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ORIGINAL RESEARCH PAPER

Divergent Perspectives on AI, Automation, and the Future of Work from the Perspective of Green Human Resource Management: Displacement, Augmentation, Abundance, and Environmental Dimensions

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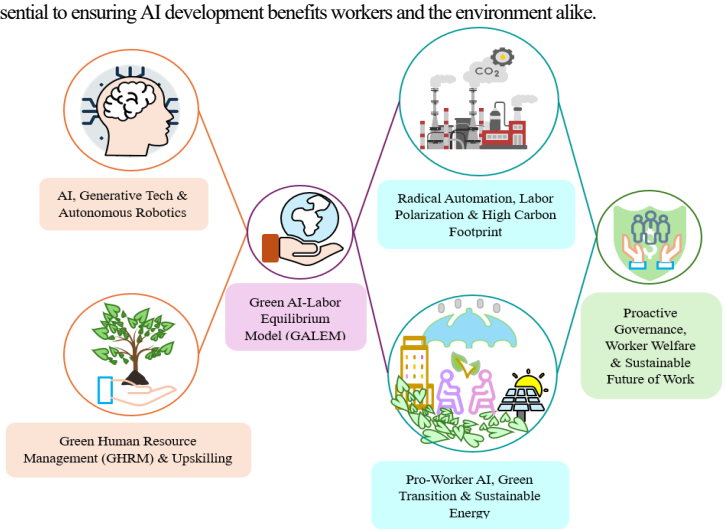
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ABSTRACT

This paper examines the implications of rapid advances in generative AI and autonomous robotics for labor markets, economic growth, and environmental sustainability, drawing on empirical and conceptual evidence through 2026. It synthesizes task-based automation, labor-market polarization, radical-abundance, and growth-environment perspectives through Green Human Resource Management (GHRM). To formalize this synthesis, the authors introduce the Green AI-Labor Equilibrium Model (GALEM), which extends task-based automation by jointly modeling environmental externalities, GHRM investment, redistribution through UBI, and worker quality of life. GALEM is used as a stylized scenario model rather than a point-forecasting system; long-horizon projections are conditional on explicitly stated parameter values and scenario assumptions. Under the baseline scenario set, the model illustrates a wide distribution of possible outcomes by 2045: automation can rise to 65 percent of tasks with labor share falling to 40 percent, while the Radical Automation case reaches 91 percent automation and a 10 percent labor share. In contrast, the Pro-Worker AI and Green Transition cases retain labor shares near 60 percent and 54 percent, respectively. AI-related energy use ranges from 3.4 EJ/year in the Green Transition to 38.0 EJ/year in Radical Automation. These are conditional scenario projections, not statistical forecasts. The paper concludes with a staged policy roadmap recommending:1.Tax neutrality 2. Augmentation-focused R&D 3.Mandatory GHRM reporting 4. Lifelong learning investment 5.Carbon pricing for computing infrastructure. Overall, the authors argue that proactive, sustainability-conscious governance is essential to ensuring AI development benefits workers and the environment alike.



1. Introduction

Something genuinely new is happening in the world economy. Between 2022 and 2025, generative AI systems based on large language models (LLMs) transitioned from research curiosities to general-purpose tools deployed across virtually every economic sector. Unlike earlier waves of information technology which primarily affected manufacturing and clerical work the current generation of AI penetrates deeply into cognitive and creative domains once considered securely human: legal

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analysis, medical diagnosis, software engineering, scientific research, and artistic production [1, 2]. At the same time, advances in humanoid robotics raise the prospect that physical labor, too, may face unprecedented competitive pressure from machines. The economic stakes are enormous. If AI proves to be a genuine general-purpose technology on the scale of electricity or the internal combustion engine, it could lift global productivity out of the secular stagnation that has characterized advanced economies since the mid-2000s [3, 4]. But the distributional consequences could be equally dramatic. If AI displaces workers faster than the economy creates new tasks and occupations, the result could be rising inequality, political instability, and a crisis of meaning for hundreds of millions of people whose identities are tied to their work. Yet this debate has largely proceeded without serious attention to its environmental dimension. The computational infrastructure required to train and deploy frontier AI models is extraordinarily energy-intensive. The International Energy Agency estimated in 2024 that global data center electricity consumption was growing at roughly 18 percent per year a trajectory that could make AI one of the largest single sources of electricity demand on the planet within a decade [5]. Any serious analysis of AI and the future of work must therefore grapple with ecological sustainability.

