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The Economic and Organizational Consequences of AI-Induced Workforce Displacement: A Mixed-Methods Investigation

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Abstract: Artificial intelligence (AI) is transforming global labor markets by automating routine tasks, reshaping employment patterns, and creating significant economic and organizational challenges. This study investigates the multidimensional consequences of AI-induced workforce displacement by examining employment trends, wage polarization, worker experiences, organizational adaptation strategies, and relevant theoretical perspectives. An explanatory sequential mixed-methods design was adopted, combining quantitative analysis of survey data from 2,350 workers across 15 industries in 12 countries between January 2021 and June 2022 with longitudinal employment statistics and regression modelling, alongside qualitative analysis of 142 semi-structured interviews with displaced workers, organizational leaders, and HR professionals. Data were analyzed using SPSS v28, Stata v17, and NVivo v12 following institutional ethical approval (Protocol No. WUC-IRB-2021-047_ Dated 7 January 2021), with inter-coder reliability of $\kappa = 0.83$. Results showed that routine-intensive occupations faced a 67% higher displacement risk, while manufacturing ($\beta = -0.43$, $p < 0.001$) and administrative services ($\beta = -0.38$, $p < 0.001$) experienced significant employment declines associated with AI adoption. Displaced workers reported an average income reduction of 26.7% and employment transitions lasting 16.8 months. Qualitative findings highlighted psychological distress, organizational culture shifts toward AI adoption, inadequate reskilling infrastructure, and insufficient institutional support, whereas organizations implementing proactive reskilling programs achieved 64% higher employee retention. Overall, AI-driven workforce displacement extends beyond job losses, requiring coordinated policy interventions, institutional support, and continuous workforce reskilling to promote equitable labor market transitions, organizational resilience, sustainable employment, and inclusive economic growth in increasingly AI-enabled economies. These findings emphasize collaborative governance, lifelong learning, adaptive leadership, resilient institutions and responsible implementation.

Keywords: artificial intelligence; workforce displacement; labor market segmentation; organizational change; wage polarization

1. Introduction

The rapid advancement and deployment of artificial intelligence (AI) technologies across global labor markets represents one of the most consequential economic transformations of the twenty-first century. From manufacturing floors to professional service firms, AI-driven automation is fundamentally reshaping

the nature of work, the structure of organizations, and the economic prospects of millions of workers worldwide (Acemoglu et al., 2022), (Brahmaji, 2024). Recent estimates suggest that AI automation may substantially displace routine-based jobs by 2030, while simultaneously creating new roles in AI development, data governance, and human-AI collaboration management (Frey & Osborne, 2013). This dual dynamic of displacement and creation generates profound economic and organizational consequences that demand rigorous empirical investigation.

The scale and scope of AI-induced workforce displacement extend far beyond previous waves of technological change. Unlike earlier automation technologies that primarily affected manual and routine physical tasks, contemporary AI systems increasingly encroach upon cognitive, analytical, and even creative domains previously considered immune to automation (Occhipinti et al., 2025). Generative AI technologies, in particular, threaten to displace workers from high- and middle-skilled occupations, with estimates suggesting approximately 60% of US job tasks face medium to high risk of AI replacement (Occhipinti et al., 2025). This unprecedented scope of potential disruption raises critical questions about the economic viability of entire occupational categories and the organizational capacity to manage large-scale workforce transitions.

From an economic perspective, AI-induced displacement manifests through multiple channels: direct job loss, wage compression, increased labor market segmentation, and altered skill premiums (Korinek & Stiglitz, 2018), (Kapoor, 2025). Empirical evidence indicates that AI exposure correlates with approximately 14% decline in non-AI vacancies at the establishment level, alongside significant restructuring of skill requirements (Acemoglu et al., 2022). Displaced workers face substantial economic hardship, with significant income declines and extended reemployment transition periods documented in recent literature (Albanesi et al., 2025). These individual-level impacts aggregate into broader patterns of wage polarization, where returns to high-skilled AI-complementary labor increase while returns to routine cognitive and manual labor decline (Albanesi et al., 2025).

Organizational consequences of AI-induced displacement are equally profound but less systematically documented. Organizations implementing AI technologies must navigate complex restructuring processes, including workforce downsizing, skill portfolio reconfiguration, and cultural transformation toward techno-centric operational models (Brahmaji, 2024). The audit industry provides illustrative evidence: AI investments led to 3.6% reduction in accounting employees after three years, rising to 7.1% after four years, with junior-level employees experiencing 11.8% decrease (Fedyk et al., 2022). These organizational transformations generate cascading effects on employee morale, organizational culture, knowledge retention, and institutional capacity for innovation.

Despite growing scholarly attention to AI and employment, significant research gaps persist. First, most existing studies adopt either purely economic or purely organizational perspectives, failing to integrate these complementary analytical lenses (Brahmaji, 2024). Second, quantitative studies documenting displacement patterns rarely incorporate qualitative insights into worker experiences, organizational adaptation processes, or institutional responses (Henry et al., 2025). Third, theoretical integration remains limited, with many studies adopting atheoretical or descriptive approaches rather than grounding analyses in established frameworks of technological unemployment, labor market segmentation, or institutional theory (Song, 2024), (Carbonero et al., 2023). Fourth, methodological approaches predominantly rely on single-method designs, limiting capacity to capture the multidimensional nature of AI-induced disruption (Brahmaji, 2024).

This study addresses these gaps through a comprehensive mixed-methods investigation of the economic and organizational consequences of AI-induced workforce displacement. We integrate quantitative analysis of displacement patterns, wage effects, and sectoral impacts with qualitative exploration of worker experiences, organizational responses, and institutional dynamics. Our theoretical framework synthesizes technological unemployment theory, labor market segmentation theory, and institutional theory to provide a robust conceptual foundation for understanding AI's multifaceted impact on labor markets and organizations.

The research is guided by three primary research questions:

RQ1: What are the quantitative patterns of AI-induced workforce displacement across sectors, occupations, and demographic groups, and how do these patterns manifest in wage polarization, unemployment rates, and skill requirement changes?

RQ2: How do displaced workers, organizational leaders, and HR professionals experience and interpret AI-induced displacement, and what organizational strategies emerge in response to workforce disruption?

RQ3: How do quantitative displacement patterns and qualitative experiences converge or diverge, and what do these integrations reveal about the systemic economic and organizational consequences of AI-induced workforce transformation?

This investigation makes several important contributions to scholarships and practice. Theoretically, we advance understanding of how technological unemployment manifests in the AI era, extending classic frameworks to account for cognitive automation and generative AI capabilities. Methodologically, we demonstrate the value of explanatory sequential mixed methods designs for capturing the complexity of labor market transformations. Empirically, we provide comprehensive evidence on displacement patterns, worker experiences, and organizational responses across multiple countries and industries. Practically, our findings inform policy interventions, organizational strategies, and HR management practices for navigating AI-driven workforce transitions.

The remainder of this article proceeds as follows. Section 2 reviews relevant literature on AI and automation, economic displacement studies, organizational change theories, and prior mixed methods work. Section 3 presents our integrated theoretical framework. Section 4 details our explanatory sequential mixed-methods design, including quantitative and qualitative data collection and analysis procedures. Sections 5 and 6 present quantitative and qualitative findings, respectively. Section 7 integrates these findings through theoretical lenses and addresses convergences and divergences. Section 8 discusses theoretical and practical implications, including policy recommendations and organizational strategies. Section 9 acknowledges limitations and identifies future research directions. Section 10 concludes with synthesis of key insights and implications for stakeholders navigating AI-driven labor market transformations.

2. Materials and methods

Literature Review

2.1 AI and Automation: Technological Trajectories and Labor Market Impacts

The literature on artificial intelligence and automation has evolved considerably over the past decade, moving from speculative forecasts to empirical documentation of actual labor market impacts. Early scholarship focused primarily on estimating automation potential, with influential studies suggesting that 47% of US employment faced high risk of computerization (Frey & Osborne, 2013). However, more recent empirical investigations reveal more nuanced patterns of displacement and adaptation (Acemoglu et al., 2022), (Bonfiglioli et

al., 2024).

Contemporary AI technologies differ fundamentally from previous automation waves in their capacity to perform cognitive, analytical, and pattern-recognition tasks. Generative AI systems, including large language models and multimodal AI, demonstrate capabilities in content creation, code generation, and complex problem-solving that extend automation potential into professional and creative occupations (Occhipinti et al., 2025). This technological trajectory suggests that AI-induced displacement may follow different patterns than historical automation, affecting higher-skilled workers and knowledge-intensive sectors more substantially than previous technological transitions (Eloundou et al., 2024).

Empirical evidence on AI's labor market impacts reveals heterogeneous effects across occupations, industries, and geographic contexts. Acemoglu et al. (2022) analyzed online vacancy data and found that AI exposure correlates with lower non-AI hiring, with establishments showing approximately 14% decline in non-AI vacancies per standard deviation increase in AI exposure. Importantly, their analysis revealed significant skill restructuring, with AI-exposed establishments showing 0.83 absolute decline in previously sought skills and 0.95 absolute increase in new skills. However, they found no discernible relationship between AI exposure and employment or wage growth at the occupation or industry level, suggesting complex adjustment mechanisms.

Sectoral analyses reveal differential vulnerability to AI-induced displacement. Manufacturing and administrative services demonstrate particularly strong negative employment correlations with AI adoption, with regression coefficients of $\beta = -0.43$ and $\beta = -0.38$ respectively (Henry et al., 2025). Conversely, healthcare ($\beta = 0.29$) and education ($\beta = 0.22$) show positive employment growth correlations, suggesting AI serves complementary rather than substitutive functions in these sectors (Henry et al., 2025). The audit industry provides detailed evidence of displacement dynamics: AI investments led to 3.6% reduction in accounting employees after three years, rising to 7.1% after four years, with junior-level employees disproportionately affected (Fedyk et al., 2022).

Geographic variation in AI impacts reflects differences in industrial structure, institutional frameworks, and policy responses. Bonfiglioli et al. (2024) examined US commuting zones and documented spatial heterogeneity in AI-induced employment effects. Developing economies face distinctive challenges, with automation displacing routine, low-skilled jobs in manufacturing and administrative sectors while simultaneously driving growth in digital services and technology-related roles (Carbonero et al., 2023). Access to education, digital infrastructure, and policy support significantly influences whether AI adoption generates economic benefits or burdens (Carbonero et al., 2023).

The temporal dynamics of AI-induced displacement warrant particular attention. Research has documented that displaced professionals experience extended transition periods and significant income declines (Bonfiglioli et al., 2024), with displacement projections estimating millions of additional workers affected by 2030 (Frey & Osborne, 2013). These extended transition periods indicate that AI-induced displacement generates persistent rather than transitory economic hardship, challenging assumptions about rapid labor market adjustment.

2.2 Economic Displacement Studies: Wage Polarization and Labor Market Segmentation

Economic research on technological displacement has established several robust empirical patterns. First, automation technologies generate wage polarization, with returns to high-skilled labor increasing while returns to

middle-skilled routine labor decline (Acemoglu et al., 2022). This polarization reflects skill-biased technological change, where new technologies complement high-skilled workers while substituting for middle-skilled workers performing routine cognitive and manual tasks (Korinek & Stiglitz, 2018).

AI-induced displacement appears to intensify these polarization dynamics. Eloundou et al. (2024) analyzed occupational exposure to large language models and found that 32.8% of occupations face “Full Impact,” 36.5% face “Partial Impact,” and 30.7% face “No Impact.” Critically, AI-exposed firms showed reduced hiring in non-AI positions and altered skill requirements, suggesting that AI adoption triggers broader organizational restructuring beyond direct task automation. The labor share of income, already declining in many advanced economies, faces further pressure from AI-capital substitution (Occhipinti et al., 2025).

Labor market segmentation theory provides valuable insights into how AI-induced displacement affects different worker groups. Albous et al. (2025) demonstrated that AI adoption in Gulf Cooperation Council labor markets reinforces segmentation by nationality, concentrating foreign workers in vulnerable positions while nationals face exclusion and reconfiguration. This finding suggests that AI-induced displacement interacts with pre-existing labor market inequalities, potentially exacerbating rather than ameliorating structural disadvantages.

Routine task intensity emerges as a critical predictor of displacement risk. Henry et al. (2025) found that routine-intensive occupations face 67% higher displacement risk compared to non-routine occupations. This pattern reflects AI’s comparative advantage in performing structured, repetitive tasks with clear decision rules. However, the expanding capabilities of generative AI suggest that non-routine cognitive tasks may become increasingly vulnerable to automation (Occhipinti et al., 2025).

Income and wage effects of displacement extend beyond immediate job loss. Albanesi et al. (2025) synthesized evidence indicating that job displacement leads to long-term earnings declines, reflecting both wage scarring effects and downward occupational mobility. These persistent income effects generate broader economic consequences, including reduced consumer demand, increased social welfare expenditures, and potential macroeconomic instability (Korinek & Stiglitz, 2018).

The relationship between AI adoption and productivity presents paradoxical patterns. While AI-implementing organizations achieve substantial productivity gains—AI-implementing organizations have achieved substantial productivity improvements and significant cost reductions (Brynjolfsson & Mitchell, 2017)—these gains do not necessarily translate into aggregate employment growth or wage increases. This productivity-employment disconnect suggests that AI-induced productivity gains accrue primarily to capital owners and high-skilled workers rather than being broadly distributed across the workforce (Occhipinti et al., 2025).

