

Within-Occupation Labor Recomposition under Generative AI: A Case Study of Amazon’s IT Workforce

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Abstract

This study examines how generative artificial intelligence (GenAI) is associated with shifts in the internal composition of IT-related work within firms, rather than eliminating the entire IT occupations. Using Amazon as a high AI exposure case study, we draw on (i) Amazon specific Washington State WARN layoff notices that report job titles and affected headcounts, (ii) a structured snapshot of publicly observable Amazon technology job postings, and (iii) U.S. Occupational Employment and Wage Statistics (OEWS) data (2020–2024) for national context. Because layoffs reflect discrete events while job postings represent cumulative demand over a broader window, the analysis focuses on distributional comparisons rather than direct replacement. We document systematic divergence between the composition of technology layoffs ($n=1,955$) and the composition of current technology openings ($n=6,075$). Layoffs are concentrated in software development and technical program management, while hiring emphasis shifts toward operations/IT support, machine learning science, security/systems engineering, and hardware-oriented roles. In addition, 23.1% of laid-off roles do not map to the current technology opening taxonomy, clustering in coordination, screening, reporting, and support functions. These patterns are consistent with task-based research indicating that AI substitutes for specific tasks and induces within-occupation task reallocation rather than immediate mass occupational displacement. The findings highlight how net employment measures can mask internal labor recomposition during early generative AI diffusion.

Keywords: Generative AI (GenAI); Labor recomposition; Task-based technological change; Within-occupation reallocation; Firm-level labor dynamics; Technology workforce; AI education; Amazon

Introduction

The rapid diffusion of generative artificial intelligence (GenAI) has intensified debate regarding its implications for labor markets. In 2025 and early 2026, several major technology firms announced large-scale layoffs, with corporate leadership in some cases attributing these reductions to efficiency gains associated with AI adoption (Bhaimiya, 2025; *Companies cutting jobs*, 2026). For example, Amazon eliminated approximately 14,000 corporate positions in late 2025 and announced an additional 16,000 reductions in January 2026 as part of an “anti-bureaucracy” and efficiency-oriented restructuring aligned with expanded AI deployment and infrastructure investment (*Amazon cuts*, 2026; Bhaimiya, 2025; Galetti, 2026). Media coverage frequently framed these developments as evidence that AI is replacing jobs at scale, elaborating concerns that generative AI may produce widespread occupational displacement, particularly within high-skill, white-collar domains (Bhaimiya, 2025; *Companies cutting jobs*, 2026).

However, emerging academic research presents a more nuanced view. Task-based analyses argue that technological change, including AI, primarily substitutes for specific tasks rather than eliminating entire occupations (Autor et al., 2003; Hampole et al., 2025). Recent empirical work suggests that while AI exposure is substantial in high-wage, knowledge-intensive work, occupation-level employment effects remain limited during early diffusion phases (Gimbel et al., 2025). Instead of wholesale job loss, firms and workers appear to adjust by reallocating effort toward less-automatable tasks within the same occupational boundary (Chopra et al., 2025; Hampole et al., 2025).

This divergence between public narratives of AI-driven layoffs and academic evidence of task reallocation raises an important question: how do AI-driven labor adjustments appear in firm-level labor signals before aggregate occupational changes become visible? In particular, when firms simultaneously lay off and hire within the same occupational domain, does this reflect job elimination or internal labor recomposition? To address this question, this study examines Amazon as a high AI exposure case. This case study focuses specifically on IT-related roles within Amazon, as IT occupations are among the most exposed to generative AI task substitution and complementarity (Hampole et al., 2025; Chopra et al., 2025). Drawing on Washington State WARN layoff notices, publicly observable technology job postings, and national Occupational Employment and Wage Statistics (OEWS) data, the study compares the distributional composition of layoffs and hiring within technology roles. Rather than inferring direct replacement, this study focuses on percentage shares to identify shifts in organizational emphasis across job categories.

