing training, well-being, and preventive safeguards such as joint committees and advance notice.

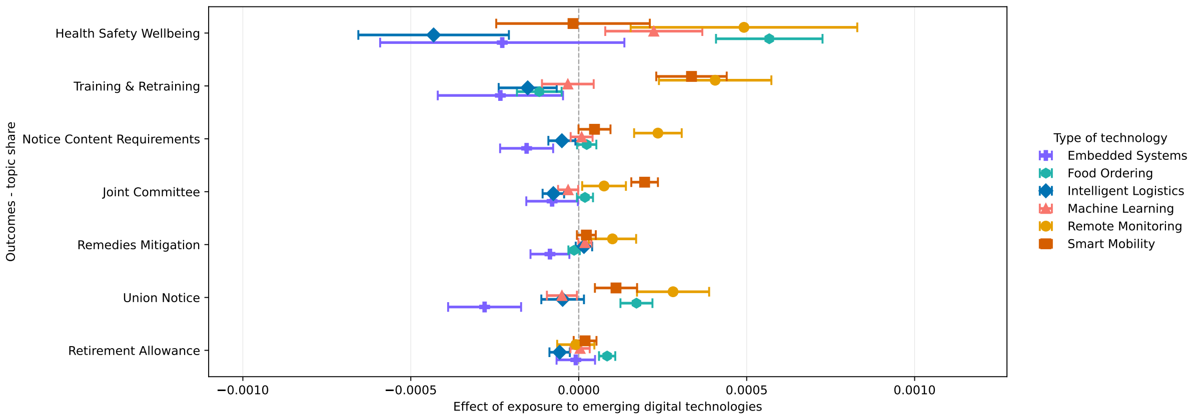


Figure 5: Exposure to Emerging Digital Technologies and CBAs (1993-2025)

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 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.

By contrast, technologies such as *embedded systems* and *intelligent logistics* are associated with weaker or even negative coefficients across most topics, indicating that these more indirect technologies elicit a limited bargaining response.

Figure 6 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 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.

Regarding other explanatory variables, Figure A.6 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.

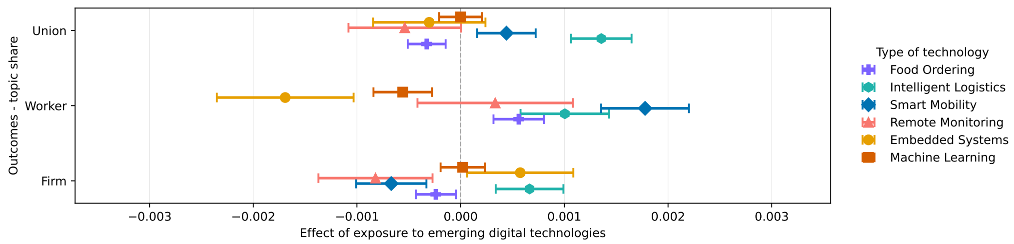


Figure 6: Exposure to Emerging Digital Technologies and CBAs (1993-2025)
Note: The figure reports the estimated effects of different forms of technological exposure on the share of each topic in the CBAs. The dependent variable, shown on the y-axis, represents the share of words devoted to each topic 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.

Overall, these results reveal a clear pattern of adaptation in collective bargaining. When technologies have the potential to monitor or alter the workflow directly, agreements prioritize preventive measures and worker protections. When technologies expand coordination or mobility, unions emphasize their governance role and collective oversight. In contrast, when technologies are more diffuse, the bargaining language remains largely unchanged, and explicit references to protections are less common. Overall, unions respond selectively to different dimensions of technological exposure, adjusting the emphasis of agreements toward health and safety, training, and procedural inclusion rather than ex post compensation.

4.6 Exposure to LLMs, AI, and Collective Wage Bargaining

We next examine the current wave of AI and LLMs. We restrict to post-2021 CBAs ($N = 788$) and use the LLM-based AI exposure described in subsection 4.3. We relate exposure along three pathways—augmentation, monitoring, and replacement—to topic shares and actor language in AI-relevant clauses. Figure 7 shows clear differences. Where exposure points to *augmentation*, agreements devote more language to worker-oriented provisions. Health, safety, and well-being rise the most; training and retraining, joint committees, notice-content requirements, union notices, and remedies or mitigation also tend to increase. Hence, when AI is expected to assist workers, agreements expand both substantive protections and the procedures that support them.

