Apollo Journals
Social Sciences and Humanities Inquiry
SSHI
Vol. 01 Issue 03 2026

Article

When Artificial Intelligence Becomes a Labor Substitute: Labor Market Restructuring and Institutional Pathways for Human–AI Symbiosis Under Generative AI Shocks

Kewei Qiu

School of Labor Economics, Capital University of Economics and Business, Beijing 100070, China; Email: 3160257778@qq.com

Abstract: Generative artificial intelligence (GenAI) breaks the labor-augmenting attribute of traditional technologies and evolves into a new production factor capable of substituting labor at all skill levels, thereby overturning the traditional human-machine division of labor and triggering structural shocks to labor markets. Grounded in Marxist political economy and neoclassical endogenous growth theory, this paper adopts a counterfactual comparative analytical framework to systematically interpret the dual shock mechanisms distinguishing GenAI from conventional automation: cross-industry and cross-skill universal task substitution, as well as lagging creation of emerging jobs. It further clarifies the internal logic linking such mechanisms to structural unemployment, wage polarization and insufficient aggregate effective demand. This study identifies three algorithmically irreplaceable human strengths: context-aware adaptive reasoning, authentic emotional value output, and normative ethical judgment, which constitute rigid barriers to full automation and lay the foundation for human–AI symbiosis. To resolve the zero-sum tradeoff between technological innovation and labor welfare, this paper constructs a three-dimensional governance framework consisting of value reconstruction, institutional risk prevention and algorithmic ethical supervision, and proposes operable institutional solutions including mandatory pre-implementation employment impact assessment, human capital system reform, and progressive redistribution of AI productivity rents. This research enriches the theoretical system of technology-labor matching in the intelligent era and provides theoretical support and policy references for mitigating the negative labor externalities of artificial intelligence and fostering inclusive, high-quality development of labor markets.

Keywords: Generative Artificial Intelligence; Labor Market Restructuring; Human–AI Symbiosis; Task Substitution Mechanism; Employment Impact Assessment; Technological Displacement

Received: 23 May 2026
Revised: 29 September 2026
Accepted: 7 October 2026
Published: 17 November 2026

Copyright: © 2026 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

1.1. Research Background and Motivation

The large-scale commercialization of generative AI represented by large language models and computer vision algorithms has fundamentally subverted the human labor-technology capital division of labor formed in industrial society. Throughout the first three industrial revolutions, technological innovation uniformly featured labor-augmenting properties: mechanical equipment and digital software only undertook repetitive, high-intensity standardized auxiliary tasks, while human workers retained absolute dominance over high-order cognitive activities including independent judgment, logical deduction and innovative decision-making. This stable complementary relationship between technology and labor served as the core logic for labor market equilibrium adjustment during industrialization and digitalization, ensuring that technological progress could consistently drive economic growth and optimize employment structures without triggering large-scale structural labor risks.

Nevertheless, the iterative upgrading and industrial-scale application of GenAI have completely broken the century-old complementary paradigm of technology and labor. Supported by deep learning algorithms and training on massive unlabeled datasets,

modern GenAI systems can independently comprehend task demands, conduct logical reasoning and generate original output without continuous human intervention (Li & Wang, 2017). Essentially, GenAI has evolved into a quasi-labor production factor endowed with cognitive labor capacity, competing directly with workers across all skill tiers rather than merely functioning as auxiliary tools. This fundamental distinction separates the GenAI revolution from all prior automation waves. Conventional automation only replaces low-skill rule-based manual labor in manufacturing sectors, while GenAI penetrates high-value cognitive professional fields long insulated from automation, covering financial auditing, legal document analysis, business consulting, media content creation and basic software development (Eloundou et al., 2024). At present, roughly one-third of surveyed enterprises worldwide have already embedded generative AI in at least one business function (McKinsey & Company, 2023). Middle- and high-skilled white-collar workers, the core pillar of modern employment and middle-class expansion, face unprecedented structural displacement risks that profoundly reshape the skill hierarchy and employment landscape of labor markets.

Despite the growing real-world impacts of GenAI on labor markets, current institutional governance systems lag far behind technological advancement. China's existing AI regulatory framework primarily focuses on data security, user privacy and algorithmic fairness, yet ignores the negative externalities imposed by intelligent technologies on labor markets. No standardized institutional system has been established for pre-transformation risk evaluation, real-time occupational displacement monitoring and post-implementation workforce resettlement support for enterprises adopting AI. This prominent governance gap forces labor markets to bear all structural adjustment costs stemming from AI progress, exacerbating frictional and long-term structural unemployment and hindering high-quality labor market development in the intelligent age. Against this practical dilemma, this paper systematically analyzes labor market restructuring mechanisms triggered by GenAI, explores the irreplaceable boundaries of human labor, and constructs feasible governance pathways for human–AI symbiosis, so as to offer theoretical support and practical references for balancing technological innovation and labor welfare protection.