The findings provide evidence consistent with within-occupation labor recomposition. Layoffs are concentrated in software development and coordination-intensive roles, while hiring emphasizes infrastructure, operations, machine learning science, security, and hardware-oriented functions. In addition, a subset of laid-off IT roles does not appear among current IT job openings, and many of these roles involved routine coordination, reporting, or documentation tasks.

These patterns align with task-based theories of technological change, which predict substitution in routine cognitive tasks and complementarity in systems-level and AI-adjacent work (Autor et al., 2003; Hampole et al., 2025; Chopra et al., 2025). By documenting how labor adjustment unfolds within IT occupational boundaries at the firm level, this study contributes to the literature on generative AI, task-based technological change, and internal labor market dynamics. The findings further suggest that aggregate or net employment measures may mask substantial internal restructuring during early phases of AI diffusion (Hampole et al., 2025; Gimbel et al., 2025).

Literature Review

AI as Task-Based Technological Change

The task-based view of technological change argues that technologies substitute for specific tasks rather than entire occupations (Autor et al., 2003). Recent research extends this framework to artificial intelligence and generative AI systems, arguing that AI affects specific task components within occupations rather than eliminating entire occupations (Hampole et al., 2025). Hampole et al. (2025), using firm-level and occupation-level data from 2010-2023, document that AI exposure is highest in high-wage, white-collar occupations, particularly in business, finance, management, and engineering. Although AI substitutes for certain analytical and data-processing tasks, occupation-level employment effects remain limited. Instead, firms and workers adjust through task reallocation, with employees shifting effort toward less-automatable tasks and productivity gains mitigating potential displacement effects.

Importantly, exposure varies within occupations. Routine analytical, coding, and documentation-intensive tasks are more susceptible to AI-driven substitution, whereas architectural, infrastructure, and systems-design functions are less exposed and may expand (Hampole et al., 2025). These findings suggest that early AI diffusion is more likely to reshape the internal composition of work than to produce immediate occupational collapse.

Aggregate Labor Market Evidence

Aggregate labor market data provide further context. An analysis by The Budget Lab at Yale examining U.S. employment, unemployment, occupational composition, and wage data from late 2022 through mid-2025, approximately 33 months after the public release of generative AI tools such as ChatGPT, finds no obvious economy-wide employment disruption (Gimbel et al., 2025). Observed adjustments resemble patterns seen in prior technological transitions, including the diffusion of computers and the internet.

Complementary evidence comes from Project Iceberg (Chopra et al., 2025), which introduces the Iceberg Index as a measure of skills-centered AI exposure. The Surface Index, capturing visible AI exposure concentrated in computing and technology roles, accounts for approximately 2.2% of total U.S. wage value. When broader administrative, financial, and professional skills are included, the Iceberg Index rises to approximately 11.7% of wage value, indicating substantial latent task overlap beyond core technology occupations.

Together, these studies suggest that although AI systems can technically perform a meaningful share of high-wage cognitive tasks, occupation-level employment effects remain limited during early diffusion. This supports the task-based prediction that labor adjustment may occur within occupations rather than through immediate job elimination.

Media Narratives and Firm-Level Restructuring

Despite the absence of aggregate employment collapse, public discourse frequently frames AI as a driver of layoffs. Media reports in 2025 indicated that more than 50,000 layoffs were linked to AI-related restructuring across major firms, including Amazon, Microsoft, Salesforce, IBM, and others (Bhaimiya, 2025). In January 2026, Amazon announced an additional 16,000 corporate workforce reductions as part of an “anti-bureaucracy” restructuring aligned with efficiency improvements and AI investment (*Amazon cuts*, 2026). This divergence between media narratives and task-based evidence motivates closer firm-level examination. If AI primarily substitutes for tasks rather than occupations, then layoffs attributed to AI may reflect internal reallocation and restructuring rather than net occupational disappearance. However, most existing research evaluates AI exposure at the occupation or national level. Less attention has been paid to how firms operationalize AI-driven adjustment within their internal labor structures.