Under *monitoring*, governance-related language expands: notice-content requirements and union notices are positively associated with monitoring exposure, though estimates are less precise. This suggests greater emphasis on disclosure and oversight when tools track or evaluate performance.

By contrast, *replacement* exposure is associated with reduced attention to worker-protective topics. Mentions of health, safety, and well-being fall, as do references to union notices and joint committees or mitigation. In agreements where job-loss risk is salient, we do not see an expansion of skill-investment or individual protections.

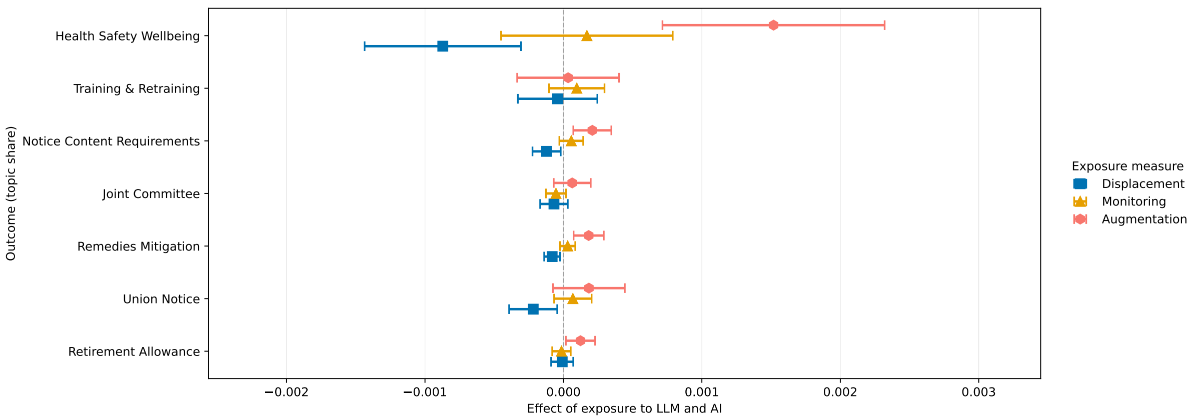


Figure 7: Exposure to AI and LLMs in Collective Wage Bargaining (2022–2025)
Note: The figure reports the estimated effects of different forms of technological exposure on the share of each topic in the CBAs. The dependent variable, shown on the y-axis, represents the share of words devoted to each topic relative to the total document length (average length: 13,239 words). In this case, topics 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.

Actor language exhibits a similar pattern (Figure 8). 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.

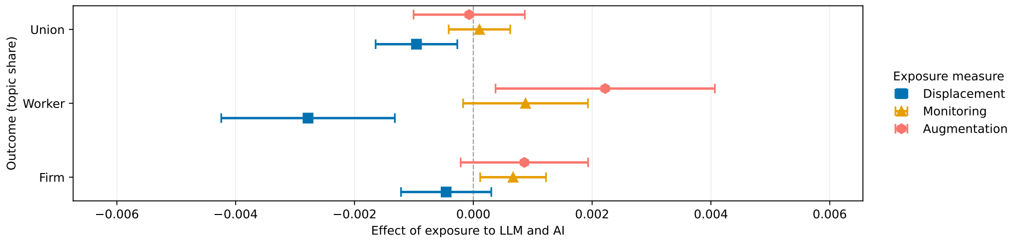


Figure 8: Predominant Actors Mentioned in AI- and LLM-Exposed Agreements (2022–2025)
Note: The figure reports the estimated effects of different forms of technological exposure on the share of each topic in the CBAs. The dependent variable, shown on the y-axis, represents the share of words devoted to 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.

One interpretation is that workers whose tasks are augmented and who face less immediate job-loss risk secure safeguards in coordination with firms. Where replacement pressure is higher, the scope to expand protections appears more limited. Monitoring exposure shifts attention to governance and advance-notice provisions.

4.7 CBAs Across the Globe

The Canadian results point to a common toolkit: early notice, information sharing, and training pathways. For external validity and concrete clause language, we present examples from other settings. A UNI Europa survey of 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). Our exploration of the recurring elements usually covered in CBAs is as follows:

Defining the scope of technological change. Agreements first clarify what constitutes "technological change," which anchors employer obligations toward employees. 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 Employer's workplace" (Bally's Las Vegas).[9] CBAs also add technology-specific definitions, especially for AI. As 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).[10] Agreements further emphasize the importance of maintaining a "human-in-the-loop" role. For example, "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).[11]

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 example: "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).[12] 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).[13] Similar rules appear in Norway's 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).