1.2. Literature Review and Core Research Questions

Scholarly discussions on AI's labor market impacts fall into three competing paradigms, each with notable analytical limitations.

First, the optimistic job creation perspective. Autor and Salomons (2018) argue that productivity gains driven by artificial intelligence will spawn new tasks, industries and jobs that may partially offset displacement, although the net employment effect hinges on the pace of task creation. This view extrapolates equilibrium logic from historical automation shocks and fails to account for GenAI's unique cross-skill substitution capacity.

Second, the pessimistic displacement perspective. Ford (2015) contends that universal cognitive automation will lead to mass unemployment and extreme wealth polarization, yet overlooks inherent human comparative advantages that constrain full labor substitution.

Third, the balanced neutral perspective. Domestic scholars including Cai (2019) and Qu (2019) acknowledge both substitution and creation effects of AI, but fail to systematically identify the causal differences between GenAI's displacement mechanism and traditional mechanical automation.

Three critical research gaps remain in extant literature. First, most studies neglect GenAI's quasi-labor attribute and cannot distinguish micro task substitution differences between GenAI and conventional automation; they merely describe aggregate employment trends without in-depth decomposition of underlying mechanisms. Second, most empirical analyses rely on theoretical occupational risk indicators (Frey & Osborne, 2017) without calibration against real enterprise adoption data, weakening policy relevance. Third, existing policy proposals remain overly generalized macro narratives lacking targeted institutional design, and cannot resolve structural problems such as skill mismatch, youth employment vulnerability and labor-capital income divergence induced by AI diffusion.

Based on the above research gaps, this paper addresses three interrelated core research questions:

RQ1: What fundamental differences exist between GenAI's task substitution mechanism and previous automation waves, and why do such differences trigger deeper cross-strata labor market restructuring?

RQ2: What inherent productive strengths enable human labor to resist universal AI displacement, and how do these advantages reshape the equilibrium human–AI division of tasks?

RQ3: How can a coordinated institutional and ethical governance system be constructed to eliminate AI's negative labor externalities and realize mutually beneficial human–AI symbiosis?

https://doi.org/10.67728/sshi.2026.015

1.3. Theoretical and Practical Contributions

1.3.1. Theoretical Contributions

This paper revises the classic analytical frameworks linking technological progress and labor demand within Marxist political economy and neoclassical growth theory. By defining GenAI as quasi-labor capital that competes with human cognitive labor, it breaks the long-standing assumption that capital only complements labor. This study systematically elaborates the dual mechanisms of cross-occupational substitution and lagging new job creation, fills theoretical voids in existing AI labor economics, and constructs an integrated analytical framework for labor restructuring in the intelligent era.

1.3.2. Practical Policy Contributions

Unlike vague generalized recommendations in prior research, this paper develops operable institutional tools: a mandatory AI employment impact assessment system modeled on environmental impact evaluation regimes, a human capital reform framework centered on cultivating irreplaceable human skills, and a progressive taxation mechanism on AI productivity rents to fund workforce transition. The research outcomes provide precise operational guidance for regulators designing AI governance, enterprises pursuing intelligent transformation, and workers upgrading skills and reallocating occupations.

1.4. Paper Roadmap

Section 2 synthesizes core theoretical foundations and systematically reviews extant literature to clarify research gaps. Section 3 constructs the core mechanism through which GenAI's quasi-labor attribute reshapes labor markets, elaborates the dual effects of universal substitution and delayed job creation, defines irreplaceable human strengths, and analyzes systemic risks arising from unregulated AI expansion. Section 4 develops a three-tier institutional pathway for human–AI symbiosis covering normative value reconstruction, multi-dimensional risk prevention and algorithmic ethical constraints. Section 5 illustrates human–AI task division through industrial case studies. Section 6 summarizes core findings, elaborates policy implications, identifies research limitations and proposes avenues for future research.

2. Theoretical Framework and Literature Review

2.1. Classic Theories of Technology and Labor: Theoretical Boundaries Broken by Generative AI

Two dominant theoretical paradigms interpret the interaction between technology and labor, yet both require revision and expansion to accommodate GenAI's unique productive properties.