Within-Occupation Labor Recomposition

Building on the task-based literature, we use the term “within-occupation labor recomposition” to describe how firms adjust employment structures during AI adoption. Rather than eliminating entire occupations, firms may reduce headcount in task-intensive or coordination-heavy roles while expanding hiring in infrastructure, research, security, and AI-adjacent functions within the same occupational boundary. Such recomposition can produce the coexistence of layoffs and hiring within IT or computing domains.

Research Gap and Contributions

While existing research demonstrates that AI substitutes for tasks rather than entire occupations (Hampole et al., 2025; Chopra et al., 2025) and aggregate evidence shows limited economy-wide disruption during early generative AI diffusion (Gimbel et al., 2025), less attention has been paid to how these adjustments

manifest within firms. Most prior analyses rely on occupation-level exposure measures or national employment statistics, which may obscure internal reallocation across job categories.

By examining firm-level layoff and hiring distributions within IT roles using a single-firm case study of Amazon, this study provides firm-level evidence consistent with within-occupation labor recomposition during early generative AI diffusion. In doing so, the study contributes to task-based theories of technological change by illustrating how AI-related adjustment may manifest as internal labor reweighting before observable occupation-level decline.

Methodology

Case Study and Data Sources

This study employs a single-firm case design to examine within-occupation labor recomposition during early GenAI diffusion. Amazon is selected due to its substantial IT workforce, documented organizational restructuring during the study period, and publicly observable layoff disclosures through Washington State WARN filings. As a large technology-intensive employer undergoing AI-related investment shifts, the firm provides an appropriate setting for examining internal compositional labor adjustment.

This study draws on three primary data sources to examine within-occupation labor recomposition at Amazon. First, layoff data are obtained from Washington State Worker Adjustment and Retraining Notification (WARN) notices (*Washington State Employment Security Department*, n.d.). WARN filings provide employer-reported layoff counts and associated job titles for affected employees. Because WARN reporting in the United States is decentralized, state-level notices represent the most detailed publicly available source of firm-specific layoff information. The layoff dataset includes 1,955 IT-related positions derived from WARN notices filed during the study period.

Second, hiring data are derived from a structured snapshot of publicly observable Amazon IT job postings collected on February 3, 2026, from the Amazon.jobs platform (Amazon.com, 2026). Job titles were recorded and classified according to primary functional responsibility. These postings reflect cumulative hiring demand over a defined observation window. The hiring dataset includes 6,075 publicly observable Amazon IT job postings recorded during this window.

Third, national occupational context is provided by the U.S. Bureau of Labor Statistics Occupational Employment and Wage Statistics (OEWS) data for 2020–2024 (U.S. Bureau of Labor Statistics, 2024). OEWS data are used to examine employment trends across selected IT occupations and to contextualize firm-level patterns within broader labor market dynamics. These data source do not provide direct evidence of Amazon’s internal AI deployment, HR decision-making, or realized hires; they provide publicly observable labor signals that allow a distributional comparison of layoffs and current hiring emphasis.

Job Classification Framework

To enable consistent comparison, Amazon layoff titles and job postings were mapped into a unified technology job category framework. Categories were constructed based on primary functional responsibility and were mutually exclusive. The resulting classification scheme is presented in Table 1.

Where possible, Amazon job titles were also mapped to Standard Occupational Classification (SOC) codes to improve occupational precision and facilitate contextual comparison with OEWS data. Titles that could not be mapped to current technology hiring categories were classified as “unmapped” and analyzed

separately. This approach allows identification of roles that are not currently reconstituted within the firm's hiring structure.