9. Bally's Las Vegas Manager, LLC and Local Joint Executive Board of Las Vegas 2019, 64
10. 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
11. 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
12. State of California and Service Employees International Union (SEIU) Local 1000 2023–26.
13. National Science Foundation and American Federation of Government Employees (AFGE) Local 3403, AFL–CIO 2022, 154.

Algorithmic management (AM) and digital rights. Telefónica, Spain's 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 AI's 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, customer service, or safety purposes can later be repurposed for surveillance or discipline.[14] 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)[15], 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)[16]. 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."[17] 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)[18]. In Italy, an agreement signed by the unions FILCAMS-CGIL and FISASCAT-CISL covering an

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

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

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

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

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

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).

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)[19] and "The Employer shall not use technological changes for the sole purpose of converting jobs from bargaining unit status to non-bargaining unit status" (IAMAW).[20] 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).[21]

Broadly, these examples show that unions are negotiating for clear definitions of technological change, early notice and information sharing, structured implementation processes, limits on monitoring, and training provisions that keep new technology work within the bargaining unit.

5 Conclusion

Our analysis reveals that digital technologies are reshaping labor relations in contingent rather than uniform ways. At the individual level, exposure to emerging technologies produces mixed effects on workers' attitudes and conditions. In occupations where innovations like machine learning, embedded systems, or digital monitoring tools are integrated into production, workers tend to be more likely to join unions. This pattern suggests that when new tools raise concerns over job security or autonomy (for instance, through heightened surveillance or restructured tasks), employees respond by mobilizing collectively. By contrast, exposure to platform-based technologies – such as algorithmic food-ordering– correlates with lower unionization rates. This latter case reflects highly individualized and precarious work environments, where fragmented employment relationships hinder collective organization.

Our findings also show that many digitally exposed workers report diminished influence over

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

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

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

workplace decisions and reduced day-to-day autonomy, with particularly negative effects under extensive monitoring regimes (e.g., smart mobility or algorithmic management). Not surprisingly, these high-exposure contexts also exhibit declines in job satisfaction and work morale. Yet the impact of technology is far from uniform: some digital tools, such as machine learning, are associated with greater employment stability, while others heighten precarity by increasing the likelihood of short-term contracts (e.g., gig work). We also find that technological disruptions reverberate in the political realm. Exposed workers tend to adopt more left-leaning attitudes, consistent with stronger demand for protective labor policies, though this trend is weaker in the most precarious platform settings, such as food ordering and intelligent logistics. In short, the micro-level evidence highlights the heterogeneous effects of digital change: new technologies can simultaneously erode aspects of worker well-being and power while strengthening others, depending on how they are implemented and experienced.

Turning to collective responses, the evidence shows that unions are not uniformly weakened by workplace digitalization, but instead exhibit conditional resilience and strategic adaptation. Our analysis of CBAs indicates that when technologies primarily monitor workers or restructure tasks, unions respond proactively. In such cases, labor organizations bargain for an array of safeguards – they secure advance notice of technological deployments, demand retraining opportunities for affected employees, and even negotiate limits on the use of new surveillance tools. At the same time, unions work to reassert their voice in how innovations are implemented, for example by establishing joint technology committees or consultation requirements that ensure transparency and worker consent in the adoption of new systems. These strategies demonstrate a deliberate effort to buffer workers from insecurity while shaping workplace change: rather than passively accepting automation or AI, unions in these settings actively carve out roles in governing the introduction of new tools.

In the post–Gen-AI period, unions in sectors where AI augments rather than replaces work have used digital change to secure gains in training, safety, and co-determination—signs of continued strength. Where AI is tied to job loss or precarious employment, responses have been weaker, reflecting the difficulty of organizing amid insecurity. Labor's ability to adapt thus depends on the nature of technological exposure: monitoring and restructuring often elicit assertive action, while displacement risks limit bargaining power.