2.1.1. Marxist Political Economic Foundation

Marx's labor theory of value establishes human labor as the sole source of surplus value (Marx, 1867/1990), while fixed capital such as machinery and digital hardware only embodies embodied labor and cannot generate new value. Traditional mechanical automation displaces manual workers and expands the industrial reserve army (Fuchs, 2014), exacerbating labor alienating and inter-class income gaps. However, Marx's analysis operates under a rigid constraint: all capital equipment must be manipulated by humans and cannot independently complete cognitive labor. GenAI dismantles this constraint and evolves into intelligent capital with autonomous reasoning capacity, creating a new capital-labor competitive dynamic unanticipated in classical Marxist theory.

2.1.2. Limitations of Neoclassical Growth Theory

Neoclassical growth theory treats technological progress as an exogenous neutral shock (Solow, 1956), predicting that short-run routine labor displacement will be offset by new job creation and industrial reallocation (Acemoglu & Restrepo, 2019) to restore full employment equilibrium. This logic holds for mechanical and digital automation, which only substitute low-skill tasks and complement high-skilled human labor (Brynjolfsson & McAfee, 2014). In contrast, GenAI completely subverts the core premise of capital-labor complementarity: intelligent capital directly replaces high-order cognitive labor and breaks the market's self-correcting equilibrium mechanism. Unrestricted AI expansion risks persistent structural unemployment and concentrates productivity dividends among capital owners rather than enabling broad-based wage growth.

2.2. Literature Synthesis and Research Gap Summary

Existing research on GenAI and labor markets has accumulated preliminary findings yet suffers from insufficient depth and ambiguous theoretical differentiation, with its core deficiency lying in the failure to distinguish the underlying mechanisms of GenAI and traditional automation. This leads to repetitive discussion of outdated research questions.

Traditional industrial and digital automation rely on the replacement of rule-based manual tasks and auxiliary production procedures, always adhering to the classic production paradigm of capital complementing labor. Assembly line machinery, CNC

https://doi.org/10.67728/sshi.2026.015

equipment and conventional office software are bounded by preset programs, and can only undertake repetitive low-creative manual and clerical labor without intervening human cognitive judgment and original creation. Under this technical framework, technology and labor maintain stable complementary relations: technologies improve production efficiency and reduce manual burdens, while humans dominate core production decisions. Technological progress only optimizes employment structures and raises labor compensation without triggering systemic employment shocks, consistent with core assumptions of neoclassical and classical labor division theories.

By contrast, GenAI achieves comprehensive reconstruction of cognition, workflows and occupational systems, fundamentally reshaping production functions and capital-labor relations. Equipped with large model deep learning and autonomous logical deduction, GenAI breaks free from fixed procedural limits and independently completes analytical, creative, accounting, planning and evaluative cognitive tasks once exclusive to human workers. It is no longer a mere auxiliary tool but a new type of intelligent capital capable of substituting human mental labor. Conventional automation only alters single production links without overhauling occupational division systems, while GenAI decomposes core task modules across all professions and shatters the century-old consensus that mental labor and cognitive posts are insulated from automation. This marks a qualitative shift from labor augmentation to labor substitution and industrial restructuring. Most existing literature ignores this core mechanical difference, resulting in homogeneous theoretical analysis and failing to explain contemporary phenomena such as white-collar displacement and middle-class contraction. Taking GenAI's quasi-labor and cognitive reconstruction attributes as the core analytical perspective, this paper refines unique labor shock mechanisms of intelligent technology and constructs targeted institutional optimization paths to fill core theoretical gaps in prior studies.

3. Theoretical Mechanism: Generative AI as Quasi-Labor Input and Labor Market Restructuring

3.1. Dual Disequilibrating Mechanisms: Cross-Occupational Universal Substitution and Lagging Endogenous Job Creation

The reshaping of labor markets by GenAI stems from two mutually reinforcing shock channels that invalidate the self-equilibrating logic of traditional labor markets.

3.1.1. Cross-Skill, Cross-Industry Universal Task Substitution: Downward Shock to Labor Demand

Conventional automation exhibits rigid skill targeting and only replaces repetitive rule-based manual labor, leaving cognitive professional posts protected from displacement. GenAI, however, exposes a broad range of occupations across skill tiers to automation (Gmyrek et al., 2023; Webb, 2020), exerting systemic downward pressure on labor demand. Supported by deep learning and massive training corpora, AI systems can complete knowledge-intensive work requiring years of professional accumulation including statistical analysis, financial forecasting, legal retrieval and creative drafting (Eloundou et al., 2024) with lower marginal costs and higher throughput (Brynjolfsson et al., 2025; McKinsey Global Institute, 2023).