Table 1. Technology Job Category Framework

Category	Description	Example Titles
Software Development	Application and platform engineering roles	Software Development Engineer, Front-End Engineer
Operations / IT Support	Infrastructure and operational maintenance	Support Engineer, IT Support Associate
Machine Learning Science	AI research and applied ML roles	Applied Scientist, ML Scientist
Systems / Security	Infrastructure and security engineering	Security Engineer, Systems Engineer
Data / BI	Data pipeline and analytics engineering	Data Engineer, BI Engineer
Product / Technical PM	Technical program and product management	Technical Program Manager
Hardware	Hardware engineering roles	Hardware Development Engineer

Analytical Strategy

The analytical objective is to identify shifts in organizational emphasis across technology job categories in order to assess whether AI-linked restructuring manifests as within-occupation labor recomposition. Because WARN notices reflect discrete restructuring events during a defined period, while job postings represent cumulative hiring demand over a broader and potentially different time window, direct headcount comparison would be misleading. The analysis therefore focuses on distributional shares of layoffs and hiring. Accordingly, the analysis should be interpreted as evidence of compositional divergence, not as evidence of direct replacement or causal attribution.

Layoff percentages are calculated using 1,955 technology layoffs, and hiring percentages are calculated using 6,075 technology openings. For each job category, the study compares the share of total technology layoffs to the share of total technology openings. The difference between hiring share and layoff share (measured in percentage points) is used to identify relative compression or expansion across categories. This approach enables evaluation of whether categories experiencing layoffs are simultaneously reweighted through hiring, thereby providing evidence consistent with internal labor recomposition.

In addition, roles not represented in the current hiring taxonomy (451 positions, or 23.1% of technology layoffs) are analyzed separately to assess whether they reflect structural removal, task compression, or strategic reprioritization. By focusing on compositional divergence instead of net employment totals, the design directly addresses the research question of how AI-driven adjustment unfolds within IT occupational boundaries while acknowledging differences in time windows between layoff and hiring data.

Data Analysis and Results

Distributional Divergence between Layoffs and Hiring

Table 2 compares the distribution of technology layoffs ($n=1,955$) and publicly observable technology openings ($n=6,075$) across the job categories defined in Table 1. Because layoffs reflect discrete restructuring events while job postings represent cumulative hiring demand over a broader window, the comparison focuses on percentage shares rather than raw headcounts.

Table 2. Distribution of Technology Layoffs and Hiring

Category	Layoff % (1,955)	Hiring % (6,075)	Difference (pp)
Software Development	40.70%	25.10%	-15.6
Operations / IT Support	2.80%	35.70%	32.9
BI & Data Engineering	5.90%	2.80%	-3.1
Data Science	0.80%	2.30%	1.5
Machine Learning Science	1.90%	5.60%	3.7
Systems / Security	3.00%	6.40%	3.4
Hardware	0.20%	5.80%	5.6
Technical PM	11.80%	10.20%	-1.6
Design	3.20%	2.20%	-1
Editorial / Content	1.10%	1.80%	0.7
Not represented in hiring taxonomy	23.10%	—	—

This pattern is consistent with task-based research suggesting that AI systems substitute more readily for routine coding and coordination-intensive tasks while complementing infrastructure, systems, and advanced technical functions (Hampole et al., 2025; Chopra et al., 2025). As shown in Figure 1, Software Development accounts for a substantially larger share of layoffs than of current hiring demand, while Operations and IT Support roles represent a disproportionately large share of openings relative to layoffs. Machine Learning, Security, and Hardware categories also exhibit higher hiring shares relative to layoff shares. These patterns indicate internal reweighting within the IT workforce and are consistent with task-based theories of technological change (Hampole et al., 2025; Chopra et al., 2025).