Taken together, our findings challenge the notion that digital technologies uniformly erode labor power. Instead, they reveal a pattern of uneven resilience: labor adapts, resists, and occasionally gains strength, depending on the type of technology and the institutional leverage available. Far from depicting an inevitable technological assault on worker voice, our evidence points to a more contingent reality—labor power weakens in some contexts even as it is reconfigured or renewed in others. The conditional nature of both worker-level responses and union strategies carries broader theoretical implications: scholars of labor, technology, and political behavior should move beyond deterministic views and instead examine the institutional, organizational, and political factors that shape whether new technologies undermine or empower workers. Future research can build on these insights to specify when and how digital tools catalyze collective action—or, alternatively, overwhelm it.

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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
Satisfaction life	How satisfied with life	10-point scale: 1 = Extremely dissatisfied, 10 = Extremely satisfied	6–11
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
Interaction (phone)	Speak with colleagues about work using a phone, 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
Left-Right	Placement on left-right scale	10-point scale: Left to Right	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
Interest politics	How interested in politics	4-point scale: Not at all interested, Hardly interested, Quite interested, Very interested	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

Table A.2: Types of Technology

Type of Technology	Description
Machine Learning & Neural Networks	Machine learning training techniques, model architectures, and data processing for computer vision applications.
Embedded Systems	- Smart Agriculture & Water Management: IoT technologies for intelligent and remote management in agriculture and water/sewage systems. - Internet of Things (IoT): Systems and devices interconnected via IoT for data collection, remote control, and real-time monitoring in applications including agriculture, home automation, and environmental monitoring. - Predictive Energy Management and Distribution: Network, data management, and AI technologies for monitoring, distribution, and efficient use of electrical power, including renewables, 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: IoT technologies for intelligent control of homes and buildings, including household appliances, home environments, and smart home integrations, often using wireless communication and monitoring.
Remote Monitoring & Control Systems	Real-time remote monitoring and management technologies for factories, building management, warehouses, intelligent homes, disaster management, and network security.
Smart Mobility	- Intelligent Logistics: Monitoring, remote control, data acquisition, and mobile robot technologies for logistics and delivery, including supply chain management, warehouse operations, package tracking, and courier services. - Autonomous Vehicles & UAVs: Developments in UAVs, drones, and autonomous driving technologies, emphasizing 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: Intra-vehicle information management for electric vehicles, including real-time monitoring, traffic information, and diagnostics. - Passenger Transportation: Technologies for ride-sharing, taxi hailing, and public transportation reservations using real-time information, electronic ticketing, and route optimization.
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.

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

A.3 Canadian Labor Relations and Technological Change Background

A.3.1 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 Canada's 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.3.2 Union Density and Coverage Rates

Canada's 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.[22] 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.3.3 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).[23] 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.

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

Table A.3: 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), Canada's largest public-sector union, released guidance in 2025 for "bargaining strong collective agreements for the digital age."[24] 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 country's largest private-sector union) has highlighted its efforts in bargaining over new technology.[25] 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)

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

have called for frameworks to manage AI's effects on jobs, emphasizing retraining and skills development, ethical use of AI, and job protection as key priorities.[26]

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,[27] 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)[28] 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.

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

A.4 Data CBAs

Table A.4: 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.5 Measuring Exposure to AI

A.5.1 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_certaint` 1–10 certainties aligned to each score.
- `Rationale`: short free-text justification (1–2 sentences). *Do not use commas; use semicolons.*

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 `E1` $= 1$, `E2` $= 0.5$, `E0` $= 0$, `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.5.2 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.5.3 Descriptives