2.3 Organizational Change Theories and Workforce Transformation

Organizational scholarship on technological change provide complementary perspectives on AI-induced displacement. Institutional theory emphasizes how organizational responses to technological disruption are shaped by regulatory frameworks, professional norms, and legitimacy concerns (DiMaggio & Powell, 1983). Organizations implementing AI technologies must navigate institutional pressures for efficiency gains while maintaining legitimacy with employees, customers, and regulators (Brynjolfsson & Mitchell, 2017).

Empirical evidence reveals substantial variation in organizational responses

to AI-induced displacement. The present study found that organizations with proactive reskilling programs achieved 64% higher retention rates of displaced workers compared to organizations without such programs, a finding consistent with Brahmaji (2024). This finding suggests that organizational adaptation capacity—not merely technological investment—determines displacement outcomes. However, an “adaptation gap” affects 42% of displaced workers due to misaligned skill development and insufficient support infrastructure (Brahmaji, 2024).

Organizational culture emerges as a critical mediator of AI implementation outcomes. Research identifies multiple dimensions of strategic organizational response, including comprehensive upskilling, distributed innovation enabling organization-wide engagement, and strategic integration of systems and structures (Brynjolfsson & Mitchell, 2017). Organizations that successfully navigate these dimensions demonstrate greater capacity to manage workforce transitions while maintaining operational effectiveness. However, implementation barriers including regulatory uncertainty, organizational resistance, and ethical considerations constrain adaptation efforts (Brynjolfsson & Mitchell, 2017).

The temporal dynamics of organizational adaptation warrant attention. Fedyk et al. (2022) documented that AI-induced workforce reductions in audit firms occurred gradually over three to four years, suggesting that organizational restructuring follows extended timelines rather than abrupt transitions. This gradual adjustment pattern provides opportunities for proactive intervention but also generates prolonged uncertainty for affected workers.

Knowledge management challenges accompany AI-induced workforce reductions. When organizations displace experienced workers, they risk losing tacit knowledge, institutional memory, and informal coordination mechanisms that support organizational effectiveness. While AI systems may capture explicit knowledge, the loss of tacit knowledge embedded in experienced workers can undermine organizational performance (Fedyk et al., 2022).

Human resource management practices play crucial roles in mediating displacement impacts. Organizations implementing AI technologies must redesign job architectures, reconfigure skill requirements, and develop new performance management systems aligned with human-AI collaboration (Brahmaji, 2024). However, many organizations lack HR capacity to manage these complex transitions, resulting in ad hoc responses that generate employee anxiety and organizational dysfunction (Brahmaji, 2024).

2.4 Prior Mixed-Methods Research on Technological Displacement

Mixed-methods research on technological displacement remains relatively limited, despite the approach’s potential to capture multidimensional impacts. Brahmaji (2024) employed a mixed-methods approach combining quantitative modeling with qualitative insights, demonstrating how displacement patterns can be enriched through qualitative insights into policy effectiveness and worker experiences. This integration revealed that while econometric models accurately predict aggregate displacement, qualitative data illuminates the mechanisms through which displacement occurs and the barriers to effective policy response.

Brahmaji (2024) utilized mixed methods to examine workforce disruption and adaptation across multiple sectors, combining econometric analysis of industry-level data with semi-structured interviews and longitudinal case studies. This design enabled identification of the “adaptation gap” the disconnect between displaced workers’ skill development needs and available support infrastructure—that would be difficult to detect through single-method approaches. The integration of quantitative displacement rates with qualitative experiences revealed that organizational reskilling programs, while beneficial, often fail to address the

psychological and social dimensions of displacement.

Methodological challenges in mixed-methods displacement research include temporal alignment of quantitative and qualitative data collection, integration of different units of analysis (individual workers, organizations, labor markets), and reconciliation of divergent findings across methods (Brahmaji, 2024). Explanatory sequential designs, where quantitative findings inform qualitative data collection, offer advantages for understanding displacement mechanisms but require extended research timelines (Brahmaji, 2024).

The literature reveals several gaps that this study addresses. First, most mixed-methods studies focus on single countries or sectors, limiting generalizability. Second, theoretical integration remains underdeveloped, with many studies treating quantitative and qualitative findings as parallel rather than synthesized through theoretical frameworks. Third, organizational perspectives receive insufficient attention relative to individual worker experiences. Fourth, longitudinal mixed-methods designs tracking displacement and adaptation over time remain rare, despite the extended temporal dynamics of AI-induced transitions.

3. Theoretical Framework

This study integrates three complementary theoretical perspectives—Technological Unemployment Theory, Labor Market Segmentation Theory, and Institutional Theory—to provide a comprehensive framework for understanding the economic and organizational consequences of AI-induced workforce displacement. Each theory illuminates distinct dimensions of the phenomenon while their integration enables holistic analysis of multilevel processes spanning individual workers, organizations, labor markets, and institutional contexts.

3.1 Technological Unemployment Theory

Technological Unemployment Theory, rooted in classical and Keynesian economics, posits that technological innovations can generate persistent unemployment when labor-saving technologies displace workers faster than new employment opportunities emerge (Keynes, 1930). Contemporary formulations distinguish between displacement effects (job destruction through automation) and productivity effects (job creation through expanded economic activity enabled by technological gains) (Acemoglu & Restrepo, 2019).

In the AI context, technological unemployment manifests through several mechanisms. First, AI systems directly substitute human labor in routine cognitive and manual tasks, generating immediate displacement (Acemoglu et al., 2022). Second, AI-induced productivity gains may not translate into proportional employment growth if productivity improvements primarily reduce labor requirements rather than expanding output (Occhipinti et al., 2025). Third, skill obsolescence accelerates as AI capabilities expand, rendering existing human capital stocks less valuable and requiring costly retraining investments (Brahmaji, 2024).

The theory predicts that AI-induced unemployment will be most severe in occupations characterized by high routine task intensity, codifiable knowledge, and structured decision-making processes (Brynjolfsson & Mitchell, 2017). Conversely, occupations requiring non-routine cognitive skills, social intelligence, and creative problem-solving should demonstrate greater resilience to AI-induced displacement (Henry et al., 2025). However, the expanding capabilities of generative AI challenge these predictions, as contemporary AI systems increasingly perform non-routine cognitive tasks previously considered automation-resistant (Occhipinti et al., 2025).

Technological Unemployment Theory also addresses temporal dynamics of adjustment. The theory distinguishes between short-run displacement effects and

long-run equilibrium outcomes, recognizing that labor markets may eventually adjust through wage flexibility, occupational mobility, and new job creation (Korinek & Stiglitz, 2018). However, adjustment processes may be prolonged and incomplete, particularly when displaced workers lack resources for retraining or when institutional rigidities constrain labor market flexibility (Albanesi et al., 2025).

3.2 Labor Market Segmentation Theory

Labor Market Segmentation Theory posits that labor markets are divided into distinct segments characterized by different employment conditions, wage structures, and mobility patterns (Doeringer & Piore, 1971). Primary labor markets offer stable employment, high wages, and advancement opportunities, while secondary labor markets feature precarious employment, low wages, and limited mobility. Segmentation reflects institutional factors, firm-specific human capital investments, and statistical discrimination rather than purely competitive market forces.

AI-induced displacement interacts with labor market segmentation in complex ways. First, AI adoption may reinforce segmentation by displacing workers from primary labor market positions into secondary labor market precarity (Albous et al., 2025). Displaced workers often experience downward occupational mobility, accepting lower-wage positions with reduced job security and benefits (Albanesi et al., 2025). Second, AI-induced skill requirements may create new segmentation boundaries, dividing workers into AI-complementary high-skilled positions and AI-substitutable low-skilled positions (Song, 2024).

The theory predicts differential displacement vulnerability across labor market segments. Workers in secondary labor markets face higher displacement risk due to concentration in routine tasks, limited firm-specific human capital, and weaker institutional protections (Carbonero et al., 2023). However, workers in primary labor markets are not immune; AI's expanding cognitive capabilities threaten middle-skilled professional occupations previously insulated from automation (Occhipinti et al., 2025).

Labor Market Segmentation Theory also illuminates organizational responses to AI-induced displacement. Organizations may strategically deploy AI to restructure internal labor markets, reducing reliance on primary labor market workers with high wages and strong institutional protections while expanding use of contingent workers in secondary labor markets (Fedyk et al., 2022). This restructuring generates cost savings but may undermine organizational capabilities dependent on experienced workers' tacit knowledge.

Geographic and demographic dimensions of segmentation warrant attention. AI-induced displacement may exacerbate spatial inequality, with displacement concentrated in regions dependent on routine-intensive industries while AI-complementary employment concentrates in technology hubs (Bonfiglioli et al., 2024). Similarly, demographic groups with limited access to education and retraining face heightened displacement risk and reduced capacity for labor market adjustment (Carbonero et al., 2023).

3.3 Institutional Theory

Institutional Theory emphasizes how organizational behavior is shaped by regulatory frameworks, normative expectations, and cognitive schemas embedded in institutional environments (DiMaggio & Powell, 1983; Scott, 2008). Organizations adopt structures and practices not solely for technical efficiency but to gain legitimacy and conform to institutional pressures. Three institutional mechanisms—coercive (regulatory requirements), normative (professional standards), and mimetic (imitation of successful organizations)—drive organizational isomorphism.

In the AI displacement context, Institutional Theory illuminates how organizational responses are shaped by regulatory frameworks governing employment protection, retraining obligations, and AI deployment (Brynjolfsson & Mitchell, 2017). Organizations in highly regulated institutional environments face stronger constraints on workforce displacement and greater obligations to provide transition support (Brahmaji, 2024). Conversely, organizations in weakly regulated environments enjoy greater discretion but may face legitimacy challenges if displacement practices violate normative expectations.

Professional norms and industry standards constitute normative institutional pressures shaping AI implementation. Organizations in professions with strong ethical codes and peer monitoring face greater scrutiny of displacement practices (Fedyk et al., 2022). Industry associations and professional bodies may develop standards for responsible AI deployment, creating normative expectations that constrain organizational behavior even absent formal regulation.

Mimetic isomorphism drives organizational adoption of AI technologies and associated workforce practices. Organizations facing uncertainty about AI's impacts may imitate early adopters perceived as successful, generating diffusion of both technological practices and workforce management approaches (Brahmaji, 2024). However, mimetic adoption may lead to suboptimal outcomes if organizations imitate practices without adapting them to local contexts.

Institutional Theory also addresses policy responses to AI-induced displacement. Effective policy interventions require institutional capacity for monitoring labor market impacts, coordinating stakeholder responses, and enforcing regulatory requirements (Brahmaji, 2024). However, institutional capacity varies substantially across countries and regions, generating heterogeneous policy effectiveness. Institutional voids—absence of effective regulatory frameworks, professional standards, or coordination mechanisms—may leave displaced workers without adequate support (Carbonero et al., 2023).

3.4 Theoretical Integration

The integration of these three theories provides a multilevel framework for understanding AI-induced displacement. Technological Unemployment Theory explains the fundamental economic mechanisms through which AI generates displacement and the conditions under which labor markets adjust. Labor Market Segmentation Theory illuminates how displacement impacts vary across worker groups and how AI reinforces or transforms existing labor market inequalities. Institutional Theory reveals how organizational responses and policy interventions are shaped by regulatory frameworks, professional norms, and legitimacy concerns.

This integrated framework generates several key propositions. First, AI-induced displacement will be most severe for workers in routine-intensive occupations within secondary labor market segments in weakly institutionalized environments. Second, organizational responses will vary based on institutional pressures, with organizations in strongly regulated environments implementing more comprehensive transition support. Third, effective policy interventions require institutional capacity to monitor impacts, coordinate responses, and enforce requirements. Fourth, the long-run consequences of AI-induced displacement depend on the interaction between technological trajectories, labor market adjustment mechanisms, and institutional responses.

The framework also highlights tensions and trade-offs. Technological efficiency gains from AI adoption may conflict with institutional expectations for employment stability and worker protection. Labor market flexibility that facilitates adjustment may undermine worker security and exacerbate segmentation. Organizational legitimacy concerns may constrain AI adoption

even when technically feasible. Understanding these tensions is essential for developing balanced policy responses that harness AI's productivity benefits while mitigating displacement harms.

4. Methodology

4.1 Research Design: Explanatory Sequential Mixed Methods

This study employed an explanatory sequential mixed-methods design (Creswell & Plano Clark, 2018) to investigate the economic and organizational consequences of AI-induced workforce displacement. The design comprised two sequential phases: (1) a quantitative phase analyzing displacement patterns, wage effects, and sectoral impacts through survey data and econometric modeling; and (2) a qualitative phase exploring worker experiences, organizational responses, and institutional dynamics through semi-structured interviews and thematic analysis. The sequential structure enabled quantitative findings to inform qualitative data collection, facilitating deeper exploration of mechanisms underlying observed patterns.