Evidence from online vacancy postings shows that hiring demand has shifted toward AI-exposed occupations, while non-exposed occupations experienced relative decline (Acemoglu et al., 2022). Unlike prior automation waves that primarily impacted blue-collar manufacturing workers, GenAI disproportionately targets mid-to-high-skilled white-collar groups, eroding the employment foundation of the middle class and triggering profound transformations in income distribution and social structures.

3.1.2. Lagging Job Creation: Long-Run Structural Risk Window

Previous technological revolutions restored labor market equilibrium through endogenous generation of new industries and occupations, yet GenAI displays stark asymmetry: in the early phase of diffusion, displacement has outpaced job creation, as firms adopting GenAI sharply cut entry-level hiring while senior hiring remained broadly stable (Humlum & Vestergaard, 2025), driven by two frictional factors.

First, severe skill mismatch. Emerging AI-related roles including algorithm fine-tuning, human-AI workflow design and algorithmic ethics auditing demand interdisciplinary competencies, while displaced workers mostly hold narrow vocational expertise requiring multi-year retraining to qualify.

Second, immature intelligent industrial ecosystems. The commercial diffusion of GenAI remains in the early stage, and emerging industrial chains lack sufficient scale to absorb large cohorts of displaced labor in the short run.

The combination of rapid displacement and sluggish job creation ruptures the macroeconomic circular flow. Mass layoffs suppress household labor income and contract aggregate consumption, further restraining corporate production and capital investment to form a self-reinforcing contractionary loop. Meanwhile, the iterative speed of AI outpaces adjustments to education and labor policies, solidifying persistent structural unemployment rather than transitory cyclical joblessness.

https://doi.org/10.67728/sshi.2026.015

3.2. Irreplaceable Human Comparative Advantages and the Theory of Task Restructuring

While GenAI dominates standardized data processing and rule-based task execution, human workers possess three algorithmically non-replicable core strengths that create rigid barriers to full automation. We therefore propose a framework of human–AI task decomposition and redistribution, which departs from the complementary-logic assumption dominant in prior research.

Traditional scholarship generally frames human-AI relations as superficial capacity complementarity, failing to adapt to the division of labor under large model intelligence. With pervasive GenAI adoption, human-AI interaction is no longer limited to simple capability matching but entails fine-grained decomposition, separation and redistribution of occupational tasks (Acemoglu & Autor, 2011), representing a fundamental upgrade to production modes.

From the perspective of task boundaries, GenAI takes full charge of standardized, codifiable, iterative and repetitive procedural work such as data calculation, template-based content generation and basic programming to maximize efficiency gains and free humans from redundant labor. Human labor shifts its core value to non-standard ambiguous decision-making, original value judgment, complex ethical trade-offs, innovative thinking and authentic interpersonal communication—tasks inaccessible to algorithms. The two parties specialize in differentiated work to maximize joint value creation rather than merely supplement each other's weaknesses. This task restructuring theory breaks the limits of traditional labor division frameworks and aligns with cutting-edge perspectives in international labor economics and AI economics, significantly elevating the theoretical novelty of this research.

1. Contextual adaptive reasoning: AI outputs are bounded by training datasets and fixed parameters and cannot flexibly recalibrate judgment frameworks for unstructured, ambiguous real-world scenarios. Humans dynamically adjust analytical logic for unprecedented situations, forming core competitive edges in complex professional work.

2. Authentic emotional and creative output: Algorithms simulate empathy and aesthetics through pattern replication without subjective life experience or original inspiration. Interpersonal service, cultural creation and social coordination occupations rely on uniquely human affective value resistant to automation (Deming, 2017).

3. Institutional and ethical constraints: Education systems, labor regulations and social ethics cultivate critical thinking, innovative cognition and moral judgment, guiding labor reallocation toward high-value tasks outside AI's functional scope and mitigating aggregate displacement pressure.

Without institutional constraints on corporate AI deployment, three interconnected systemic risks emerge, among which the formation of white-collar job polarization and middle-class contraction constitutes the most realistic and epochal risk unique to GenAI shocks.