This paper organizes the debate around four distinct intellectual perspectives:

1. **The Displacement Perspective**, rooted in Acemoglu and Restrepo's [6] task-based framework, which emphasizes the risk that AI automates tasks without generating sufficient productivity gains or new labor-intensive activities to compensate displaced workers.
2. **The Polarization-Augmentation Perspective**, associated with David Autor and collaborators, which highlights automation's selective nature substituting for routine tasks while complementing non-routine cognitive and interpersonal skills and explores AI's potential to democratize expertise [7].
3. **The Abundance Perspective**, articulated by Elon Musk and echoed by Ray Kurzweil, which holds that AI and robotics will eventually render most human labor obsolete, ushering in an era of radical material abundance.
4. **The Growth-Environment Perspective**, grounded in Nordhaus's macroeconomic and climate modeling, which asks whether AI can trigger explosive economic growth and whether the planet can survive if it does [8].

We integrate these four perspectives through a fifth lens: Green Human Resource Management (GHRM), arguing that it provides a crucial micro-level bridge between macro debates about growth and displacement and the practical organizational challenges of adopting AI responsibly. The study is guided by one overarching research question: How do AI-driven task automation and augmentation interact with GHRM investment, environmental externalities, and redistribution to shape labor demand, productivity, inequality, and social welfare through 2045? The analysis therefore asks under which institutional and organizational conditions automation is offset by worker augmentation and new-task creation while environmental damages remain bounded.

1.2. Theoretical Foundations

1.2.1. The Task-Based Framework of Automation

The dominant analytical framework in modern labor economics for thinking about automation is the task-based model of Acemoglu and Restrepo [6, 9, 10], building on Autor, Levy, and Murnane [11]. The key insight is that production involves a large number of distinct tasks, and automation's effect on labor depends on the balance of several competing forces.

The most direct is the displacement effect: when a task previously performed by a human is taken over by a machine, labor demand in that task falls to zero. Working against this are three countervailing forces. The productivity effect arises because automation lowers production costs, raising real incomes and generating demand throughout the economy. The capital accumulation effect refers to the increase in the capital stock accompanying profitable automation, which can raise the marginal product of labor in non-automated tasks And the reinstatement effect captures the creation of entirely new tasks and occupations where human labor retains a comparative advantage.

The crucial question is whether productivity and reinstatement effects are large enough to offset displacement. Acemoglu's central worry elaborated in *Power and Progress* [12] and his 2024 macroeconomics analysis is that the current AI wave is excessively oriented toward "so-so automation": technologies good enough to replace workers but not good enough to generate large productivity gains, producing a worst-of-both-worlds outcome. He contrasts this with "pro-worker AI": tools designed to provide workers with better information and richer capabilities, expanding the range of tasks where human expertise is valuable. Which path the economy follows is not technologically determined it depends on choices made by firms, governments, and societies.

1.2.2. Labor Market Polarization and the Democratization of Expertise

Autor's research with Dorn [13] documented the polarization of the U.S. labor market: employment growth concentrated at the top and bottom of the wage distribution, with the middle hollowed out as routine cognitive and manual tasks were automated. Non-routine cognitive tasks (management, complex problem-solving) and non-routine manual tasks (personal care, maintenance) remained relatively intact.

The generative AI revolution introduces a new wrinkle. Unlike earlier information technologies, LLMs can perform many non-routine cognitive tasks: drafting legal briefs, writing code, interpreting medical images, synthesizing complex information. In his 2024 Ely Lecture, Autor argued this could lead to the "democratization of expertise" a world where AI tools enable less-specialized workers to perform tasks that previously required years of training. The implications are double-edged: it could compress wage inequality from the top while also vastly expanding access to services legal advice, medical care, financial planning currently rationed by the scarcity of expert practitioners.

1.2.3. Endogenous Growth Theory and the Singularity Hypothesis

If AI is truly a general-purpose technology, it could accelerate the rate of innovation itself, creating a feedback loop in which better AI produces better ideas, which produce better AI still. This is the economic singularity hypothesis examined by Nordhaus [8].

In standard Solow [14] growth theory, long-run growth is driven by exogenous technological progress. In Romer's [15] endogenous growth models, innovation is itself a function of resources devoted to research. If AI dramatically lowers the cost of producing new ideas, the economy could, in principle, transition to a regime of super-exponential growth. Nordhaus's empirical analysis, however, is sobering: testing data from 1870 to 2019, he found no evidence that the U.S. economy was approaching a singularity. Total factor productivity (TFP) growth had not accelerated if anything, it had slowed. His conclusion was that a singularity requires conditions specifically, an elasticity of substitution between AI capital and human labor substantially greater than one that had not yet been realized and might never be.