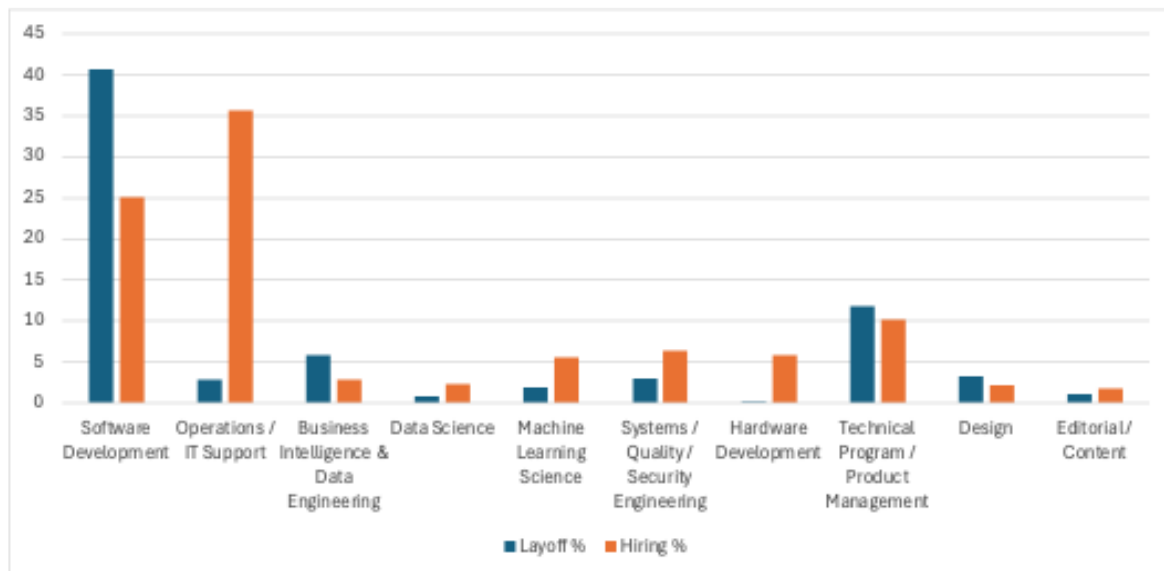


Figure 1. Distribution of IT Layoffs and Hiring by Job Category

Several categories exhibit substantial divergence between layoff share and hiring share. Software Development accounts for 40.7% of technology layoffs but 25.1% of technology openings, representing a difference of -15.6 percentage points. In contrast, Operations, IT, and Support Engineering represent 2.8% of layoffs but 35.7% of openings, a difference of +32.9 percentage points.

Machine Learning Science, Systems/Security Engineering, and Hardware Development also show higher representation in hiring relative to layoffs. These categories collectively account for a modest share of

layoffs but a substantially larger share of current openings. These distributional differences indicate relative reweighting within Amazon’s technology workforce. Coding-intensive and coordination-heavy roles are overrepresented in layoffs compared to hiring emphasis, whereas infrastructure, systems, and AI-oriented functions are more heavily represented in current hiring demand.

Importantly, because hiring data are not temporally matched to individual layoff events, these findings should not be interpreted as direct replacement. Instead, they suggest organizational rebalancing within the technology workforce. The observed shifts are consistent with task-based theories of technological change, which emphasize substitution at the task level and reallocation within occupations rather than wholesale occupational displacement (Autor et al., 2003; Hampole et al., 2025; Chopra et al., 2025).

IT & Computing Subsample Analysis

To determine whether the observed divergence reflects exit from the technology domain or redistribution within it, the analysis is restricted to roles currently defined as IT & Computing under the hiring taxonomy (n=1,504). As shown in Table 3, substantial divergence persists within the IT related only subset. Software Development represents 52.9% of IT layoffs but only 25.1% of IT openings (-27.8 percentage points), while Operations and IT Support increase from 3.7% of layoffs to 35.7% of openings (+32.0 percentage points). Similar patterns are observed in Machine Learning, Security, and Hardware categories, which exhibit higher hiring shares relative to layoffs.