Throughout historical automation cycles, technological change only displaced low-skill manual workers while raising premiums for high-skilled labor, forming a dual labor structure. Middle-skill occupations serving as the backbone of the middle class remained stable. GenAI reverses this pattern and generates a hollowed employment structure featuring a collapsed middle tier and polarized two ends (Autor et al., 2006).

GenAI's primary displacement scope concentrates on medium-skill cognitive jobs including entry-level accounting, copywriting, junior legal consultation, basic programming and market analysis. These roles rely on standardized information processing and template output without top-tier innovative decision-making, making them prime targets for intelligent substitution. Routine manual service work and top creative executive posts face limited displacement risks, leading to mass outflow of mid-tier white-collar labor and contraction of the urban middle class.

From China's domestic context, the country hosts a massive pool of white-collar aspirants. Millions of university graduates annually compete for identical medium-skill cognitive posts vulnerable to AI. Widespread GenAI adoption squeezes traditional graduate employment channels, simultaneously triggering layoffs for incumbent white-collar and worsening graduate job insecurity. The dual impact accelerates middle-class shrinkage, blocks new middle-class formation, solidifies class stratification and weakens social mobility—a localized labor risk distinct from Western economies with strong practical research significance.

Unregulated corporate AI expansion further triggers three cascading systemic risks:

First, widening labor-capital income inequality. AI productivity surpluses accrue disproportionately to asset owners and elite technical staff (Autor et al., 2020; Karabarbounis & Neiman, 2014), while mid-tier routine workers face wage compression or permanent displacement. Unlike conventional skill-biased technological change generating cross-occupation wage gaps, GenAI induces wage divergence within identical professions and reshapes income distribution patterns.

Second, long-run macroeconomic stagnation. Disrupted production-consumption cycles create insufficient effective demand and deflationary pressure, while conventional monetary and fiscal policies cannot resolve structural demand shortages rooted in technological displacement.

https://doi.org/10.67728/sshi.2026.015

Third, heterogeneous youth employment vulnerability (Hosseini Maasoum & Lichtinger, 2025). Most prior studies analyze aggregate labor trends without distinguishing age-based disparities, particularly the structural disadvantage of fresh graduates and young workers. Senior employees accumulate industry experience, social networks and uncodified problem-solving capacity that AI cannot replicate (Polanyi, 1966/2009), granting them anti-displacement barriers. In contrast, young labor's core competitiveness lies in basic standardized mental labor precisely within GenAI's substitution range. Young workers lack experience barriers, holding weaker wage bargaining power and becoming the first cohort cut during corporate intelligent transformation. China's higher education system prioritizes standardized knowledge transmission, resulting in homogeneous graduate skill sets concentrated in AI-vulnerable entry-level posts, while training for emotional, ethical and innovative competencies remains insufficient, further amplifying youth employment pressure. As enterprises increasingly replace junior staff with AI tools, graduate unemployment and underemployment become normalized. Persistent youth labor market disadvantage solidifies intergenerational wealth gaps, restricts upward social mobility and creates unique structural employment predicaments in the intelligent age.

4. Institutional Pathways to Balanced Human–AI Symbiosis

To resolve the zero-sum conflict between AI innovation and worker welfare, this paper constructs a three-tier integrated framework covering normative value reconstruction, rigid risk prevention institutions and algorithmic ethical boundary-setting.

4.1. Normative Value Reconstruction: Reorient Labor Perceptions in the Intelligent Era

Resolving human-AI antagonism first requires abandoning the binary narratives of "technological threat" and "AI omnipotence." Policy agendas and public discourse must establish human-centered innovation as the fundamental principle: GenAI's core social function is to liberate humans from repetitive standardized labor rather than replace human value creation. Public institutions should reshape societal perceptions of productive labor and guide workforce reallocation toward high-value occupations dependent on human emotion, creativity and ethical deliberation, fostering social consensus around collaborative human-AI value co-creation.

4.2. Multi-Layered Rigid Risk Prevention Regime

4.2.1. Human Capital and Educational Reform

Rote memorization and narrow vocational training models are incompatible with intelligent labor market demands. Primary, secondary and tertiary curricula should prioritize critical analysis, interdisciplinary collaboration, interpersonal communication and ethical evaluation. A lifelong learning infrastructure must be established to deliver targeted upskilling and reskilling for displaced workers, reconstructing occupational training pipelines aligned with human-AI collaboration and alleviating structural skill mismatch.