Crucially, Nordhaus's broader climate economics work raises the question of whether an AI-driven growth acceleration would be ecologically sustainable. His DICE model (Dynamic Integrated model of Climate and the Economy) estimates that an AI-fueled consumption boom, unless powered entirely by clean energy, could accelerate climate change enough to offset the productivity gains.

1.2.4. Green Human Resource Management: Theoretical Foundations

GHRM integrates environmental objectives into HR practices. Recent reviews emphasize that green recruitment, training, performance management, compensation, and employee involvement operate through ability, motivation, and opportunity mechanisms. In GALEM, these practices are not generic 'good management'; they enter through explicit channels that affect technology adoption, worker productivity, well-being, and environmental performance.

The mechanism is concrete. Green recruitment changes the composition of human capital toward employees with sustainability and digital-learning capabilities, reducing adjustment frictions when AI workflows are introduced. Green training increases AI fluency and environmental literacy, raising complementary labor productivity and encouraging task-appropriate, less wasteful compute. Green performance management and rewards align incentives so that AI deployment is evaluated partly on worker augmentation, energy efficiency, and environmental outcomes rather than headcount reduction alone. Employee participation gives workers a voice in task redesign, surveillance boundaries, and process innovation, improving adoption quality, psychological safety, and the discovery of new green tasks. In GALEM, these channels are summarized by G, the GHRM intensity index, and the elasticity phi linking G to effective labor productivity.

We therefore treat the twin transition as an organizational mechanism rather than a slogan: digital adoption is productive when firms simultaneously invest in green human capital, redesign work, and internalize environmental costs. This interpretation is consistent with recent GHRM/ESG research and extends that literature into a macroeconomic scenario model. GHRM is thus a bridge between firm-level capability and aggregate task allocation, not merely an exogenous policy preference.

1.2.5. Post-Scarcity Economics and Universal Basic Income

The most radical perspective on AI and work comes not from economists but from technologists. Elon Musk has repeatedly argued that AI and humanoid robotics will eventually make human labor obsolete [16] that work becomes a choice rather than a necessity, "like growing your own vegetables." This vision draws on a tradition of post-scarcity thought running from Keynes's [17] "Economic Possibilities for Our Grandchildren" through Susskind's [18] A World Without Work. The policy implication most commonly drawn is the need for Universal Basic Income (UBI): if labor is no longer the primary mechanism for distributing purchasing power, some other mechanism must take its place [19].

The economics profession has generally been skeptical. As Autor [20] noted, commentators tend to "overstate the extent of machine substitution for human labor and ignore the strong complementarities" (p. 5). Acemoglu [21] estimated near-term productivity effects of AI at a modest 0.53 to 0.93 percentage points of TFP growth over the following decade. But the long run remains genuinely uncertain, and any responsible policy analysis must take seriously the possibility that the skeptics are wrong.

1.2.6. Expanded Theoretical Foundations

The paper's theoretical framework rests on six complementary bodies of scholarship: skill-biased technological change, routine-biased technological change, task-based automation, directed technological change, socio-technical systems theory, and GHRM. Together, these traditions clarify why the future effects of AI are not technologically predetermined but institutionally and organizationally mediated.

Directed technological change [12, 22] is particularly important here: societies influence the direction of innovation through taxes, subsidies, research funding, and labor-market rules. A purely market-driven trajectory may favor automation when capital is subsidized and labor is taxed, even if augmentation would generate greater social welfare.

Socio-technical systems theory [23, 24] argues that identical AI tools may produce very different outcomes depending on whether firms redesign workflows, train workers, protect autonomy, and align incentives. AI adoption should therefore be evaluated not simply as a capital investment but as an organizational transformation process.