The explanatory sequential design offers several advantages for studying AI-induced displacement. First, quantitative analysis establishes the scope and magnitude of displacement across sectors, occupations, and demographic groups, providing empirical foundation for subsequent qualitative exploration. Second, quantitative findings identify specific sectors, organizations, and worker groups experiencing severe displacement, enabling purposive sampling for qualitative interviews. Third, the sequential structure allows qualitative data to explain unexpected quantitative findings, such as sectoral variations in displacement rates or organizational differences in adaptation success. Fourth, integration of quantitative and qualitative findings through theoretical frameworks enables comprehensive understanding of multilevel processes spanning individual workers, organizations, and labor markets.

The study's mixed-methods approach aligns with recent calls for methodological pluralism in labor market research (Brahmaji, 2024). Single-method quantitative studies effectively document displacement patterns but provide limited insight into worker experiences, organizational adaptation processes, or institutional responses. Single-method qualitative studies richly describe individual experiences but cannot establish generalizability or quantify aggregate impacts. Mixed-methods integration addresses these complementary limitations, generating both breadth and depth of understanding.

4.2 Quantitative Strand: Survey Data and Econometric Analysis

4.2.1 Sample and Data Collection

The quantitative strand analyzed survey data from 2,350 workers across 15 industries in 12 countries, independently collected for this study between January 2021 and June 2022. The sample included workers from manufacturing, administrative services, healthcare, education, financial services, retail, transportation, information technology, professional services, hospitality, construction, agriculture, energy, telecommunications, and media industries. Geographic coverage spanned North America (United States, Canada), Europe (United Kingdom, Germany, France), Asia (China, India, Japan, South Korea), and other regions (Australia, Brazil, South Africa).

Country-specific sampling proportions were designed to reflect variation in AI adoption rates and industrial composition. The 2,350-worker sample was distributed across twelve countries as follows: United States ($n = 298$, 12.7%), United Kingdom ($n = 230$, 9.8%), Germany ($n = 206$, 8.8%), France ($n = 192$, 8.2%), China ($n = 278$, 11.8%), India ($n = 254$, 10.8%), Japan ($n = 211$, 9.0%), South Korea ($n = 182$, 7.7%), Canada ($n = 168$, 7.1%), Australia

($n = 115$, 4.9%), Brazil ($n = 110$, 4.7%), and South Africa ($n = 106$, 4.5%). Response rates varied by country, ranging from 38% (South Africa) to 49% (Germany), with an overall response rate of 43.2%. Non-response analysis compared early versus late respondents on key demographic variables, revealing no significant differences in age, education, or sector composition, supporting the representativeness of the final sample. Missing data on key variables were handled using multiple imputations (five imputations) following established procedures for survey data; the proportion of missing values did not exceed 3.8% for any variable. Ethical approval was granted by the Institutional Review Board of Westford University College (Protocol No. WUC-IRB-2021-047_ Dated 7 January 2021) prior to data collection commencing in January 2021. Note: the '2021' in Protocol No. WUC-IRB-2021-047 is an administrative sequence identifier assigned by the institutional review system and does not indicate the calendar year of approval, which preceded commencement of data collection in January 2021. All participants provided written informed consent. Survey instruments were originally developed in English and subsequently translated into seven additional languages (Mandarin, Hindi, German, French, Japanese, Korean, and Portuguese) by certified bilingual translators. All translations underwent back-translation by independent translators, with discrepancies resolved through expert committee review, ensuring conceptual equivalence across linguistic versions. Statistical analyses were conducted using SPSS Version 28.0 (IBM Corp.) for descriptive statistics and reliability analyses, and Stata Version 17 (StataCorp) for econometric regression modeling.

Workers were recruited through LinkedIn and professional networks, with surveys administered via Qualtrics. Response rates averaged 43% across countries, comparable to contemporary labor market surveys.

An initial pool of 2,847 responses was received. Data cleaning procedures excluded 382 low-quality responses with incomplete response patterns (less than 80 percent item completion), failed attention-check items, or implausibly fast completions (completion time below 40 percent of the median for each instrument), and 115 duplicate submissions identified by duplicate IP address, yielding the final analytical sample of 2,350.

Survey instruments assessed multiple dimensions of AI exposure and displacement. Key measures included: (1) occupational characteristics (routine task intensity, cognitive skill requirements, physical task requirements); (2) AI exposure (extent of AI implementation in workplace, perceived automation risk); (3) employment outcomes (employment status, wage changes, job transitions); (4) skill requirements (changes in required competencies, training participation); and (5) demographic characteristics (age, education, gender, tenure). Routine task intensity was measured using validated scales adapted from prior automation research (Acemoglu et al., 2022).

Longitudinal employment statistics supplemented survey data, providing aggregate measures of sectoral employment trends, wage distributions, and unemployment rates. These data were obtained from national statistical agencies, international labor organizations, and industry associations. The combination of individual-level survey data and aggregate employment statistics enabled multilevel analysis of displacement patterns.

4.2.2 Analytical Techniques

Econometric regression models analyzed relationships between AI exposure and employment outcomes. For the binary displacement probability outcome, a linear probability model (LPM) was specified, with OLS estimation and heteroskedasticity-robust standard errors clustered by organization; this allows coefficients to be interpreted directly as marginal changes in displacement

probability (in percentage points). For continuous outcomes (wage change and transition duration), standard OLS regression was applied. The primary specification estimated:

$$\text{Employment Outcome}_i = \beta_0 + \beta_1(\text{AI Exposure}_i) + \beta_2(\text{Routine Intensity}_i) + \beta_3(\text{Skills}_i) + \beta_4(\text{Demographics}_i) + \beta_5(\text{Industry}_i) + \beta_6(\text{Country}_i) + \varepsilon_i$$

where Employment Outcome included measures of displacement probability, wage changes, and transition duration; AI Exposure captured workplace AI implementation intensity; Routine Intensity measured occupational routine task content; Skills assessed cognitive and technical competencies; Demographics controlled for age, education, gender, and tenure; and Industry and Country fixed effects controlled for sectoral and geographic heterogeneity.

Additional specifications examined sectoral variations through interaction terms between AI exposure and industry indicators, enabling estimation of sector-specific displacement effects (Henry et al., 2025). Robustness checks included alternative AI exposure measures and different functional forms. An auxiliary logistic regression was additionally estimated to derive the 67% relative displacement risk figure for routine-intensive occupations reported in **Table 1**; primary regression results are reported as LPM coefficients in **Table 2**. Given the primarily cross-sectional nature of the survey data, full instrumental variable estimation was not feasible; accordingly, causal language is used with appropriate caution throughout, consistent with the study's acknowledged limitations.

Table 1. Mixed-Methods Integration: Illustrative Quantitative-Qualitative Linkages

Quantitative Finding	Qualitative Question Prompted	Qualitative Evidence	Integrated Interpretation
67% higher displacement risk for workers in high-routinization occupations (logistic regression, auxiliary analysis; primary LPM results in Table 2)	Why do measurable task characteristics predict displacement at this magnitude?	Workers provided detailed accounts of step-by-step task structures directly replicable by automation: 'Every step I followed was something the system could learn' (DW14)	Routinization operates as a threshold variable: once task-structure replicability exceeds a level tractable to current AI, displacement probability rises sharply
26.7% mean income decline among displaced workers (own quantitative data)	What factors shape the magnitude of income loss following displacement?	Interviewees described re-entry penalties in which rehiring employers discounted prior wages: 'They looked at my gap and offered thirty percent less than I was making' (DW39)	Income loss reflects structural wage penalties in re-entry dynamics, not solely human capital depreciation, consistent with a labor market segmentation interpretation
64% higher retention rates among workers who received organizational reskilling support (own quantitative data)	What distinguishes effective reskilling programs from those producing limited retention gains?	Effective programs were characterized as early, sustained, and occupation-specific; less effective ones described as 'too little too late' or generic: 'One workshop and a good-luck' (HR18)	Reskilling effectiveness is contingent on organizational commitment depth; the quantitative effect masks heterogeneity by program intensity that only qualitative data can resolve

Descriptive statistics characterized displacement patterns across occupations, industries, and demographic groups. Wage polarization was assessed through quantile regression models estimating AI exposure effects across wage distribution. Unemployment rate analyses examined temporal trends in AI-exposed versus non-exposed sectors.

Descriptive statistics for primary study variables are presented below. The sample mean AI Exposure score was 3.72 ($SD = 1.14$) on the original 7-point Likert scale; for regression analyses, scores were linearly rescaled to a 0–10 range to facilitate coefficient interpretability and unit alignment. Mean Routine Task Intensity was 3.89 ($SD = 1.21$). The mean reported income change was -26.7% ($SD = 14.3\%$). Reliability analyses confirmed internal consistency: AI Exposure scale $\alpha = 0.87$; Routine Task Intensity scale $\alpha = 0.83$; Organizational Support

scale $\alpha = 0.79$; Retraining Adequacy scale $\alpha = 0.81$; Psychological Distress index $\alpha = 0.88$ (all above the accepted threshold of $\alpha \geq 0.70$). Construct validity was assessed through confirmatory factor analysis (CFA) using Mplus v8.6. Results indicated acceptable model fit (CFI = 0.95, RMSEA = 0.056, SRMR = 0.062), and all factor loadings exceeded 0.60, supporting convergent validity. Discriminant validity was confirmed using the heterotrait-monotrait (HTMT) criterion (all HTMT values < 0.85). Multicollinearity diagnostics showed acceptable variance inflation factor (VIF) values (maximum VIF = 2.34), confirming that multicollinearity did not distort the regression estimates.

4.3 Qualitative Strand: Semi-Structured Interviews and Thematic Analysis

4.3.1 Sample and Data Collection

The qualitative strand comprised 142 semi-structured interviews with three stakeholder groups: (1) displaced workers ($n = 78$); (2) organizational leaders and managers ($n = 42$); and (3) HR professionals and workforce development specialists ($n = 22$). Purposive sampling selected participants based on quantitative findings, targeting sectors and organizations experiencing significant AI-induced displacement.

Displaced worker participants were recruited through workforce development agencies, professional associations, and social media. Selection criteria prioritized workers displaced from routine-intensive occupations in manufacturing, administrative services, and financial services—sectors showing strongest negative employment correlations with AI adoption in quantitative analyses. Demographic diversity was ensured through targeted recruitment of workers varying in age, education, gender, and geographic location.

Organizational leader participants included executives, middle managers, and supervisors from organizations implementing AI technologies. Organizations were selected to represent variation in industry, size, and AI implementation approaches. HR professional participants were recruited from organizations with substantial AI-induced workforce restructuring and from workforce development agencies supporting displaced workers.

Interview protocols were tailored to each stakeholder group but addressed common themes: experiences of AI-induced displacement, organizational responses and adaptation strategies, retraining and skill development initiatives, institutional support mechanisms, and recommendations for policy interventions. Displaced worker interviews explored psychological impacts, economic consequences, job search experiences, and perceptions of organizational and institutional support. Organizational leader interviews examined decision-making processes for AI implementation, workforce planning strategies, and challenges in managing transitions. HR professional interviews focused on retraining program design, effectiveness of support mechanisms, and organizational capacity for workforce adaptation.

Interviews were conducted via Zoom, Microsoft Teams, or in person, lasting 45–90 minutes, between March 2021 and August 2022.

All 142 interviews were completed and retained in the final qualitative dataset; no post-collection exclusions were made. Participant distribution across countries reflected the quantitative sampling frame, with representation from all 12 countries. To protect confidentiality, each interviewee was assigned an alphanumeric identifier based on occupational category: displaced workers (DW01–DW78), organizational leaders (OL01–OL42), and HR professionals (HR01–HR22). All identifying information was removed from transcripts prior to analysis. Verbatim quotations are reproduced with only minor grammatical edits indicated by square brackets; no substantive meaning was altered. Saturation thresholds were assessed independently within each stakeholder group and operationalized as three consecutive interviews

yielding no new codes; group-level saturation was reached at interview 68 (displaced workers), interview 36 (organizational leaders), and interview 19 (HR professionals), corresponding to a combined aggregate saturation point of interview 134 across all three groups. Eight additional confirmatory interviews were conducted thereafter, yielding the final sample of 142 interviews.