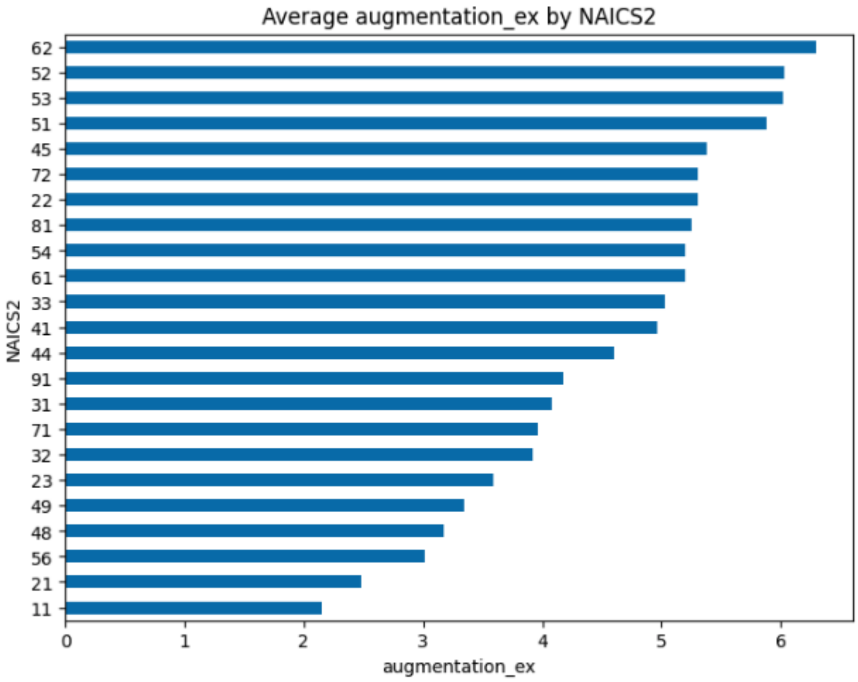

Figure A.1: AI Augmentation by NAICS 2 digits

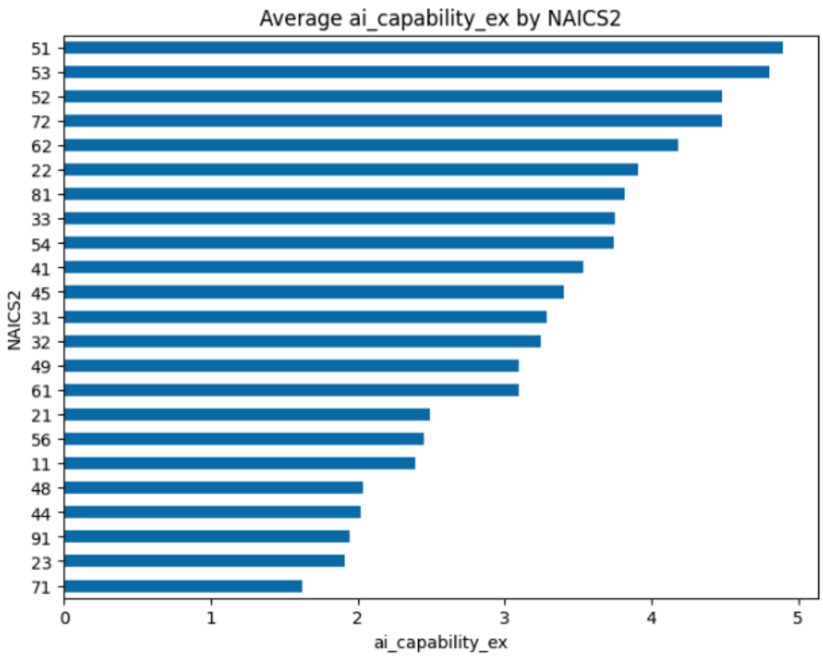

Figure A.2: AI Capabilities by NAICS 2 digits

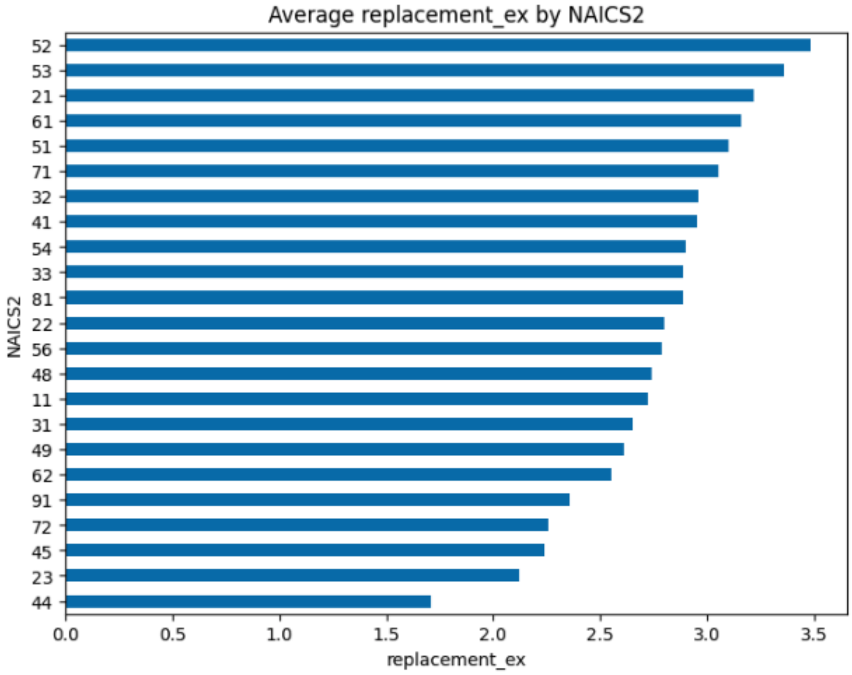