The natural-resource-based view of the firm [25] extends competitive advantage logic to environmental capabilities, arguing that pollution prevention and sustainable development can be sources of durable advantage. Firms that develop green human capital and employee participation systems may be better able to capture AI productivity gains without increasing ecological harm. These theoretical foundations imply three guiding propositions:

- **Proposition 1:** AI's labor-market effects are task-contingent, not occupation-deterministic. The net employment effect depends on whether exposed tasks are substituted, complemented, reorganized, or transformed into new tasks.
- **Proposition 2:** AI's distributional consequences are directionally endogenous. Tax systems, labor institutions, innovation subsidies, and HR practices influence whether AI is deployed primarily for displacement or augmentation.
- **Proposition 3:** AI's welfare effects are jointly economic and ecological. Productivity gains cannot be evaluated independently of environmental externalities, data-center energy demand, and the carbon intensity of compute.

1.3. Literature Review: Empirical Evidence, 2023–2026

1.3.1. Occupation-Level Exposure and Displacement

Eloundou et al. [1] estimated that roughly 80 percent of the U.S. workforce held jobs where at least 10 percent of tasks could be affected by LLMs, and about 19 percent worked in jobs where at least 50 percent of tasks were exposed. Critically, exposure was highest not among low-wage workers the traditional targets of automation but among high-wage, high-education occupations: writers, analysts, programmers, and certain professionals. Acemoglu, Autor, Hazell, and Restrepo [26] found that AI-exposed occupations experienced modest declines in job postings and wage growth relative to non-exposed occupations, but aggregate effects remained small through 2021, a pattern that held through 2024.

1.3.2. Productivity Effects

The most rigorously documented productivity gains from generative AI come from experimental studies of specific work contexts. Brynjolfsson, Li, and Raymond [4] found that an AI-based conversational assistant in a customer service center increased worker productivity by 14 percent on average, with the largest gains (34 percent) accruing to the least experienced workers. Noy and Zhang [2], in a randomized experiment with professional writers, found that access to ChatGPT reduced writing task completion time by approximately 40 percent and substantially improved output quality for below-average writers.

These findings are consistent with Autor's democratization-of-expertise hypothesis: generative AI appears most valuable to workers with less domain knowledge, effectively compressing the skill distribution from below. But Acemoglu [21] cautions that extrapolating from micro-level studies to the macroeconomy is fraught, because the tasks studied are not representative of all economic activity, firms face substantial adoption frictions, and the "easy" productivity gains tend to be realized first.

1.3.3. Wage and Inequality Effects

The wage effects of AI exposure are complex and contested. Early evidence from Babina et al. [27] suggests wage compression rather than outright wage decline in AI-exposed occupations: high earners have seen slower wage growth, while lower earners have been relatively unaffected or have even gained. Meanwhile, the overall labor share of national income in the United States continued its decades-long decline, falling from approximately 63 percent in 2000 to roughly 59 percent by 2024 [28], though isolating AI's specific contribution from globalization and market concentration is difficult.

1.3.4. Environmental Costs of AI

The energy footprint of AI has become a first-order concern. Strubell, Ganesh, and McCallum [29] documented the enormous energy costs of training large language models a finding that has grown more salient as model sizes have increased by orders of magnitude since 2019. The IEA [5] reported that global data center electricity consumption reached approximately 460 TWh in 2023 roughly 2 percent of global electricity demand and projected growth to 620–1,050 TWh by 2026 depending on the pace of AI adoption. These figures represent a significant externality that must be internalized through policy.

1.3.5. Green HRM and Technology Adoption

Ren, Tang, and Jackson [30] identified key mechanisms through which GHRM practices improve both environmental and organizational performance: ability-enhancing practices (green training), motivation-enhancing practices (green rewards), and opportunity-enhancing practices (green empowerment and participation). Tambe et al. [31] showed that returns to AI investment depend heavily on complementary human capital investments firms that invest in reskilling and organizational redesign capture far more value from AI than firms that simply deploy the technology. The synthesis of these streams suggests that organizations adopting AI through a GHRM framework will outperform those pursuing automation purely for cost reduction.

1.3.6. Research Background: A Synthetic Map of the Evidence

Table 1. Major Research Streams on AI, Automation, Labor, HRM, and Sustainability