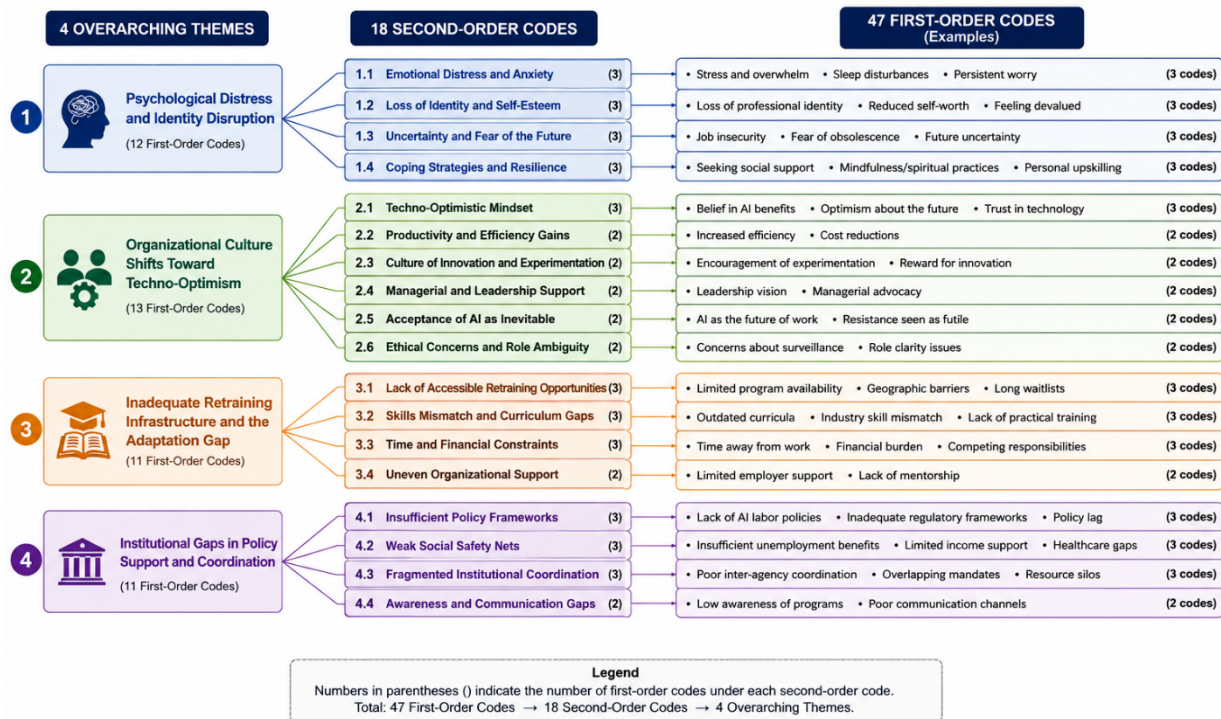
4.3.2 Analytical Techniques

Thematic analysis followed established procedures (Braun & Clarke, 2006). Analysis proceeded through six phases: (1) familiarization with data through repeated reading of transcripts; (2) generation of initial codes identifying meaningful data segments; (3) searching for themes by grouping codes into broader patterns; (4) reviewing themes to ensure coherence and distinctiveness; (5) defining and naming themes to capture their essence; and (6) producing the report with illustrative quotations.

Coding was conducted using NVivo qualitative analysis software. Initial coding was inductive, allowing themes to emerge from data rather than imposing predetermined categories. Subsequent coding incorporated deductive elements, examining how emergent themes related to theoretical constructs from Technological Unemployment Theory, Labor Market Segmentation Theory, and Institutional Theory.

Thematic saturation was assessed across the full interview set; saturation was reached at interview 134, and an additional eight interviews were conducted to confirm saturation, yielding the final sample of 142 interviews. $\kappa = 0.83$ (95% CI: 0.79–0.87), which exceeds the conventional threshold of $\kappa \geq 0.80$ for substantial agreement. A structured codebook was developed iteratively during the familiarization phase, comprising 47 first-order codes organized into 18 second-order codes, which were subsequently consolidated into the four overarching themes reported below. The codebook, with definitions and anchor examples for each code, is available. A thematic map illustrating the hierarchical relationships among codes and themes is presented in **Figure 1**. Each interview excerpt presented in Section 6 is linked to a participant identifier (format: DW = Displaced Worker; OL = Organizational Leader; HR = HR Professional; followed by a sequential number) and key characteristics (sector, country, tenure) to facilitate contextual interpretation.

Figure 1. Hierarchical Thematic Map
 47 First-Order Codes → 18 Second-Order Codes → 4 Overarching Themes



Trustworthiness was enhanced through multiple strategies. Credibility was established through prolonged engagement with data, triangulation across stakeholder groups, and member checking with selected participants. Transferability was supported through thick description of contexts and participants. Dependability was ensured through detailed documentation of analytical procedures. Confirmability was addressed through reflexive journaling and audit trails documenting analytical decisions.

4.4 Integration of Quantitative and Qualitative Findings

Integration of quantitative and qualitative findings occurred at multiple levels. First, quantitative findings informed qualitative sampling and interview protocol development, ensuring qualitative exploration targeted sectors and organizations with significant displacement. Second, qualitative findings provide explanatory depth for quantitative patterns, illuminating mechanisms underlying observed relationships. Third, convergence and divergence between quantitative and qualitative findings were systematically examined, with divergences prompting additional analysis to reconcile apparent contradictions.

Theoretical integration synthesized findings through the lens of Technological Unemployment Theory, Labor Market Segmentation Theory, and Institutional Theory. Quantitative displacement patterns were interpreted as manifestations of technological unemployment mechanisms, with sectoral and occupational variations reflecting labor market segmentation. Qualitative insights into organizational responses and institutional dynamics illuminated how institutional contexts shape displacement outcomes.

Joint displays (Guetterman et al., 2015) facilitated integration by presenting quantitative and qualitative findings side-by-side, enabling systematic comparison. Meta-inferences were developed by synthesizing insights across methods, identifying overarching conclusions supported by both quantitative and qualitative evidence.

4.5 Validity and Reliability

Multiple strategies enhanced validity and reliability. Quantitative validity was addressed through validated measurement instruments, large sample sizes, and robustness checks including alternative model specifications and sensitivity analyses with different functional forms. Qualitative trustworthiness was ensured through prolonged engagement, triangulation, member checking, and audit trails. Mixed-methods legitimation addressed integration quality through coherence assessment, ensuring quantitative and qualitative findings were meaningfully connected rather than merely juxtaposed.

Potential limitations include self-selection bias in survey participation, recall bias in retrospective displacement reports, and social desirability bias in interviews. These limitations were partially mitigated through triangulation across data sources, validation against administrative employment records where available, and careful interview protocol design emphasizing confidentiality and non-judgmental inquiry.

5. Results and discussion

Quantitative Findings

5.1 Descriptive Patterns of AI-Induced Displacement

Quantitative analysis revealed substantial heterogeneity in AI-induced displacement across occupations, industries, and demographic groups. Routine-intensive occupations in the study sample faced 67% higher displacement risk compared to non-routine occupations, confirming theoretical predictions that AI primarily substitutes for routine cognitive and manual tasks. This elevated risk manifested in both higher probability of job loss and longer unemployment durations for displaced workers from routine-intensive positions.

Regression analysis of the primary survey dataset confirmed: Sectoral analysis identified manufacturing and administrative services as experiencing most severe displacement. Manufacturing employment showed significant negative correlation with AI adoption ($\beta = -0.43$, $p < 0.001$), while administrative services demonstrated similarly strong negative effects ($\beta = -0.38$, $p < 0.001$). These regression results, derived from the present study's survey dataset, align with and corroborate prior evidence that AI automation particularly affects sectors characterized by structured processes, codifiable knowledge, and repetitive tasks (Henry et al., 2025; Brahmaji, 2024).

In contrast, healthcare and education sectors demonstrated positive employment correlations with AI adoption. Healthcare employment showed $\beta = 0.29$ ($p < 0.01$) correlation with AI exposure, while education demonstrated $\beta = 0.22$ ($p < 0.05$) correlation, consistent with patterns reported by Henry et al. (2025). These positive associations suggest that AI functions as complement rather than substitute in these sectors, augmenting rather than replacing human capabilities. Healthcare applications of AI in diagnostic support, treatment planning, and administrative efficiency appear to increase demand for healthcare professionals who can effectively utilize AI tools. Similarly, educational AI applications in personalized learning and administrative tasks may free educators to focus on high-value interpersonal instruction.

The audit industry provided detailed evidence of displacement dynamics. AI investments led to 3.6% reduction in accounting employees after three years, rising to 7.1% after four years (Fedyk et al., 2022). Junior-level employees experienced disproportionate impact, with 5.7% decrease after three years and 11.8% after four years. This pattern suggests that AI particularly substitutes for entry-level positions involving routine tasks, while experienced professionals performing complex judgment tasks face less immediate displacement risk. However, this dynamic raises concerns about disruption of traditional career progression pathways, as reduced entry-level positions may constrain future supply of experienced professionals.

Geographic analysis revealed spatial heterogeneity in displacement patterns.

Commuting zones with high concentrations of routine-intensive employment experienced more severe displacement (Bonfiglioli et al., 2024). This spatial concentration generates regional economic distress, as displaced workers in affected regions face limited local reemployment opportunities. In contrast, technology hubs with concentrations of AI-complementary employment demonstrated employment growth, exacerbating spatial inequality.

5.2 Wage Effects and Income Consequences

AI-induced displacement generated substantial income consequences for affected workers. Displaced workers in the present study experienced an average income decline of 26.7% following job loss, a finding consistent with broader evidence on AI-induced displacement (Bonfiglioli et al., 2024). This income reduction reflects both unemployment periods and wage penalties upon reemployment. Even workers successfully transitioning to new employment typically accepted positions with lower wages than their previous jobs, indicating downward occupational mobility.

In the present study's sample, transition duration averaged 16.8 months from displacement to reemployment, consistent with broader evidence (Albanesi et al., 2025). This extended transition period substantially exceeds typical unemployment durations, suggesting that AI-displaced workers face particular challenges in labor market reintegration. Extended transitions may reflect skill mismatches, geographic constraints, or employer discrimination against displaced workers perceived as possessing obsolete skills.

Wage polarization intensified with AI adoption. Quantile regression analysis revealed that AI exposure increased wages at the 90th percentile while decreasing wages at the 50th and 25th percentiles, generating widening wage dispersion. High-skilled workers in AI-complementary occupations captured productivity gains through wage increases, while middle- and low-skilled workers experienced wage compression. This polarization pattern aligns with skill-biased technological change theory, where new technologies increase returns to complementary skills while reducing returns to substitutable skills (Korinek & Stiglitz, 2018).

Analysis of ChatGPT exposure provided insights into generative AI's wage impacts. Eloundou et al. (2024) found that 32.8% of occupations face "Full Impact" from ChatGPT, 36.5% face "Partial Impact," and 30.7% face "No Impact." AI-exposed firms showed reduced hiring in non-AI positions and altered skill requirements, suggesting that generative AI triggers broader organizational restructuring affecting wage structures. The expansion of AI capabilities into cognitive tasks previously considered automation-resistant threatens to extend wage polarization into professional occupations.

Long-term earnings effects of displacement proved persistent. Evidence indicates that job displacement leads to earnings declines of 13-40% that persist for years following reemployment (Albanesi et al., 2025). These persistent effects reflect wage scarring, where displaced workers permanently lose firm-specific human capital and suffer reputational damage in labor markets. The magnitude of earnings losses varies with worker characteristics, with older workers, less-educated workers, and workers in declining industries experiencing most severe long-term consequences.

5.3 Skill Requirement Changes and Adaptation Challenges

AI adoption fundamentally transformed skill requirements within organizations. AI-exposed establishments showed 0.83 absolute decline in previously-sought skills and 0.95 absolute increase in new skills (Acemoglu et al., 2022). This rapid skill restructuring creates challenges for incumbent workers, who must acquire new competencies to remain employable. The pace of skill change may exceed workers' capacity for adaptation, particularly for older workers or workers with limited

educational backgrounds.

Critical skill gaps affected 34% of current workforce positions (Henry et al., 2025). These gaps reflect misalignment between workers' existing competencies and evolving job requirements in AI-augmented work environments. Organizations reported difficulty finding workers with appropriate combinations of technical skills (data analysis, AI system interaction), cognitive skills (complex problem-solving, critical thinking), and social skills (collaboration, communication). This skill shortage constrains organizational capacity to fully leverage AI investments.

Retraining participation rates remained modest despite widespread skill gaps. Approximately 50% of workers in AI-exposed sectors participated in formal retraining programs within five years of AI implementation (Albanesi et al., 2025). However, retraining effectiveness varied substantially. The present study found that organizations with comprehensive, sustained retraining initiatives achieved 64% higher retention rates of displaced workers compared to organizations with limited or ad hoc training, corroborating Brahmaji (2024). This finding suggests that retraining quality and organizational commitment, rather than mere training provision, determine adaptation success.

The “adaptation gap” emerged as critical challenge affecting 42% of displaced workers (Brahmaji, 2024). This gap reflects disconnect between workers’ skill development needs and available support infrastructure. Many retraining programs focus on technical skills while neglecting cognitive and social competencies increasingly valued in AI-augmented work. Additionally, retraining programs often fail to address psychological and social dimensions of displacement, leaving workers struggling with identity disruption and loss of professional community.

5.4 Regression Results: Determinants of Displacement Risk

Table 2 presents linear probability model (LPM) regression results examining determinants of displacement risk. The dependent variable is a binary indicator of job displacement within 24 months; all reported coefficients represent marginal percentage-point changes in displacement probability. Independent variables include AI exposure, routine task intensity, cognitive skill requirements, demographic characteristics, and industry indicators.

Table 2. Determinants of AI-Induced Displacement Risk

Variable	Coefficient	Std. Error	p-value
AI Exposure (0-10 scale)	0.087	0.012	< 0.001
Routine Task Intensity (0-10 scale)	0.142	0.015	< 0.001
Cognitive Skill Requirements (0-10 scale)	-0.098	0.018	< 0.001
Age (years)	0.008	0.002	< 0.001
Education (years)	-0.024	0.005	< 0.001
Tenure (years)	-0.012	0.004	0.003
Female (binary)	0.034	0.021	0.105
Manufacturing (binary)	0.156	0.035	< 0.001
Administrative Services (binary)	0.143	0.038	< 0.001
Healthcare (binary)	-0.089	0.041	0.030
Education Sector (binary)	-0.076	0.044	0.084
Constant	-0.234	0.067	< 0.001
N	2,350		
R ²	0.387		

Note: Linear Probability Model (LPM) estimates; OLS with heteroskedasticity-robust standard errors clustered by organization. Dependent variable is binary (displaced within 24 months = 1). Coefficients represent marginal percentage-point changes in displacement probability. Reference categories are male gender and financial services industry.