Figure A.3: AI Replacement by NAICS 2 digits

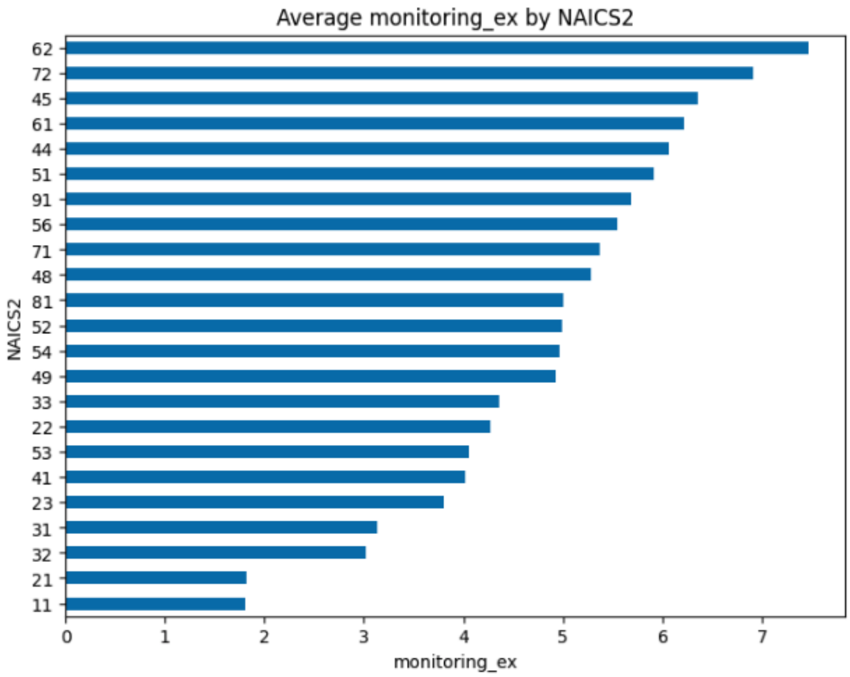

Figure A.4: AI Monitoring by NAICS 2 digits

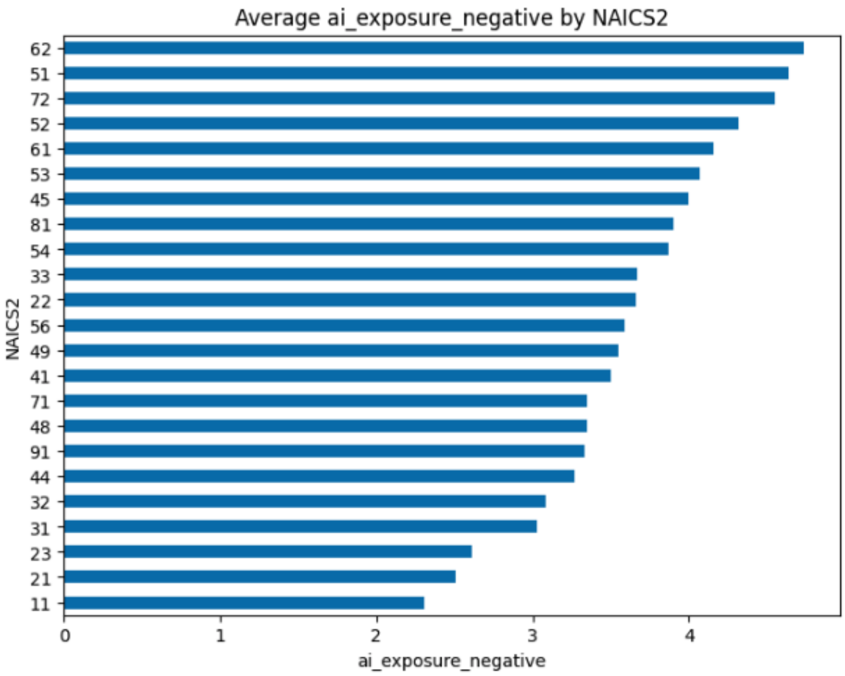

Figure A.5: AI Negative Exposure by NAICS 2 digits