Table 3. Distribution within IT & Computing Roles

IT & Computing Category	IT Layoff % (1,504)	IT Openings % (6,075)	Difference (pp)
Software Development	52.90%	25.10%	-27.8
Operations / IT Support	3.70%	35.70%	32
Business Intelligence & Data Engineering	7.70%	2.80%	-4.9
Data Science	1.10%	2.30%	1.2
Machine Learning Science	2.50%	5.60%	3.1
Research Science	0.60%	1.30%	0.7
Systems / Security Engineering	3.90%	6.40%	2.5
Hardware Development	0.20%	5.80%	5.6
Project / Technical PM	15.30%	10.20%	-5.1
Design	4.20%	2.20%	-2.0
Editorial / Content	1.40%	1.80%	0.4

Roles Not Reconstituted in Current Hiring Structure

Of 1,955 technology layoffs, 451 roles (23.1%) do not map to any current technology hiring category. These roles cluster into recurring job families, including recruiting and sourcing, HR systems and specialists, non-data science business analysts, non-technical program managers, finance and financial analysts, risk and compliance, marketing operations, and technical documentation.

To interpret this structural absence, the unmapped roles are grouped into three conceptual categories. First, some roles exhibit characteristics consistent with AI-related task substitution, particularly those centered on screening, reporting, and documentation-intensive functions. Second, some roles are likely affected by productivity augmentation, where AI tools enable fewer workers to perform the same function. Third, some reductions appear more consistent with strategic reprioritization or business-cycle adjustments rather than direct AI exposure. The absence of these roles from the current technology hiring taxonomy suggests possible structural removal or role redefinition, although it may also reflect role renaming, relocation, contracting, outsourcing, delayed rehiring or classification limits. A substantial share of unmapped roles

falls into functions plausibly exposed to AI-related demand compression, while the remainder reflect broader organizational restructuring.

Table 4. Roles not Represented in Current Hiring Taxonomy (n=451)

Role Family	Laid-off Count
Program Managers (non-technical)	94
Recruiting & Sourcing	88
HR Systems / Specialists	41
Finance / Analysts	39
Business Analysts	34
Risk & Compliance	29
Marketing Ops	26
Legal / Public Policy	23
Other	77
Total	451

National Occupational Context (OEWS 2020–2024)

To contextualize the firm-level findings, national employment trends in selected IT-related occupations are examined using Occupational Employment and Wage Statistics (OEWS) data from 2020 to 2024. As shown in Table 5, employment patterns reveal substantial heterogeneity within IT related occupations.

Several legacy or routine-oriented occupations experienced notable employment declines during this period. In contrast, higher-level and systems-oriented roles expanded. While some observed decline may reflect occupational reclassification under updated SOC definitions, the broader pattern indicates uneven growth within IT rather than uniform contraction.

Employment expansion is concentrated in oversight, security, and research-oriented functions, whereas declines are more evident in programming and certain support-oriented roles. These macro-level patterns are consistent with task-based research suggesting that technological change reshapes internal task composition within occupations before producing widespread occupation-level displacement (Hampole et al., 2025).

Table 5. Selected IT Occupations: Employment Change (2020–2024)

Occupation	2020 Employment	2024 Employment	% Change
Computer Programmers	178,140	109,870	–38.3%
Computer Systems Analysts	574,450	497,800	–13.3%
Network Support Specialists	184,220	146,450	–20.5%
Computer & IS Managers	457,290	645,970	41.30%
Information Security Analysts	138,000	179,430	30.00%
Computer & Info Research Scientists	30,250	38,510	27.30%

Discussion

Within-Occupation Labor Recomposition

The results provide evidence consistent with within-occupation labor recomposition during early generative AI diffusion. Rather than observing uniform contraction across IT related roles, the findings reveal systematic divergence between layoff and hiring distributions within the same occupational boundary.

Software Development and coordination-intensive roles account for a disproportionately large share of layoffs relative to current hiring demand, while infrastructure, operations, security, machine learning, and hardware roles account for a larger share of openings. These patterns suggest internal reweighting of task bundles rather than elimination of the IT occupation itself.