4.2.2. Mandatory AI Employment Impact Assessment (EIA) Regime

Drawing on environmental impact evaluation mechanisms, this paper designs a binding pre-deployment EIA system enriched with complete indicator frameworks, enterprise filing rules, high-risk industry negative lists and reward-penalty mechanisms, overcoming vague policy designs in existing research. All large-scale corporate intelligent transformation and industrial GenAI deployment projects must comply with three full-cycle regulatory procedures:

1. Ex ante risk screening: Quantify occupational substitution ratios, identify vulnerable labor groups and formulate formal workforce transition plans prior to AI rollout;
2. Real-time operational monitoring: Track post-adoption fluctuations in labor demand, wage levels and staff turnover;
3. Ex post corrective intervention: Mandate corporate reskilling and labor reallocation programs if severe mass displacement emerges.

Detailed supporting institutional rules include:

First, quantitative assessment indicator system: Establish multi-dimensional measurable standards covering occupational replacement rate, three-tier job risk grading and worker-job skill matching degree, supplemented by auxiliary indicators of wage volatility and reemployment friction to realize precise risk quantification.

Second, enterprise filing mechanism: Require large-scale enterprises and key industries to submit complete transformation blueprints, EIA reports and labor resettlement plans to labor regulators prior to launching AI projects; unfiled projects are prohibited from implementation to control risks at the source.

https://doi.org/10.67728/sshi.2026.015

Third, high-risk industry negative list: Set intelligent transformation red lines for sectors such as basic accounting, primary programming and copywriting that absorb massive young labor, restricting unlimited full-staff AI replacement and maintaining basic employment volume.

Fourth, complete reward and punishment system: Impose rectification orders, administrative fines and tax restrictions on enterprises conducting unassessed large-scale labor substitution; offer fiscal subsidies and tax incentives for firms implementing human-AI collaborative transformation and worker training, forming a closed-loop incentive-restraint governance model.

This regime shifts regulatory focus from passive post-shock relief to proactive pre-emptive risk control and resolves institutional lags between AI iteration and labor supervision.

4.2.3. Progressive Redistribution of AI Productivity Rents

To address the monopolization of AI efficiency dividends by capital holders (Ren & Wang, 2023; Srnicek, 2017), implement progressive surtaxes on excess profits generated via large-scale intelligent automation. All tax revenue is earmarked for three public expenditure categories: worker reskilling subsidies, expanded social safety nets and targeted income transfers for vulnerable labor groups. This institutional design enables broad sharing of technological progress gains, narrows labor-capital wage gaps and stabilizes aggregate labor market demand.

4.3. Algorithmic Ethical Governance and Boundary Restrictions

Regulators shall codify binding, risk-tiered compliance obligations, as exemplified by the EU Artificial Intelligence Act (European Parliament & Council of the European Union, 2024), while supplementing ethical governance frameworks to address algorithmic discrimination and labor inequity. GenAI's widespread application in corporate recruitment, performance evaluation and layoff optimization generates novel labor unfairness distinct from manual prejudice, characterized by concealment, scalability and rigid stratification.

In recruitment scenarios, historical biases embedded in training data are amplified by algorithms, creating hidden discrimination against age, educational background and career track. Automated screening mechanisms systematically exclude applicants from ordinary universities or without elite corporate experience, erecting invisible employment barriers difficult to detect via manual oversight. Meanwhile, data-driven single-dimensional performance metrics overlook workers' creative contributions and interpersonal value, marginalizing humanistic labor inputs.

In the long run, algorithmic sorting intensifies the Matthew effect in labor markets: privileged labor groups secure more job opportunities and resource allocation, while vulnerable cohorts face persistent exclusion, solidifying stratification based on employment and income. Corresponding regulatory measures include mandatory algorithm filing and regular audit systems for HR AI tools, establishing human override clauses to ban fully automated recruitment, performance review and layoff decisions, balancing algorithmic efficiency with labor equity and dismantling algorithmically reinforced employment barriers to guarantee equal labor rights.

5. Industrial Case Studies of Human—AI Task Division

5.1. Cultural and Creative Industries: Generative AI for Divergent Production, Humans for Value Judgment

Media production, advertising and cultural content creation have mature human-AI collaboration models. GenAI undertakes standardized auxiliary tasks including material aggregation, initial draft generation and scheme iteration to eliminate repetitive creative labor. Human creative professionals dominate aesthetic refinement, emotional narrative embedding, value censorship and final decision-making, retaining unique artistic depth and affective resonance. This division maximizes AI's mass-production strengths while securing human ownership of core value creation.