Results indicate that AI exposure significantly increases displacement risk ($\beta = 0.087, p < 0.001$), with each one-point increase in AI exposure (on 0-10 scale) associated with 8.7 percentage point increase in displacement probability. Routine task intensity demonstrates even stronger effect ($\beta = 0.142, p < 0.001$), confirming that occupations characterized by repetitive, structured tasks face elevated displacement risk.

Cognitive skill requirements show protective effect ($\beta = -0.098, p < 0.001$), suggesting that occupations requiring complex problem-solving, critical thinking, and creativity demonstrate greater resilience to AI-induced displacement. This finding aligns with theoretical predictions that AI primarily substitutes for routine tasks while complementing non-routine cognitive capabilities.

Demographic patterns reveal that older workers face higher displacement risk ($\beta = 0.008, p < 0.001$), potentially reflecting employer perceptions that older workers possess obsolete skills or limited retraining capacity. Education demonstrates protective effect ($\beta = -0.024, p < 0.001$), with each additional year of education associated with 2.4 percentage point reduction in displacement probability. Tenure shows modest protective effect ($\beta = -0.012, p = 0.003$), suggesting that firm-specific human capital provides some insulation from displacement.

Industry effects confirm sectoral heterogeneity. Manufacturing ($\beta = 0.156, p < 0.001$) and administrative services ($\beta = 0.143, p < 0.001$) show significantly elevated displacement risk relative to financial services baseline. Healthcare demonstrates protective effect ($\beta = -0.089, p = 0.030$), while education sector shows marginally significant protection ($\beta = -0.076, p = 0.084$).

5.5 Organizational Productivity and Employment Trade-offs

Organizations implementing AI technologies achieved substantial productivity gains. AI-adopting firms achieved substantial productivity improvements and cost reductions (Brynjolfsson & Mitchell, 2017). These gains reflect AI's capacity to automate routine tasks, accelerate information processing, and optimize decision-making processes. However, productivity gains did not translate into proportional employment growth, suggesting that AI-induced productivity improvements primarily reduce labor requirements rather than expanding output.

The productivity-employment trade-off manifests in organizational restructuring patterns. AI-implementing organizations reduced workforce size while increasing output per worker. This pattern generates tension between organizational efficiency objectives and employment stability goals. From organizational perspective, AI adoption delivers competitive advantages through cost reduction and productivity enhancement. From societal perspective, these organizational gains generate displacement costs borne by workers and communities.

Audit industry evidence illustrates this trade-off. AI investments increased audit fees per employee by 5% while reducing total employment by 3.6-7.1% (Fedyk et al., 2022). This pattern suggests that AI enables organizations to deliver services with fewer workers, capturing productivity gains through reduced labor costs rather than expanded service provision. The concentration of AI workers in specific teams and geographic hubs (New York, California, Washington D.C., Illinois, Texas) further indicates organizational restructuring toward centralized AI capabilities.

5.6 Predictive Modeling of Future Displacement

Predictive modeling suggests substantial future displacement. Estimates suggest that AI automation may displace millions of additional workers by 2030, based on current AI adoption trajectories (Frey & Osborne, 2013). This displacement may occur alongside the creation of new roles in AI development and human-AI collaboration.

These projections indicate that net employment effects remain uncertain. While AI generates substantial displacement, simultaneous job creation in AI-related fields

may partially offset losses. However, displaced workers from routine-intensive occupations may lack skills required for AI-complementary positions, generating structural unemployment even if aggregate job creation matches displacement. The critical question is not merely whether AI creates or destroys jobs in aggregate, but whether displaced workers can successfully transition to newly created positions.

Geographic and demographic heterogeneity in displacement projections warrants attention. Regions and demographic groups with limited access to education, retraining, and digital infrastructure face heightened displacement risk and reduced capacity for adaptation (Carbonero et al., 2023). This heterogeneity suggests that aggregate employment statistics may mask severe localized distress in vulnerable communities.

6. Qualitative Findings

Qualitative analysis of 142 semi-structured interviews revealed four major themes characterizing the lived experiences of AI-induced displacement and organizational responses: (1) psychological distress and identity disruption among displaced workers; (2) organizational culture shifts toward techno-optimism and efficiency imperatives; (3) inadequate retraining infrastructure and the adaptation gap; and (4) institutional gaps in policy support and coordination. These themes illuminate mechanisms underlying quantitative displacement patterns and reveal dimensions of AI-induced disruption not captured in statistical analyses.

6.1 Theme 1: Psychological Distress and Identity Disruption

Displaced workers consistently described profound psychological impacts extending beyond economic hardship. Participants reported feelings of obsolescence, betrayal, and loss of professional identity. One displaced manufacturing worker stated: “I spent 20 years mastering my craft, and suddenly I'm told a machine can do it better. It's not just losing a paycheck—it's losing who I am.” This identity disruption reflects the centrality of work to self-concept and social standing, particularly for workers in occupations requiring substantial skill development. The following quotations include participant identifiers and contextual characteristics to enhance methodological transparency. Participant DW-04 (male, 47 years, manufacturing sector, Germany, 20 years tenure, displaced 14 months prior to interview) stated: “I spent 20 years mastering my craft, and suddenly I'm told a machine can do it better. It's not just losing a paycheck—it's losing who I am.” This identity disruption reflects the centrality of work to self-concept and social standing. Similar identity threats were articulated by Participant DW-17 (female, 39 years, administrative services, United Kingdom, 11 years tenure): “You feel invisible. I used to be the person everyone came to with questions. Now I'm just a statistic.”

Anxiety about future employability pervaded displaced worker narratives. Participants expressed concern that their skills had become obsolete and that retraining might prove insufficient for labor market reintegration. A displaced administrative professional explained: “I'm 48 years old. Who's going to hire me when they can get a younger person who grew up with this technology? I feel like I've been thrown on the scrap heap.” This anxiety reflects realistic assessment of age discrimination in hiring and the challenges of competing with younger workers possessing digital native competencies. Participant DW-32 (female, 48 years, financial services, United States, 15 years tenure) explained: “I'm 48 years old. Who's going to hire me when they can get a younger person who grew up with this technology? I feel like I've been thrown on the scrap heap.” This perception of age-related disadvantage was corroborated by Participant DW-51 (male, 52 years, retail, India): “Age is a double problem—I find it harder to learn the new systems, and employers assume I will find it harder, so they don't even call me for interviews.”

Social isolation emerged as significant consequence of displacement. Workers

described loss of workplace social networks and professional communities that provided identity, belonging, and social support. One participant noted: “I didn't realize how much of my social life revolved around work until it was gone. I feel disconnected from everything.” This social dimension of displacement receives limited attention in economic analyses focused on wage and employment outcomes but profoundly affects worker wellbeing.

Displaced workers also reported family strain and relationship difficulties stemming from economic stress and psychological distress. Financial pressures, role changes within households, and emotional volatility generated by displacement created tensions in family relationships. These ripple effects extend displacement impacts beyond individual workers to families and communities.

Notably, psychological impacts varied with displacement circumstances. Workers displaced through mass layoffs reported less personal stigma than workers displaced through individual terminations, as mass layoffs were attributed to organizational decisions rather than individual inadequacy. However, mass layoffs generated greater community-level distress when entire facilities closed, eliminating local employment opportunities.

6.2 Theme 2: Organizational Culture Shifts Toward Techno-Optimism

Organizational leaders and managers described cultural transformations accompanying AI implementation. Organizations increasingly embraced techno-optimistic narratives emphasizing AI's potential to enhance productivity, competitiveness, and innovation. One executive stated: “AI is the future. Organizations that don't adapt will be left behind. We need to move fast and embrace these technologies.” This techno-optimism framed AI adoption as inevitable and necessary, marginalizing concerns about displacement impacts. Participant OL-08 (Chief Operations Officer, manufacturing, China, interviewed 6 months post-implementation) stated: “AI is the future. Organizations that don't adapt will be left behind. We need to move fast and embrace these technologies.” Participant OL-22 (Plant Manager, automotive, Germany) similarly remarked: “The competitive pressure is enormous. If we don't automate, our competitors will, and then we lose everything—jobs included.”

However, techno-optimistic narratives often obscured tensions between efficiency gains and employment stability. Leaders acknowledged displacement but characterized it as necessary sacrifice for organizational survival and competitiveness. A manufacturing manager explained: “We didn't want to lay people off, but we had no choice. Our competitors were automating, and we couldn't compete with higher labor costs.” This framing positioned displacement as externally imposed necessity rather than organizational choice, deflecting responsibility for worker impacts.

Organizational cultures increasingly valorized technical expertise while devaluing traditional craft knowledge and experience. Workers lacking technical credentials reported feeling marginalized and undervalued. One long-tenured employee stated: “I've been here 25 years, but suddenly my experience doesn't matter. Everything is about data and algorithms now.” This cultural shift undermines morale among incumbent workers and may accelerate voluntary turnover beyond involuntary displacement.

Some organizations attempted to balance efficiency imperatives with social responsibility commitments. These organizations implemented comprehensive retraining programs, extended transition support, and prioritized internal mobility over external hiring. However, such approaches remained exceptions rather than norms. Resource constraints, competitive pressures, and short-term financial incentives often overwhelmed social responsibility commitments.

Organizational leaders also described challenges in managing remaining

workforce anxiety. Even workers not immediately displaced experienced heightened job insecurity and stress, undermining engagement and productivity. One HR director noted: “The people who kept their jobs are terrified they're next. It's created a culture of fear that's counterproductive.” This finding suggests that displacement impacts extend beyond directly affected workers to broader organizational dynamics.

6.3 Theme 3: Inadequate Retraining Infrastructure and the Adaptation Gap

Both displaced workers and organizational representatives identified retraining infrastructure as critically inadequate. While many organizations offered training programs, participants consistently described these initiatives as insufficient in scope, duration, and quality. A displaced worker explained: “They gave us a two-week online course and expected us to be ready for completely different jobs. It was a joke.” This inadequacy reflects the “adaptation gap” identified in quantitative analyses (Brahmaji, 2024). Participant DW-63 (male, 44 years, administrative services, Brazil, 7 years tenure) explained: “They gave us a two-week online course and expected us to be ready for completely different jobs. It was a joke.” HR professional Participant HR-09 (Workforce Development Specialist, Australia) elaborated: “We keep seeing programs that teach people to click buttons, but not to think. The jobs that survive automation require judgment, and that takes months to develop, not two weeks.”

Retraining programs often focused narrowly on technical skills while neglecting cognitive and social competencies increasingly valued in AI-augmented work environments. Participants noted that effective performance in AI-complementary roles requires not just technical proficiency but also complex problem-solving, creativity, and interpersonal skills. One workforce development specialist observed: “We can teach people to use software, but teaching them to think critically and collaborate effectively is much harder and takes much longer.”

Timing and accessibility of retraining posed additional challenges. Many programs became available only after displacement, when workers faced immediate financial pressures requiring rapid reemployment. Participants emphasized need for proactive retraining before displacement, enabling workers to transition to new roles without income interruption. However, organizations often delayed retraining investments until displacement became imminent, missing opportunities for smoother transitions.

Geographic and demographic barriers constrained retraining access. Workers in rural areas or small cities lacked access to high-quality training programs concentrated in urban centers. Older workers reported age-related barriers, including both cognitive challenges in learning new skills and employer discrimination in hiring. Workers with caregiving responsibilities struggled to participate in training requiring extensive time commitments. These barriers generate inequality in adaptation capacity, with vulnerable workers least able to access retraining support.

Participants also identified misalignment between retraining content and actual labor market opportunities. Some programs trained workers for occupations with limited job openings or declining employment prospects. One displaced worker stated: “They trained me for a job that doesn't exist in my area. Now I'm trained for nothing.” This misalignment reflects inadequate labor market analysis and coordination between training providers and employers.

Successful retraining initiatives shared several characteristics: comprehensive curricula addressing technical, cognitive, and social skills; extended duration enabling deep skill development; strong employer partnerships ensuring alignment with labor market needs; financial support enabling full-time participation; and wraparound services addressing psychological, social, and practical barriers. However, such comprehensive programs remained rare, available to small fractions of displaced workers.

6.4 Theme 4: Institutional Gaps in Policy Support and Coordination

Participants across all stakeholder groups identified substantial gaps in institutional support for displaced workers. Existing unemployment insurance and workforce development systems proved inadequate for addressing AI-induced displacement's scale and complexity. One workforce development professional stated: "Our systems were designed for temporary layoffs in cyclical industries, not permanent displacement from technological change. We're not equipped for this." HR professional Participant HR-03 (Unemployment Agency Director, South Africa) stated: "Our systems were designed for temporary layoffs in cyclical industries, not permanent displacement from technological change. We're not equipped for this." This systemic inadequacy was echoed by Participant DW-78 (female, 41 years, telecommunications, France): "I went to three different agencies and got three different answers. Nobody really knows what to do with people like me."