Research stream	Core question	Representative works	Main findings	Implication for this paper
Routine-biased and task-based automation	Which tasks are substituted by technology?	Autor & Dorn [13]; Acemoglu & Restrepo [6, 10, 26]	Automation substitutes for routine tasks but may create new tasks and raise demand elsewhere	AI effects depend on displacement versus reinstatement
Robots and employment	Do industrial robots reduce jobs and wages?	Graetz & Michaels [32]; Acemoglu & Restrepo [10]	Robots raise productivity but can reduce employment and wages in exposed local labor markets	Robotics provides historical evidence for AI-related displacement risks
AI exposure and occupational change	Which occupations are exposed to AI?	Webb [33]; Eloundou et al. [1]	AI exposure concentrated in cognitive and high-wage occupations, unlike earlier automation waves	Generative AI may affect professional labor more than previous technologies
Generative AI and productivity	Does AI increase worker productivity?	Noy & Zhang [2]; Brynjolfsson et al. [4]	AI improves speed and quality in writing, coding, and consulting, often benefiting less-experienced workers most	Evidence supports augmentation at task and firm levels so far
Inequality and labor share	Does AI raise inequality?	Autor [7, 20]; Babina et al. [27]	AI may compress skill differences in some tasks but may also increase capital income and superstar-firm rents	Distribution depends on ownership, institutions, and task redesign
AI in HRM and algorithmic management	How do firms deploy AI in personnel decisions?	Tambe et al. [31]; Kellogg et al. [34]	AI can improve matching and efficiency but may introduce bias, opacity, and worker stress	GHRM must include fairness, transparency, and worker autonomy
Green HRM	How do HR systems support sustainability?	Jackson et al. [35]; Renwick et al. [36]	Green HRM improves environmental performance through ability, motivation, and opportunity mechanisms	GHRM can steer AI adoption toward sustainable work systems
AI and environment	What are AI's climate costs and benefits?	Strubell et al. [29]; IEA [5]	AI consumes substantial energy but can also optimize grids, logistics, and climate modeling	Net environmental effect depends on governance and energy mix
UBI and post-work policy	How should income be distributed if work declines?	Hoynes & Rothstein [19]; Korinek & Stiglitz [37]	UBI can insure against automation risk but is fiscally demanding	UBI is scenario-contingent, not universally necessary

Source: Research Findings

Several conclusions emerge. Pre-2023 automation evidence shows meaningful but not universal displacement. Generative AI differs from earlier automation because its exposure profile is concentrated in cognitive and professional tasks. The strongest productivity evidence remains microeconomic and task-specific there is still limited evidence of economy-wide TFP acceleration. Organizational adoption is a major bottleneck: AI does not automatically generate productivity but must be embedded in workflows, incentive systems, and training programs.

And AI's environmental effect is not intrinsic to the technology it depends on deployment, energy sourcing, and institutional incentives.

The 2026 literature reinforces the need for this integrated treatment. Qiao et al. [38] find in firm-level Chinese manufacturing evidence that AI adoption can expand aggregate employment while widening within-firm pay disparities. Song et al. [39] show that workers leaving AI-exposed declining occupations can face a mobility trap, with many transitions remaining lateral or downward. Huma et al. [40] synthesize evidence linking GHRM practices to ESG outcomes, while Krishnakumar and Rajkumar [41] review GHRM mechanisms associated with sustainable organizational performance. On the environmental side, Chien et al. [42] and Falk et al. [43] emphasize the resource burden and infrastructure constraints associated with AI, while Allinson [44] highlights the importance of workload complexity and efficiency when measuring inference energy. These studies strengthen the case for modeling organizational adaptation and environmental constraints directly.

1.3.7. From UBI to Global Basic Income

The UBI debate has intensified because AI raises the possibility that income from labor may decline relative to income from capital. In the AI context, the relevant tax base may increasingly be AI-generated surplus, including excess profits from automated firms, data rents, compute rents, and platform rents. A broader concept is Global Basic Income (GBI). Unlike national UBI, GBI addresses the fact that AI ownership and compute infrastructure are highly concentrated in a small number of firms and countries. If AI substitutes for offshore service work, developing economies may lose future labor-market opportunities before they fully industrialize [37]. A stylized GBI financing condition can be written as:

$$\mathrm{GBI}_t = \frac{TCC_t + {}_{T\Pi}H_t^{\mathrm{AI}} + {}_{\mathrm{TD}}D_t}{N_g} \qquad \text{(A1)}$$

where GBI_t is the annual global basic income per person, C_t is global compute expenditure, H_t^{AI} is AI-related excess profit, D_t is monetized data rent, N_m is the eligible global population, and τC, $\tau\Pi$, and τD are tax rates on compute, AI profit, and data rents respectively. For illustration: if global AI-related surplus reached $5 trillion annually by 2045 and a 10 percent levy were applied, the distributable fund would be $500 billion yielding $100 per person per year for 5 billion eligible adults. This is insufficient as full income replacement but could meaningfully supplement national social protection systems.