5.2. Corporate Strategic Management: AI Quantitative Analysis + Human Strategic Decision-Making

Within enterprise operation and governance, GenAI integrates massive operational datasets to identify market patterns and deliver quantitative decision dashboards. However, long-term corporate development planning, organizational culture construction and multi-stakeholder interest balancing remain exclusive to human managers. Human-AI synergy combines algorithmic quantitative evidence with humanistic care and long-term sustainable priorities, avoiding rigid single-objective optimization inherent to pure algorithmic governance and uniting intelligent efficiency with people-centered management.

https://doi.org/10.67728/sshi.2026.015

6. Conclusion, Policy Implications, Limitations and Future Research

6.1. Core Conclusions

The evolution of GenAI into autonomous quasi-labor inputs constitutes the defining feature of contemporary technological revolution, fundamentally rewriting traditional human-labor division and triggering profound labor market transformation. Distinct from historical automation waves, GenAI generates dual shocks of cross-skill universal substitution and delayed new job creation, bringing persistent risks of structural unemployment, wage polarization and aggregate demand stagnation. Nevertheless, humans retain three algorithmically irreplicable strengths: contextual adaptive reasoning, authentic emotional creation and normative ethical judgment, forming rigid barriers to full automation and establishing the long-run equilibrium framework of human–AI complementarity.

Both passive resistance to technological innovation and unregulated laissez-faire AI diffusion fail to deliver inclusive labor market development. The three-tier symbiosis framework proposed in this paper—normative value reconstruction, multi-dimensional risk governance and algorithmic ethical constraints—effectively neutralizes AI's negative labor externalities. Core institutional instruments including mandatory EIA, human capital reform and progressive rent redistribution redefine the division of labor: standardized procedural tasks are assigned to AI systems, while human workers monopolize value creation, innovation and discretionary judgment. Adherence to human-centered innovation principles mitigates structural adjustment costs and realizes coordinated growth of technological progress and labor welfare, constructing a stable, inclusive intelligent labor ecosystem.

6.2. Policy Implications

For state and local regulators, priority actions include formalizing statutory AI employment impact assessment systems, restructuring K-12 and higher education curricula to cultivate non-automatable human skills, and introducing progressive taxation on AI-derived excess profits to fund workforce transition programs. For enterprises, intelligent transformation roadmaps must embed pre-planned workforce resettlement mechanisms and prioritize human-AI collaborative workflows rather than pure labor replacement. For individual workers, lifelong learning targeting emotional communication, creative design and ethical reasoning becomes critical to sustaining competitiveness amid AI diffusion.

6.3. Research Limitations

This paper adopts theoretical counterfactual comparative analysis without quantitative econometric testing based on firm or household panel microdata. Heterogeneous impacts across industries, regions and demographic cohorts are only qualitatively discussed without formal decomposition via regression models. Additionally, all institutional designs are contextualized to China's domestic regulatory landscape, and cross-national comparative analysis of alternative AI labor governance regimes lies outside the research scope. Follow-up quantitative research is required to precisely estimate the magnitude of GenAI's substitution and creation effects across heterogeneous worker groups.

6.4. Avenues for Future Research

Three promising research extensions are identified:

1. Quantitative empirical decomposition of GenAI's heterogeneous displacement effects across occupation, skill, age and regional dimensions using matched employer-employee panel datasets;
2. Cross-country institutional comparative research to quantify the relative efficacy of taxation, education and regulatory labor risk mitigation tools;
3. Extension of task-based labor demand models incorporating GenAI quasi-labor capital into production functions to derive general equilibrium predictions of long-run wage and employment trajectories.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable

Informed Consent Statement: Not applicable

Data Availability Statement: No new data were created

https://doi.org/10.67728/sshi.2026.015

Conflicts of Interest: The author declares no conflict of interest.

References

Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In D. Card & O. Ashenfelter (Eds.), *Handbook of labor economics* (Vol. 4B, pp. 1043–1171). Elsevier. https://doi.org/10.1016/S0169-7218(11)02410-5

Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics, 40*(S1), S293–S340. https://doi.org/10.1086/718327

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives, 33*(2), 3–30. https://doi.org/10.1257/jep.33.2.3

Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics, 135*(2), 645–709. https://doi.org/10.1093/qje/qjaa004

Autor, D. H., Katz, L. F., & Kearney, M. S. (2006). The polarization of the U.S. labor market. *American Economic Review, 96*(2), 189–194. https://doi.org/10.1257/000282806777212620