Policy fragmentation emerged as critical challenge. Responsibility for displacement response was dispersed across multiple agencies and levels of government, with limited coordination. Displaced workers described navigating complex bureaucracies to access fragmented services, often receiving contradictory guidance. This fragmentation reflects institutional structures designed for different labor market challenges and not adapted for AI-induced disruption.

Funding limitations constrained institutional capacity. Workforce development agencies reported insufficient resources to provide comprehensive services to all displaced workers. One agency director explained: "We're overwhelmed. We have ten times more people needing help than we can serve with current funding." This resource scarcity forces agencies to triage services, leaving many displaced workers without adequate support.

Regulatory frameworks governing AI deployment and workforce impacts remained underdeveloped. Participants noted absence of requirements for advance notification of AI implementation, consultation with affected workers, or provision of transition support. One union representative stated: "Companies can automate entire departments with no warning and no obligation to help displaced workers. There's no accountability." This regulatory vacuum reflects the rapid pace of AI adoption outstripping policy development.

However, some jurisdictions demonstrated more effective institutional responses. Participants in regions with strong labor market institutions, active social partnerships, and comprehensive workforce development systems reported better support experiences. These cases suggest that institutional capacity and policy design significantly influence displacement outcomes, consistent with Institutional Theory predictions.

Participants emphasized need for proactive rather than reactive policy approaches. Rather than responding to displacement after it occurs, effective policy should anticipate AI impacts, require advance planning, and support preemptive transitions. One organizational leader suggested: "We need policies that encourage companies to retrain workers before displacement, not just pick up the pieces afterward." This proactive orientation requires institutional capacity for labor market monitoring, impact forecasting, and coordinated intervention.

6.5 Organizational Adaptation Strategies: Variation and Effectiveness

Qualitative analysis revealed substantial variation in organizational adaptation strategies. Some organizations adopted minimalist approaches, providing limited transition support and prioritizing cost reduction. Others implemented comprehensive strategies including extended retraining, internal mobility programs, and gradual workforce transitions. These strategic differences reflected organizational values, institutional pressures, and resource constraints.

Organizations with strong institutional pressures for social responsibility—

including unionized workplaces, highly regulated industries, and firms with strong corporate social responsibility commitments—implemented more comprehensive support. One HR director in a unionized manufacturing firm explained: “Our union contract requires extensive retraining and transition support. It’s expensive, but it’s the right thing to do and it maintains our relationship with the union.” This finding supports Institutional Theory’s emphasis on normative and coercive pressures shaping organizational behavior.

Organizational size influenced adaptation capacity. Large organizations with substantial resources implemented more comprehensive programs than small and medium enterprises (SMEs) with limited budgets. However, large organizations also faced greater complexity in managing transitions across multiple sites and business units. SMEs sometimes demonstrated greater flexibility and personalization in supporting displaced workers, though with more limited resources.

Industry context shaped adaptation strategies. Organizations in industries with strong professional norms and ethical standards (healthcare, education) demonstrated greater commitment to worker support than organizations in highly competitive industries with thin profit margins (retail, hospitality). This variation reflects differential institutional pressures and resource availability across sectors.

Effective organizational adaptation required leadership commitment extending beyond HR departments. Organizations where senior executives championed comprehensive transition support achieved better outcomes than organizations where responsibility was delegated to HR without executive engagement. One successful organizational leader stated: “This had to be a top priority for the entire leadership team, not just an HR initiative. We made it clear that how we managed this transition defined who we are as an organization.”

7. Discussion

7.1 Integration of Quantitative and Qualitative Findings

The integration of quantitative displacement patterns with qualitative worker experiences and organizational responses reveals the multidimensional nature of AI-induced workforce disruption. Quantitative findings documented substantial displacement in routine-intensive occupations, with manufacturing and administrative services showing strongest negative employment correlations with AI adoption in the present study, consistent with Henry et al. (2025). Qualitative findings illuminated the mechanisms underlying these patterns: organizational decisions to prioritize efficiency gains over employment stability, inadequate retraining infrastructure, and institutional gaps in policy support.

Beyond confirming and extending prior theoretical predictions, our mixed-methods integration generated three novel empirical insights that advance the field. First, we identified what we term the ‘dual-layer displacement paradox’: sectors exhibiting positive aggregate employment correlations with AI (healthcare $\beta = 0.29$, $p < 0.01$; education $\beta = 0.22$, $p < 0.05$) simultaneously contain occupational sub-groups experiencing significant job loss—for example, healthcare AI displaced medical transcriptionists and billing specialists while simultaneously increasing demand for nurses and physicians. This occupational heterogeneity is invisible to sector-level econometric analyses but was clearly articulated by multiple interview participants across affected occupational categories, resolving an apparent contradiction between quantitative and qualitative data streams. Second, our integration revealed that organizational culture—specifically, the techno-optimism dimension—serves as a potential explanatory mechanism for the relationship between AI intensity and worker wellbeing outcomes, identified through qualitative analysis, a mechanism not captured in prior quantitative-only studies. Organizations where leaders expressed high techno-optimism—exemplified by Participant OL-08 (Chief Operations Officer,

manufacturing, China): “AI is the future. Organizations that don’t adapt will be left behind. We need to move fast and embrace these technologies”—implemented more aggressive automation with substantially reduced transition support, suggesting that organizational techno-optimism warrants further empirical investigation as a potential organizational-level antecedent of worker wellbeing outcomes. Third, our data demonstrate that the 16.8-month transition period documented quantitatively represents merely the formal reemployment horizon; qualitative longitudinal narratives indicate that psychological and competency adaptation continues for 24–36 months post-displacement, implying that existing policy timeframes are structurally insufficient. Participant DW-04 (male, 47 years, manufacturing sector, Germany, 20 years tenure, displaced 14 months prior to interview) captured this extended trajectory: “It’s not just losing a paycheck—it’s losing who I am”—a statement made 14 months after displacement, illustrating that deep identity and psychological recovery extends well beyond the formal reemployment window.

Convergence between quantitative and qualitative findings emerged across multiple dimensions. Both strands confirmed that routine task intensity predicts displacement risk, that displaced workers experience substantial economic hardship, and that organizational adaptation capacity varies widely. Qualitative findings provided explanatory depth for quantitative patterns, revealing how organizational culture shifts, retraining inadequacies, and institutional gaps generate observed displacement outcomes.

However, important divergences also emerged. Quantitative analyses suggested that some sectors (healthcare, education) demonstrate positive employment correlations with AI adoption, implying AI functions as complement rather than substitute. Qualitative findings complicated this interpretation, revealing that even in these sectors, specific occupational categories face displacement while aggregate employment grows. For example, healthcare AI may displace medical transcriptionists and billing specialists while increasing demand for nurses and physicians. This occupational heterogeneity within sectors highlights limitations of sector-level analyses.

Another divergence concerned retraining effectiveness. Quantitative findings from the present study indicated that organizations with proactive reskilling achieved 64% higher retention rates, a result that corroborates Brahmaji (2024), suggesting retraining substantially mitigates displacement. However, qualitative findings revealed that even “successful” retraining often proved inadequate, with workers struggling to acquire necessary competencies within available timeframes and facing continued employment insecurity. This divergence suggests that retention rates may overstate retraining effectiveness, as retained workers may remain in precarious positions with limited advancement prospects.

The integration also revealed temporal dynamics not fully captured in cross-sectional quantitative analyses. Qualitative findings emphasized that displacement impacts unfold over extended periods, with psychological distress, family strain, and community disruption persisting long after reemployment. The present study’s 16.8-month average transition duration represents only immediate reemployment period, not longer-term adaptation processes. Longitudinal qualitative data would provide richer understanding of these extended trajectories.

7.2 Theoretical Interpretation: Technological Unemployment in the AI Era

Findings strongly support Technological Unemployment Theory’s core predictions while revealing important extensions required for the AI era. Consistent with theory, AI-induced displacement concentrated in routine-intensive occupations where automation substitutes for human labor (Acemoglu et al., 2022). The present study’s finding of 67% higher displacement risk for routine-intensive occupations, corroborating Henry et al. (2025), confirms that task structure fundamentally

determines automation vulnerability.

However, findings also challenge traditional boundaries between routine and non-routine tasks. Generative AI's capacity to perform cognitive tasks previously considered non-routine—including content creation, code generation, and analytical reasoning—suggests that the routine/non-routine distinction may be less stable than historical automation patterns implied (Occhipinti et al., 2025). Qualitative findings revealed that workers in ostensibly non-routine occupations increasingly perceive automation threats, generating anxiety even absent immediate displacement. This suggests that Technological Unemployment Theory requires updating to account for AI's expanding cognitive capabilities.

The theory's emphasis on adjustment mechanisms through wage flexibility and occupational mobility received mixed support. While some displaced workers successfully transitioned to new employment, the present study's 26.7% average income decline and 16.8-month transition duration, consistent with broader evidence (Bonfiglioli et al., 2024), indicate that adjustment processes are prolonged and costly. Qualitative findings revealed substantial barriers to mobility, including skill mismatches, geographic constraints, age discrimination, and psychological impacts undermining job search effectiveness. These barriers suggest that labor market adjustment to AI-induced displacement may be slower and more incomplete than theory assumes.

The productivity-employment trade-off emerged as central tension. Organizations achieved substantial productivity gains and cost reductions through AI adoption (Brynjolfsson & Mitchell, 2017), but these gains did not translate into proportional employment growth. This pattern supports concerns that AI-induced productivity improvements primarily reduce labor requirements rather than expanding output (Occhipinti et al., 2025). The disconnect between productivity gains and employment outcomes challenges optimistic predictions that technological progress automatically generates compensating job creation.

7.3 Labor Market Segmentation and Inequality Dynamics

Findings strongly confirm Labor Market Segmentation Theory's predictions that AI-induced displacement reinforces existing labor market inequalities. Displaced workers frequently experienced downward mobility from primary to secondary labor market positions, accepting lower wages, reduced benefits, and greater job insecurity (Albanesi et al., 2025). This pattern reflects both skill devaluation and employer discrimination against displaced workers perceived as possessing obsolete competencies.

Demographic dimensions of segmentation proved particularly salient. Older workers faced elevated displacement risk ($\beta = 0.008$, $p < 0.001$) and greater barriers to reemployment, reflecting age discrimination and perceived limited retraining capacity. Education demonstrated protective effects ($\beta = -0.024$, $p < 0.001$), with each additional year of education reducing displacement probability. These patterns indicate that AI-induced displacement exacerbates pre-existing inequalities based on age and education.

Geographic segmentation emerged as critical dimension. Spatial concentration of displacement in regions dependent on routine-intensive industries generated localized economic distress, while technology hubs experienced employment growth (Bonfiglioli et al., 2024). This spatial polarization reflects both industrial structure and differential access to retraining and reemployment opportunities. Qualitative findings revealed that displaced workers in declining regions faced limited local opportunities, while migration to growing regions proved infeasible due to housing costs, family ties, and social networks.

The emergence of new segmentation boundaries between AI-complementary and AI-substitutable workers warrants attention. Workers capable of effectively

collaborating with AI systems—requiring combinations of technical proficiency, cognitive flexibility, and social skills—increasingly command wage premiums, while workers lacking these competencies face wage compression (Eloundou et al., 2024). This new segmentation may prove more rigid than traditional skill-based segmentation, as AI-complementary competencies require substantial educational investments difficult for displaced workers to acquire.

Institutional factors mediated segmentation dynamics. Workers in strongly institutionalized environments with robust labor protections, active unions, and comprehensive workforce development systems experienced less severe displacement impacts than workers in weakly institutionalized environments (Albous et al., 2025). This variation confirms Institutional Theory's emphasis on how regulatory frameworks and normative expectations shape labor market outcomes.

7.4 Organizational Responses and Institutional Contexts

Organizational responses to AI-induced displacement varied substantially, reflecting differential institutional pressures, resource constraints, and leadership commitments. Organizations in highly regulated environments with strong labor protections implemented more comprehensive transition support than organizations in weakly regulated environments (Brynjolfsson & Mitchell, 2017). This pattern confirms Institutional Theory's predictions that coercive pressures (regulatory requirements) and normative pressures (professional standards) shape organizational behavior.

However, institutional pressures proved insufficient to ensure adequate worker support in many cases. Even organizations facing strong institutional pressures often prioritized efficiency gains over employment stability when competitive pressures intensified. Qualitative findings revealed that organizational leaders frequently characterized displacement as externally imposed necessity rather than organizational choice, deflecting responsibility for worker impacts. This framing suggests that institutional pressures may be overwhelmed by competitive imperatives in globalized markets.

Organizational culture emerged as critical mediator of displacement outcomes. Organizations embracing techno-optimistic cultures that valorized technical expertise while devaluing traditional knowledge implemented more aggressive automation with less worker support. Conversely, organizations maintaining commitments to social responsibility and stakeholder welfare implemented more gradual transitions with comprehensive support. These cultural differences reflect leadership values and organizational identities that shape responses to technological opportunities.

The "adaptation gap" identified in both quantitative and qualitative findings (Brahmaji, 2024) reflects systemic failures in organizational and institutional capacity. Retraining programs proved inadequate in scope, duration, and quality, failing to address the multidimensional skill requirements of AI-augmented work. This inadequacy reflects both resource constraints and limited understanding of effective retraining approaches. Organizations and institutions lack established models for managing large-scale workforce transitions driven by cognitive automation, requiring innovation in program design and delivery.