A.6 Additional Results CBAs

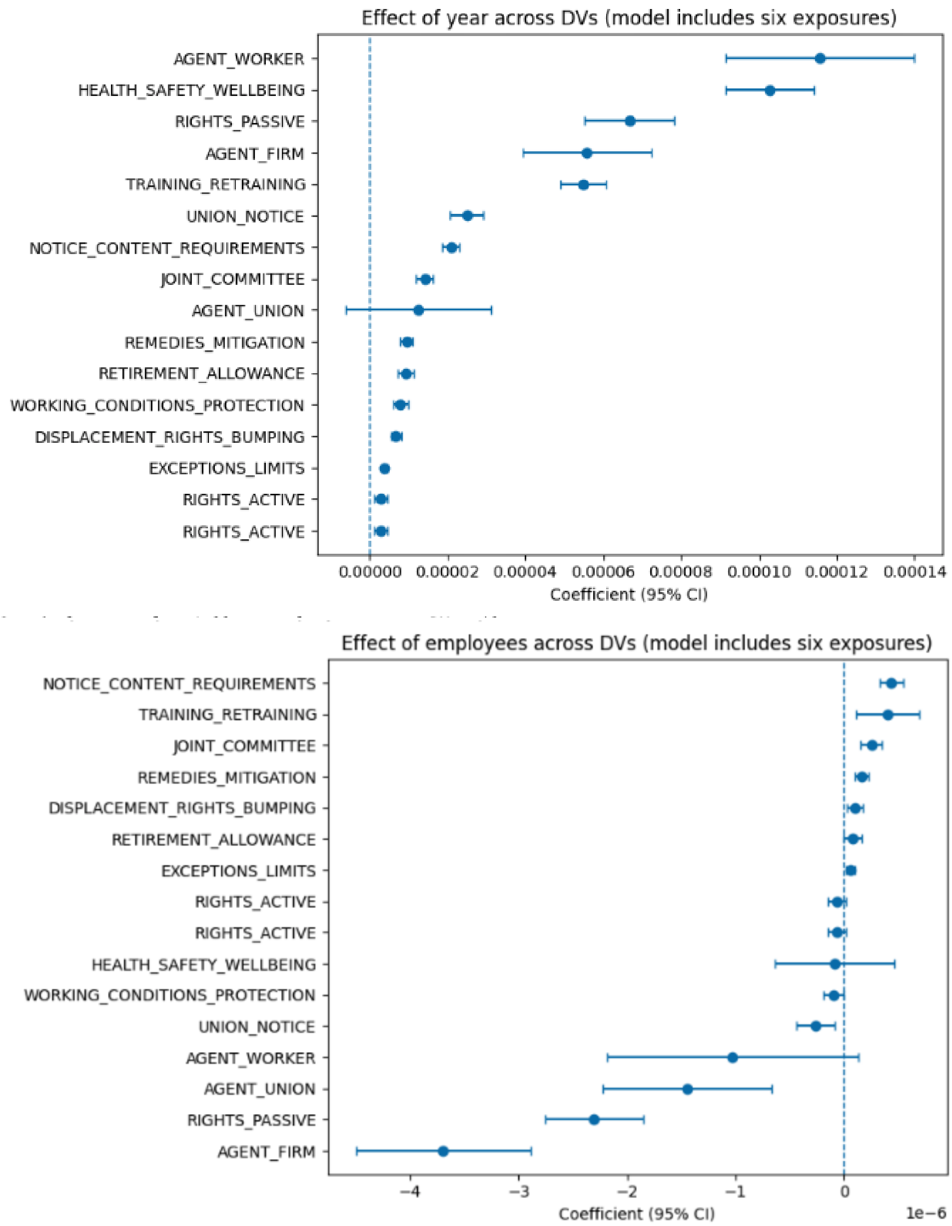

Figure A.6: Exposure to Emerging Digital Technologies and CBAs
Note: Each panel reports coefficient estimates with 95% confidence intervals.