This mechanism aligns with task-based models of technological change, which predict that technologies substitute for specific task components while complementing others (Autor et al., 2003; Hampole et al., 2025). In the context of generative AI, coding, documentation, screening, and coordination-intensive tasks may become more automated or productivity-amplified, reducing demand for additional workers in those functions. At the same time, AI deployment increases demand for infrastructure, systems reliability, and advanced research roles that support model development and integration. Importantly, this recomposition occurs within the occupational boundary. The coexistence of layoffs and hiring in IT suggests that internal restructuring precedes occupation-level decline.

Reconciling Firm-Level Restructuring and Aggregate Stability

The findings help reconcile two seemingly contradictory observations in the emerging AI–labor debate. On the one hand, firms publicly attribute workforce reductions to AI-enabled efficiency gains (Bhaimiya, 2025; Galetti, 2026). On the other hand, aggregate labor statistics do not show widespread occupational collapse during the early generative AI diffusion period (Gimbel et al., 2025). The evidence presented here suggests that both observations can coexist. Firm-level restructuring may compress demand for certain task bundles while simultaneously expanding others, producing internal redistribution without immediate net employment decline. Aggregate statistics may therefore mask substantial internal recomposition within occupations. This perspective extends task-based exposure measures such as the Iceberg Index (Chopra et al., 2025) by illustrating how exposure manifests operationally inside firms.

Structural Removal and Role Redefinition

Approximately 23.1% of IT layoffs do not map to current hiring categories, indicating structural removal or redefinition of selected roles. These roles cluster in screening, documentation, reporting, and coordination-intensive functions, as well as certain strategic support domains. While not all such reductions can be attributed directly to AI exposure, a substantial portion exhibits characteristics consistent with AI-enabled task compression or productivity amplification. This suggests that generative AI may reduce headcount requirements in functions where output can be maintained with fewer workers. Some of the eliminated roles are more plausibly explained by strategic reprioritization or business-cycle conditions rather than direct AI exposure. Distinguishing these mechanisms is important to avoid overstating the role of AI in organizational restructuring.

Implications

The findings have several implications. For researchers, the study demonstrates that occupation-level employment measures may underestimate the impact of AI during early diffusion phases. Firm-level compositional analysis provides a complementary lens for detecting technological adjustment. For firms, the results highlight that AI adoption reshapes internal skill demand rather than eliminating technical work altogether. Demand shifts toward infrastructure, security, systems engineering, and applied AI research roles. For policymakers and workforce planners, the evidence suggests that retraining within occupational domains may be more relevant than wholesale occupational transitions during early generative AI adoption.

For higher education and workforce development, the findings suggest that adaptation within existing IT disciplines may align more closely with observed labor market dynamics than wholesale program replacement. In high-AI-exposure fields such as computer science and software engineering, curricular emphasis may increasingly shift toward systems design, AI integration, model governance, security,

infrastructure, and human–AI coordination, reflecting evolving internal task demands rather than occupational displacement. This suggests that curricular recalibration within established programs may better correspond to firm-level labor recomposition than the creation of entirely new occupational tracks.

Limitations and Future Research

This study has several limitations that should be considered when interpreting the findings. First, the analysis focuses on a single firm. Although Amazon represents a large, high-exposure technology employer and provides rich publicly observable data, the results may not generalize uniformly across industries or organizational contexts. Firms with different AI adoption strategies, organizational structures, or market conditions may exhibit different patterns of labor adjustment. Future research should extend this firm-level compositional approach to additional organizations to assess the robustness of within-occupation recomposition across contexts. In addition, the layoff analysis relies on Worker Adjustment and Retraining Notification (WARN) filings from Washington State. While Washington represents Amazon's headquarters and a major employment hub, WARN coverage does not capture layoffs occurring in other states or international locations. As a result, the observed layoff distribution may not fully reflect the firm's complete geographic restructuring pattern.