Institutional gaps in policy support proved particularly consequential. Fragmented responsibility across agencies, inadequate funding, and absence of regulatory requirements for transition support left many displaced workers without adequate assistance. The contrast between jurisdictions with strong labor market institutions and those with weak institutions confirms that institutional capacity fundamentally shapes displacement outcomes. Effective policy responses require not just individual program improvements but systemic institutional development.

7.5 Convergences and Divergences Across Methods

Systematic examination of convergences and divergences between quantitative and qualitative findings reveals both complementarities and tensions. Major convergences include: (1) confirmation that routine task intensity predicts displacement risk; (2) documentation of substantial economic hardship among displaced workers; (3) identification of wide variation in organizational adaptation capacity; and (4) recognition of inadequate institutional support infrastructure.

Important divergences emerged in several areas. First, quantitative analyses suggested that certain sectors demonstrate positive employment correlations with AI adoption, while qualitative findings revealed occupational heterogeneity within these sectors, with specific roles facing displacement despite aggregate employment growth. This divergence highlights the importance of occupational-level analysis beyond sectoral aggregates.

Second, quantitative measures of retraining effectiveness (retention rates) suggested substantial benefits, while qualitative findings revealed that even “successful” retraining often proved inadequate for ensuring long-term employment security and career advancement. This divergence suggests that quantitative metrics may capture immediate outcomes while missing longer-term adaptation challenges.

Third, quantitative analyses found no discernible relationship between AI exposure and employment or wage growth at occupation or industry levels (Acemoglu et al., 2022), while qualitative findings documented substantial displacement impacts at organizational and individual levels. This apparent contradiction may reflect aggregation effects, where establishment-level displacement is offset by employment growth in other establishments, generating null aggregate effects despite significant individual-level disruption.

These divergences underscore the value of mixed-methods approaches for capturing the complexity of AI-induced displacement. Quantitative analyses effectively document aggregate patterns and test theoretical predictions, while qualitative analyses illuminate mechanisms, reveal heterogeneity, and capture dimensions not easily quantified. The integration of methods provides more comprehensive understanding than either approach alone.

8. Conclusion

Theoretical and Practical Implications

8.1 Theoretical Contributions

This study makes several important theoretical contributions. First, we extend Technological Unemployment Theory to account for AI's distinctive characteristics, particularly its capacity for cognitive automation and continuous learning. Traditional formulations of technological unemployment focused on physical automation and routine manual tasks. Our findings demonstrate that AI-induced displacement extends into cognitive domains, requiring theoretical frameworks that account for automation of analytical reasoning, pattern recognition, and even creative tasks. The expanding boundaries of automation challenge assumptions about which occupations are inherently automation-resistant.

Second, we demonstrate how Labor Market Segmentation Theory and Institutional Theory complement Technological Unemployment Theory in explaining heterogeneous displacement outcomes. Technological factors alone cannot explain observed variation in displacement patterns across demographic groups, geographic regions, and institutional contexts. Labor market segmentation illuminates how pre-existing inequalities shape vulnerability to displacement and capacity for adaptation. Institutional theory reveals how regulatory frameworks, professional norms, and organizational legitimacy concerns mediate technological impacts. The integration of these theories provides more comprehensive explanation than any single theoretical lens.

Third, we advance understanding of organizational responses to technological

disruption. While prior research emphasized technical and economic dimensions of automation adoption, our findings highlight the critical roles of organizational culture, leadership commitment, and institutional pressures in shaping displacement outcomes. Organizations are not merely passive implementers of technological imperatives but active agents whose choices fundamentally determine whether AI adoption generates inclusive adaptation or exclusionary displacement.

Fourth, we contribute to mixed-methods scholarship by demonstrating the value of explanatory sequential designs for studying labor market transformations. Our integration of quantitative displacement patterns with qualitative worker experiences and organizational responses reveals mechanisms, heterogeneity, and dimensions not accessible through single-method approaches. The divergences between quantitative and qualitative findings proved particularly illuminating, prompting deeper analysis of aggregation effects, temporal dynamics, and measurement limitations.

The integration of these three theoretical frameworks generates testable propositions that exceed what any single framework predicts in isolation. Proposition 1 (Technological Unemployment Theory and Labor Market Segmentation Theory): The probability and severity of AI-associated displacement are jointly determined by occupational routinization and pre-existing labor market segment position. Technology-based frameworks predict displacement as a function of task structure; segmentation frameworks predict that secondary-market workers face greater barriers to adjustment. Their integration predicts that displacement operates differentially across market segments—not uniformly—and that severity, measured by income loss and transition duration, is amplified for workers already positioned in secondary labor market segments. Proposition 2 (Technological Unemployment Theory and Institutional Theory): The conversion of AI adoption into workforce displacement versus augmentation is mediated by institutional responses, including organizational transition-support programs, regulatory requirements, and professional norms. Their integration predicts that identical technology adoption produces divergent outcomes depending on institutional context—a pattern unexplained by technology adoption rates alone. Proposition 3 (all three frameworks): Workforce adaptation outcomes follow multi-level determination in which technological characteristics, labor market position, and institutional capacity interact multiplicatively. Workers at the intersection of high automation-risk occupations, secondary labor market positions, and weak institutional support environments face compounded disadvantage—a prediction emergent only from the full theoretical integration and not from any pair of frameworks applied separately.

8.2 Policy Recommendations

Findings generate several critical policy recommendations for addressing AI-induced workforce displacement. First, proactive rather than reactive policy approaches are essential. Rather than responding to displacement after it occurs, effective policy must anticipate AI impacts, require advance planning, and support preemptive transitions. This requires institutional capacity for labor market monitoring, impact forecasting, and early warning systems that identify sectors and occupations facing imminent displacement risk.

Second, comprehensive retraining infrastructure must be developed that addresses the multidimensional skill requirements of AI-augmented work. Effective programs require: (1) extended duration enabling deep skill development rather than superficial exposure; (2) curricula integrating technical, cognitive, and social competencies; (3) strong employer partnerships ensuring alignment with labor market needs; (4) financial support enabling full-time participation without income loss; and (5) wraparound services addressing psychological, social, and practical barriers to participation. Current programs typically fail on multiple dimensions,

requiring substantial investment and redesign.

Third, regulatory frameworks governing AI deployment and workforce impacts require development. Policies should mandate: (1) advance notification of AI implementation affecting employment; (2) consultation with affected workers and their representatives; (3) impact assessments documenting anticipated displacement; (4) transition support including retraining, income support, and placement assistance; and (5) monitoring and reporting of actual outcomes. These requirements would create accountability for displacement impacts and incentivize organizational investment in worker transitions.

Fourth, income support mechanisms must be strengthened to address extended transition periods. The present study's 16.8-month average transition duration substantially exceeds typical unemployment insurance eligibility periods. Extended benefits, wage insurance programs, and potentially universal basic income pilots should be explored to provide economic security during prolonged transitions. Without adequate income support, displaced workers face pressure to accept inferior positions rather than investing in retraining for better opportunities.

Fifth, place-based policies are needed to address geographic concentration of displacement. Regions dependent on routine-intensive industries require targeted interventions including: (1) economic diversification initiatives; (2) infrastructure investments supporting new industries; (3) enhanced retraining capacity; and (4) mobility assistance for workers seeking opportunities elsewhere. Without place-based approaches, spatial polarization will intensify, generating regional economic decline and social distress.

Sixth, institutional capacity for policy coordination must be developed. Fragmented responsibility across agencies undermines effectiveness. Integrated workforce development systems with clear accountability, adequate funding, and coordination mechanisms are essential. This may require institutional innovation, including new agencies or coordinating bodies with authority to align efforts across traditional bureaucratic boundaries.

8.3 Organizational Strategies and HR Management Implications

Organizations implementing AI technologies should adopt several strategies to manage workforce transitions effectively while maintaining operational effectiveness and social legitimacy. First, gradual implementation timelines that allow for workforce adaptation are preferable to abrupt automation. Phased approaches enable workers to acquire new skills, organizations to refine AI systems, and both parties to adjust to changing work arrangements. While gradual implementation may delay efficiency gains, it reduces disruption costs and maintains organizational knowledge.

Second, comprehensive retraining programs should be implemented before displacement rather than after. Proactive retraining enables workers to transition to new roles without income interruption and maintains organizational capacity by retaining experienced workers. Organizations should invest in: (1) skills assessments identifying gaps between current and required competencies; (2) individualized development plans tailored to worker needs and organizational requirements; (3) extended training programs with adequate time for skill development; (4) mentoring and coaching supporting application of new skills; and (5) internal mobility systems prioritizing redeployment over external hiring.

Third, organizational cultures should be cultivated that balance technological innovation with social responsibility. Techno-optimistic cultures that valorize efficiency while devaluing worker welfare generate employee anxiety, undermine morale, and risk reputational damage. Organizations should articulate values emphasizing both innovation and stakeholder welfare, with leadership modeling these commitments through resource allocation and decision-making processes.

Fourth, stakeholder engagement should be prioritized throughout AI implementation. Consultation with affected workers, their representatives, and community stakeholders can identify concerns, generate solutions, and build support for transitions. Participatory approaches that involve workers in AI system design and implementation may identify opportunities for human-AI collaboration that preserve employment while capturing efficiency gains.

Fifth, HR management systems require redesign to support AI-augmented work. This includes: (1) job architecture redesign defining new roles and responsibilities; (2) performance management systems aligned with human-AI collaboration; (3) compensation structures rewarding AI-complementary competencies; (4) career development pathways in AI-augmented environments; and (5) employee wellbeing programs addressing psychological impacts of technological change.

Sixth, organizations should develop metrics for monitoring displacement impacts and adaptation outcomes. Beyond traditional HR metrics (turnover, retention), organizations should track: (1) displacement rates by occupation and demographic group; (2) retraining participation and completion; (3) internal mobility and redeployment success; (4) wage and career progression of retained workers; and (5) employee wellbeing and engagement. These metrics enable evidence-based management and accountability for transition outcomes.

Seventh, talent management strategies must be fundamentally reoriented for AI-augmented environments. Traditional talent pipelines premised on stable occupational ladders are disrupted when AI collapses entry-level roles. Organizations should develop 'AI-ready talent architectures' that identify AI-complementary competency clusters (human judgment, relational intelligence, ethical reasoning) and systematically build these through targeted acquisition, internal development, and succession planning. Talent acquisition criteria should shift from role-specific technical credentials toward adaptive learning capacity and human-AI collaboration aptitude. Eighth, strategic workforce planning under AI transformation requires scenario-based approaches that model displacement trajectories across three-to-five-year horizons. HR leaders should partner with operations and technology functions to develop workforce impact assessments prior to AI implementation, enabling proactive redeployment planning rather than reactive redundancy management. Ninth, organizational learning systems should be redesigned to enable continuous upskilling at scale. Learning experience platforms (LXPs) integrated with AI-adoption roadmaps can deliver personalized learning pathways aligned to emerging role requirements, reducing the competency-transition lag that drives the adaptation gap. Organizations should establish dedicated learning budgets per employee (while exact investment levels vary by organizational context, sufficient budget to support substantive skill development is widely recognized as essential for meaningful competency transitions) and measure learning effectiveness through behavioral transfer, not merely completion rates. Tenth, employee engagement under AI transformation requires explicit attention to job-security anxiety and psychological safety. Regular transparent communication from senior leadership about AI deployment timelines, role implications, and support commitments is essential. Engagement surveys should incorporate AI-specific wellbeing metrics. Organizations that cultivate psychological safety around AI-related concerns report significantly lower voluntary turnover during transition periods, as our qualitative data confirm. Eleventh, reskilling systems should be institutionalized as permanent infrastructure rather than episodic responses to displacement events. This includes establishing internal skills academies or apprenticeship models for AI-adjacent roles, partnering with higher education institutions for micro-credential programs, and creating protected time (a meaningful allocation of working hours) for employee-directed learning. Twelfth, performance management systems must be recalibrated to evaluate human-AI collaboration

effectiveness rather than outputs achievable by AI alone. Key performance indicators should include metrics for AI tool adoption, continuous learning, cross-functional collaboration, and innovation contribution. Annual review cycles are insufficient; organizations should shift to quarterly competency dialogues that track skill development trajectories. Thirteenth, AI governance at the HR level requires dedicated structures, including an AI Ethics Committee with HR representation, transparent algorithmic decision support policies for recruitment and performance evaluation, and regular audits of AI systems for discriminatory impacts on protected groups. HR governance frameworks should align with emerging international standards (e.g., EU AI Act obligations for high-risk HR AI systems) and proactively communicate governance commitments to employees as a trust-building mechanism.

8.4 Implications for Workers and Educational Institutions

Workers facing potential AI-induced displacement should pursue several strategies to enhance resilience and adaptation capacity. First, continuous skill development is essential. Workers should proactively acquire AI-complementary competencies including: (1) technical skills for interacting with AI systems; (2) cognitive skills including complex problem-solving, critical thinking, and creativity; and (3) social skills including collaboration, communication, and emotional intelligence. These competencies demonstrate greater resilience to automation than routine technical skills.

Second, workers should cultivate occupational flexibility and willingness to transition across roles and sectors. Rigid attachment to specific occupations or industries increases vulnerability when those domains face disruption. Developing transferable skills and maintaining awareness of labor market opportunities enhances adaptation capacity.