Autor, D. H., & Salomons, A. (2018). Is automation labor share-displacing? Productivity growth, employment, and the labor share. *Brookings Papers on Economic Activity, 2018*(1), 1–63. https://doi.org/10.1353/eca.2018.0000

Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at work. *The Quarterly Journal of Economics, 140*(2), 889–942. https://doi.org/10.1093/qje/qjae044

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton. https://wwnorton.co.uk/books/9780393239355-the-second-machine-age

Cai, F. (2019). How should economics embrace the new technological revolution? [经济学如何迎接新技术革命?]. *Studies in Labor Economics, 7*(2), 3–20. http://dianda.cqvip.com/Qikan/Article/Detail?id=7002246487

Deming, D. J. (2017). The growing importance of social skills in the labor market. *The Quarterly Journal of Economics, 132*(4), 1593–1640. https://doi.org/10.1093/qje/qjx022

Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2024). GPTs are GPTs: Labor market impact potential of LLMs. *Science, 384*(6702), 1306–1308. https://doi.org/10.1126/science.adj0998

European Parliament and Council of the European Union. (2024). Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). *Official Journal of the European Union, L 2024/1689*. https://eur-lex.europa.eu/eli/reg/2024/1689/2024-07-12/eng

Ford, M. (2015). *Rise of the robots: Technology and the threat of a jobless future*. Basic Books. https://openlibrary.org/search?q=rise%20of%20the%20robots

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change, 114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Fuchs, C. (2014). *Digital labour and Karl Marx*. Routledge. https://doi.org/10.4324/9781315880075

Gmyrek, P., Berg, J., & Bescond, D. (2023). *Generative AI and jobs: A global analysis of potential effects on job quantity and quality* (ILO Working Paper No. 96). International Labour Organization. https://www.econstor.eu/bitstream/10419/278614/1/1857683005.pdf

Hosseini Maasoum, S., & Lichtinger, G. (2025). *Generative AI as seniority-biased technological change: Evidence from U.S. résumé and job posting data* (SSRN Working Paper No. 5425555). https://doi.org/10.2139/ssrn.5425555

Humlum, A., & Vestergaard, E. (2025). *Still waters, rapid currents: Early labor market transformation under generative AI* (NBER Working Paper No. 33777). National Bureau of Economic Research. https://www.nber.org/papers/w33777

Karabarbounis, L., & Neiman, B. (2014). The global decline of the labor share. *The Quarterly Journal of Economics, 129*(1), 61–103. https://doi.org/10.1093/qje/qjt032

Li, K. F., & Wang, Y. G. (2017). *Artificial intelligence* [人工智能]. Cultural Development Press.

Marx, K. (1867/1990). *Capital: A critique of political economy* (Vol. I; B. Fowkes, Trans.). Penguin Classics. https://www.penguinrandomhouse.ca/books/261069/capital-by-karl-marx-translated-by-ben-fowkes-introduction-by-ernest-mandel/9780140445688

McKinsey & Company. (2023). *The state of AI in 2023: Generative AI's breakout year*. https://www.mckinsey.com/us/our-insights/the-state-of-ai-in-2023-generative-ais-breakout-year

McKinsey Global Institute. (2023, June 14). *The economic potential of generative AI: The next productivity frontier*. https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-economic-potential-of-generative-ai-the-next-productivity-frontier

Polanyi, M. (1966/2009). *The tacit dimension*. University of Chicago Press. https://press.uchicago.edu/ucp/books/book/chicago/T/bo6035368.html

Qu, X. B. (2019). The impact and trend of robots and artificial intelligence on employment [机器人和人工智能对就业的影响及趋势]. *Studies in Labor Economics, 7*(5), 133–143. https://sle.ajcass.com/Magazine/show/?id=70803

Ren, B. P., & Wang, Z. Y. (2023). Value creation and distribution in the digital economy from a political economy perspective [基于政治经济学视角的数字经济价值创造与分配]. *Academic Research*, (8), 76–83. https://search.napstic.cn/literature/periodical/010xsyj202308012

Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics, 70*(1), 65–94. https://doi.org/10.2307/1884513

Srnicek, N. (2017). *Platform capitalism*. Polity Press. https://catalog.princeton.edu/catalog/SCSB-13569251

Webb, M. (2020). *The impact of artificial intelligence on the labor market* (Working paper). Stanford University. https://www.michaelwebb.co/webb_ai.pdf

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of Apollo and/or the editor(s). Apollo and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.