Second, the hiring data reflect a structured snapshot of publicly observable job postings rather than realized hires. Job postings represent cumulative demand over an observation window and may not correspond one-to-one with eventual headcount changes. Because layoffs and openings are not temporally matched at the individual job level, the analysis does not infer direct replacement. Instead, it examines distributional divergence. In addition, the hiring postings reflect broader geographic demand across multiple regions, whereas the layoff data are derived from Washington State WARN filings. As a result, the comparison captures compositional differences at a high level rather than geographically matched labor flows. Future work incorporating longitudinal hiring data or internal headcount records would allow more precise measurement of dynamic labor reallocation.

Third, although the analysis links observed patterns to task-based theories of technological change, it does not directly measure firm-level AI adoption intensity or tool deployment at the job-task level. As such, interpretations regarding AI-related task compression are necessarily inferential and grounded in consistency with prior exposure research (Hampole et al., 2025; Chopra et al., 2025). Future research could integrate firm-level AI adoption indicators, internal productivity metrics, or task-level workflow data to strengthen causal inference.

Fourth, some observed occupational shifts at the national level may reflect changes in Standard Occupational Classification (SOC) definitions rather than pure employment decline. While OEWS data are used only for contextual comparison, occupational reclassification may partially influence trend interpretation. Future work could incorporate microdata that tracks workers across occupational codes to disentangle classification effects from structural change.

Finally, the classification of job titles into technology categories necessarily involves judgment. Although categories were defined consistently based on primary functional responsibility, alternative taxonomies could produce slightly different compositional shares. Replication using automated text classification or multiple independent coders would further strengthen robustness. Despite these limitations, the study provides systematic firm-level evidence of within-occupation labor recomposition during early generative AI diffusion. By focusing on compositional divergence rather than net employment change, the analysis highlights an adjustment mechanism that may lead observable occupational decline.

Beyond firm-level analysis, future research could examine whether higher education institutions respond to early GenAI diffusion through curricular recomposition within computing disciplines. If within-occupation labor recomposition characterizes firm adjustment, universities may similarly rebalance instructional emphasis toward AI-complementary systems skills, governance, and integration rather than creating entirely separate occupational tracks. Empirical analysis of curriculum evolution, course offerings, and skill emphasis across institutions would provide insight into whether educational adaptation mirrors observed firm-level labor recomposition.

Conclusion

This study examines how GenAI-related restructuring may appear as employment recomposition within occupations rather than as occupational elimination. Using Amazon as a high-AI-exposure case, the analysis combines WARN layoff data, publicly observable IT job postings, and national occupational statistics to investigate compositional divergence within the technology workforce. The findings provide evidence consistent with within-occupation labor recomposition. While certain IT roles, particularly software development and coordination-intensive functions, are disproportionately represented in layoffs, hiring demand is concentrated in infrastructure, operations, security, machine learning, and hardware-oriented roles. In addition, a substantial subset of laid-off roles does not reappear in the firm's current IT hiring taxonomy, suggesting structural removal or redefinition of selected functions.

These patterns align with task-based theories of technological change, which predict substitution in routine cognitive tasks and complementarity in systems-level and advanced technical work (Autor et al., 2003; Hampole et al., 2025). Importantly, the coexistence of layoffs and hiring within the same occupational boundary indicates that labor adjustment under generative AI may first appear as internal reweighting of task bundles rather than as wholesale occupational collapse.

By focusing on distributional divergence rather than net employment change, this study highlights how aggregate labor statistics may mask substantial internal restructuring during early AI diffusion. The results suggest that generative AI reshapes internal skill demand within IT occupations before observable occupation-level decline emerges. As generative AI technologies continue to evolve, understanding how firms operationalize technological change within their internal labor structures will be critical for researchers, firms, and policymakers. Firm-level compositional analysis offers a complementary lens for examining technological disruption beyond traditional occupation-level metrics.

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