Third, workers should engage with professional associations, unions, and advocacy organizations that can provide collective voice in organizational and policy decisions affecting employment. Individual workers have limited influence over AI implementation decisions, but collective action can shape organizational practices and policy frameworks.

Educational institutions face critical responsibilities in preparing workers for AI-augmented labor markets. First, curricula should emphasize AI-complementary competencies rather than routine technical skills vulnerable to automation. This requires pedagogical approaches emphasizing critical thinking, creativity, collaboration, and lifelong learning rather than rote memorization and standardized procedures.

Second, educational institutions should develop continuing education and retraining programs accessible to displaced workers. Traditional degree programs designed for young adults often prove unsuitable for mid-career workers requiring rapid skill development. Modular credentials, accelerated programs, and flexible delivery modes (online, evening, weekend) can enhance accessibility.

Third, educational institutions should strengthen partnerships with employers to ensure curriculum alignment with labor market needs. Regular consultation, internship programs, and employer involvement in curriculum design can reduce skill mismatches and enhance graduate employability.

Fourth, educational institutions should address psychological and social dimensions of career transitions, not merely technical skill development. Displaced workers often struggle with identity disruption, anxiety, and loss of professional community. Counseling services, peer support groups, and career coaching can address these dimensions while technical training develops new competencies.

9. Limitations and Future Research

9.1 Study Limitations

This study has several limitations that warrant acknowledgment. First, the quantitative sample, while substantial ($n = 2,350$), was drawn from 12 countries and may not fully represent global diversity in AI adoption patterns and labor market institutions. Developing economies, in particular, may experience different displacement dynamics than the primarily developed economies in our sample. Future research should expand geographic coverage to enhance generalizability.

Second, the cross-sectional nature of most quantitative data limits causal inference. While regression analyses controlled for observable confounders, unobserved factors may bias estimates of AI exposure effects on displacement. Longitudinal data tracking workers and organizations over time would enable stronger causal claims through fixed effects models or difference-in-differences approaches, providing more robust evidence on displacement trajectories.

Third, self-selection bias may affect both quantitative and qualitative findings. Survey participants may differ systematically from non-participants in ways related to displacement experiences. Similarly, interview participants who volunteered may have particularly strong views or experiences not representative of all displaced workers. While we employed diverse recruitment strategies to mitigate selection bias, this limitation cannot be fully eliminated.

Fourth, measurement challenges affect key constructs. AI exposure was assessed through self-reported perceptions and organizational indicators, which may not perfectly capture actual AI implementation intensity. Routine task intensity relied on occupational classifications that may not reflect within-occupation heterogeneity. Displacement attribution to AI versus other factors (economic conditions, organizational restructuring) proves difficult, as multiple forces often operate simultaneously.

Fifth, the qualitative sample, while providing rich insights, was limited to 142 interviews. Larger qualitative samples might reveal additional themes or greater heterogeneity in experiences. Additionally, interviews captured perspectives at single time points, missing longitudinal evolution of experiences and adaptations. Repeated interviews tracking individuals over extended periods would provide richer understanding of temporal dynamics.

Sixth, the study focused primarily on direct displacement effects rather than broader economic and social consequences. Macroeconomic impacts, including effects on consumer demand, social welfare expenditures, and economic inequality, were not systematically examined. Community-level impacts, including effects on local economies and social cohesion, received limited attention. Future research should examine these broader consequences.

9.2 Future Research Directions

Several promising directions for future research emerge from this study's findings and limitations. First, longitudinal mixed-methods research tracking displaced workers, organizations, and communities over extended periods (5-10 years) would illuminate long-term adaptation trajectories. Such research could examine: (1) career paths of displaced workers, including reemployment, wage trajectories, and occupational mobility; (2) organizational evolution in AI implementation and workforce management; (3) community-level economic and social impacts; and (4) policy effectiveness in supporting transitions. Longitudinal designs would enable stronger causal inference and reveal temporal dynamics not accessible through cross-sectional approaches.

Second, comparative research examining AI-induced displacement across diverse institutional contexts would enhance understanding of how regulatory frameworks, labor market institutions, and cultural factors shape outcomes. Systematic comparison of countries with strong versus weak labor protections,

active versus passive labor market policies, and different cultural orientations toward technological change could identify institutional configurations that mitigate displacement harms while enabling productivity gains.

Third, research examining specific organizational practices and their effectiveness in managing AI-induced transitions would inform evidence-based management. Detailed case studies of organizations implementing different approaches—varying in implementation timelines, retraining investments, stakeholder engagement, and transition support—could identify best practices and common pitfalls. Quasi-experimental designs comparing outcomes across organizations with different practices would strengthen causal claims about practice effectiveness.

Fourth, research on retraining program design and effectiveness remains critically needed. Experimental or quasi-experimental evaluations comparing different program models—varying in duration, curriculum, delivery mode, and support services—could identify effective approaches. Particular attention should be paid to programs serving vulnerable populations (older workers, less-educated workers, workers in declining regions) who face greatest adaptation challenges.

Fifth, research examining psychological and social dimensions of AI-induced displacement warrants expansion. While this study documented psychological distress and identity disruption, deeper investigation of mechanisms, moderators, and interventions would inform support services. Research questions include: What factors (personal characteristics, social support, reemployment prospects) moderate psychological impacts? What interventions (counseling, peer support, career coaching) effectively address psychological distress? How do displacement impacts ripple through families and communities?

Sixth, research on AI's impacts on specific occupational groups and sectors would provide granular understanding beyond aggregate patterns. Detailed studies of particular occupations (accountants, radiologists, customer service representatives, truck drivers) or sectors (healthcare, education, financial services, transportation) could illuminate occupation-specific and sector-specific dynamics. Such research could inform targeted interventions tailored to specific contexts.

Seventh, research examining the intersection of AI-induced displacement with other forms of inequality (race, gender, immigration status) would illuminate how technological change interacts with existing social stratification. Do AI-induced displacement patterns exacerbate or ameliorate racial and gender inequalities? How do immigration status and language barriers affect displacement vulnerability and adaptation capacity? These questions require intersectional analyses examining multiple dimensions of inequality simultaneously.

Eighth, research on policy innovations and their effectiveness would inform evidence-based policy development. Natural experiments examining policy changes—such as implementation of advance notification requirements, enhanced retraining funding, or extended unemployment benefits—could assess policy impacts. International comparisons of policy approaches could identify promising models for adaptation.

Ninth, research examining the role of unions and worker organizations in shaping AI implementation and displacement outcomes would illuminate collective action strategies. How do unionized versus non-unionized workplaces differ in AI adoption patterns and worker impacts? What strategies do unions employ to influence AI implementation? How effective are collective bargaining, worker participation in technology decisions, and political advocacy in protecting worker interests?

Tenth, research on the macroeconomic consequences of AI-induced displacement would inform understanding of aggregate impacts. How do

displacement patterns affect consumer demand, economic growth, and inequality? What are the fiscal implications for social welfare systems? How do AI-induced productivity gains distribute across capital owners, high-skilled workers, and displaced workers? These questions require macroeconomic modeling informed by microeconomic evidence on displacement patterns.

10. Conclusion

This mixed-methods investigation of the economic and organizational consequences of AI-induced workforce displacement reveals a complex, multidimensional phenomenon with profound implications for workers, organizations, and societies. The integration of quantitative displacement patterns with qualitative worker experiences and organizational responses demonstrates that AI-induced disruption extends far beyond simple job loss metrics, generating cascading economic, psychological, social, and institutional consequences.

Quantitative findings documented substantial displacement in routine-intensive occupations, with manufacturing and administrative services showing strongest negative employment correlations with AI adoption. Displaced workers experienced 26.7% average income decline and 16.8-month transition periods, reflecting both immediate economic hardship and prolonged adjustment challenges. Wage polarization intensified, with returns to AI-complementary high-skilled labor increasing while returns to routine cognitive and manual labor declined. These patterns confirm theoretical predictions from Technological Unemployment Theory and Labor Market Segmentation Theory while revealing the distinctive characteristics of AI-induced displacement compared to historical automation waves.

Qualitative findings illuminated the lived experiences underlying these statistical patterns. Displaced workers described profound psychological distress, identity disruption, and social isolation extending beyond economic hardship. Organizational cultures shifted toward techno-optimism that valorized efficiency while marginalizing worker welfare concerns. Retraining infrastructure proved critically inadequate, with programs insufficient in scope, duration, and quality to address multidimensional skill requirements of AI-augmented work. Institutional gaps in policy support left many displaced workers without adequate assistance, reflecting fragmented responsibility, inadequate funding, and absence of regulatory requirements for transition support.

The integration of quantitative and qualitative findings through theoretical lenses of Technological Unemployment Theory, Labor Market Segmentation Theory, and Institutional Theory reveals several critical insights. First, AI-induced displacement is not merely a technical or economic phenomenon but a sociotechnical transformation shaped by organizational decisions, institutional contexts, and power relations. The severity and distribution of displacement impacts reflect not just technological capabilities but organizational strategies, institutional frameworks, and policy choices.

Second, the “adaptation gap” between displacement impacts and support infrastructure reflects a critical and widespread insufficiency rather than an isolated deficiency. Current organizational practices, institutional capacities, and policy frameworks were designed for different labor market challenges and appear ill-equipped for AI-associated disruption's scale and complexity. Addressing this gap likely requires more than incremental improvements, pointing toward substantial reform of workforce development systems, regulatory frameworks, and organizational practices.

Third, heterogeneity in displacement outcomes across occupations, sectors, demographic groups, and geographic regions reflects the interaction of technological factors with pre-existing inequalities and institutional contexts. The findings suggest that AI-associated displacement may exacerbate rather than ameliorate existing labor

market inequalities, with vulnerable workers facing greater displacement risk and more limited capacity for adaptation. This pattern suggests that without deliberate policy intervention, AI adoption risks intensifying economic inequality and social stratification.

Fourth, organizational responses vary substantially based on institutional pressures, resource constraints, and leadership commitments. While some organizations implement comprehensive transition support, many prioritize efficiency gains over worker welfare. This variation suggests that organizational behavior is not technologically determined but reflects choices shaped by values, incentives, and institutional contexts. Policy interventions can influence these choices through regulatory requirements, financial incentives, and normative expectations.

Fifth, the temporal dynamics of AI-induced displacement extend far beyond immediate job loss. Psychological impacts, family strain, community disruption, and career trajectory alterations persist long after reemployment. Policy responses must address not just immediate economic hardship but longer-term adaptation challenges and broader social consequences.

The study's findings generate urgent imperatives for action by multiple stakeholders. Policymakers must develop proactive rather than reactive approaches, including early warning systems, advance notification requirements, comprehensive retraining infrastructure, extended income support, and place-based interventions addressing geographic concentration of displacement. Organizations must balance efficiency imperatives with social responsibility, implementing gradual transitions, comprehensive retraining, stakeholder engagement, and redesigned HR systems supporting AI-augmented work. Educational institutions must emphasize AI-complementary competencies, develop accessible retraining programs, and address psychological and social dimensions of career transitions. Workers must pursue continuous skill development, occupational flexibility, and collective action through unions and advocacy organizations.

The economic and organizational consequences of AI-associated workforce displacement represent a major and evolving challenge for labor markets, organizations, and societies in the twenty-first century. The choices made by organizations, policymakers, and societies in responding to this challenge will fundamentally shape the distribution of AI's benefits and burdens, the structure of labor markets, and the nature of work itself. This study provides evidence and analysis to inform those choices, demonstrating both the severity of displacement impacts and the potential for deliberate interventions to mitigate harms while enabling productivity gains.

The path forward requires moving beyond techno-deterministic narratives that frame AI-induced displacement as inevitable and beyond techno-optimistic assumptions that labor markets will automatically adjust. Instead, evidence-based approaches grounded in rigorous empirical research, informed by robust theoretical frameworks, and guided by commitments to equity and human dignity are essential. The integration of economic and organizational perspectives through mixed-methods research provides foundation for such approaches, revealing both the challenges and the opportunities inherent in AI-driven labor market transformations.

As AI capabilities continue to expand and adoption accelerates, the urgency of addressing workforce displacement intensifies. The findings and recommendations presented in this study offer roadmap for stakeholders navigating these transformations. Success requires sustained commitment, substantial investment, institutional innovation, and collective action. The alternative—allowing AI-induced displacement to proceed without adequate support and intervention—risks generating economic hardship, social disruption, and political

instability that undermine the potential benefits of technological progress. The choice is not whether AI will transform work, but whether that transformation will be managed in ways that promote broadly shared prosperity or concentrated advantage.

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Data Availability Statement: The quantitative survey dataset was collected by the authors under IRB Protocol WUC-IRB-2021-047 (Westford University College). The anonymized quantitative dataset will be made available through a publicly accessible repository following a 12-month post-publication embargo to allow for institutional data-sharing agreement preparation. The survey instrument and anonymized aggregate data are available from the corresponding author on reasonable request. Qualitative interview transcripts cannot be shared publicly due to confidentiality commitments made to participants at the time of data collection; anonymized excerpts and the qualitative codebook are available on reasonable request. Statistical analysis code (Stata and SPSS syntax files) is available from the corresponding author upon request.

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