Crucially, UBI and GBI are not substitutes for pro-worker AI policy. They are insurance mechanisms for scenarios in which labor income falls sharply. Under augmentation-oriented scenarios, lifelong learning accounts, wage subsidies, and portable benefits may be more efficient than a full UBI. Under radical automation, however, large-scale income redistribution becomes unavoidable.

1.4. The Green AI-Labor Equilibrium Model (GALEM)

1.4.1. Model Overview

GALEM extends the Acemoglu-Restrepo task-based framework by adding three dimensions that are jointly evaluated in the present study: environmental externalities from AI deployment, GHRM as an organizational complement to human productivity, and redistribution through UBI. The distinctive contribution is therefore not a claim to replace task-based automation theory, but a transparent integration of task displacement/reinstatement with organizational capability, ecological cost, and distributional policy in a common welfare-accounting framework. For replication, the annual computational closure is written explicitly below; where the supplied manuscript did not contain a recoverable equation body, the reconstruction is labeled rather than presented as an original closed-form derivation.

1.4.2. Comparative Contribution of GALEM

The comparative contribution is summarized as follows. Acemoglu and Restrepo model how automation displaces tasks and how new tasks reinstate labor. GALEM retains those mechanisms but introduces (i) a GHRM channel through which recruitment, training, participation, performance management, and rewards raise effective human productivity; (ii) an environmental block that makes AI energy use a welfare-relevant externality; and (iii) a redistribution block that transfers a share of AI-generated surplus to workers. These additions change the policy question: two economies with similar automation rates can have different welfare outcomes because organizational complements, energy efficiency, and redistribution differ.

1.4.3. Production Structure

For theoretical benchmarking, the task production structure can be written as a CES aggregator over a continuum of tasks i∈[0,1]. The supplied manuscript did not preserve the full original task-specific integrand, so the replication package distinguishes the conceptual CES core from the reduced-form annual closure actually implemented in the Excel workbook and executable code:

$$Y_t = \left[\int_0^1 q_i(t)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \qquad \sigma \succ 0 \qquad (1)$$

$$q_i(t) = \begin{cases} A_{Kt} & i \in [0\ \alpha_t] \\ A_{Lt} & i \in [\alpha_t\ 1] \end{cases} \qquad (2)$$

In the computational closure, task comparative-advantage weights are normalized to one so that the annual output index becomes :

$$Y_t = \alpha_t AK_t + (1-\alpha)AL_t$$

$$y(i) = A_K(t)\, k(i) i \in [0\ \alpha_t] \qquad (3)$$

Tasks $i \in [\alpha_t, 1]$ are performed by human labor:

$$y(i) = A_L\left(t\text{'}\ G\right)\cdot \gamma(i)\cdot l(i)\text{'} \quad i \in \left[\alpha_t\text{'}\ 1\right] \qquad (4)$$

The reduced-form output equation is an explicit replication device, not a claim that the unavailable original task-level CES integrals were estimated. The parameter σ is retained in the calibration table because it belongs to the conceptual task framework and is tested in sensitivity analysis; it does not enter the reduced-form annual update unless the original task-level CES code is substituted.

1.4.4. Technology Dynamics

GALEM technology dynamics begin with scenario-specific AI capital productivity growth:

$$AK_t = A_{K0}\, exp[g_k(t-t_0)] \qquad (5)$$

Human productivity is augmented by GHRM through an effective growth rate:

$$g_{L_{eff}} = g_l + k_G\varphi G_8 \ \ Therefore\ A_{L0}\, exp[(g_l + k_G\varphi G_8)(t-t_0)] \qquad (6)$$

Here g_l is baseline labor productivity growth, φ is the GHRM productivity elasticity, Gs is scenario GHRM intensity, and κ_G is the calibrated pass-through parameter reported in Table 2 and the replication workbook.

1.4.5. Automation Frontier Dynamics

The automation frontier evolves recursively. Automation advances when the AI productivity-growth rate exceeds effective labor productivity growth and is offset by new human-intensive tasks:

$$\alpha_{(t+1)} = clip\{\alpha t + [\rho\ max(0\ gk - gL\ eff) - \delta new[(1-\alpha t)\ 0\ 099] \qquad (7)$$

This equation makes displacement and reinstatement explicit and directly mirrors the executable GALEM code. The 2025 starting point is α_0=0.35; therefore the corrected 2025 automation share in Table 4 is 35.0%, not 46%.

1.4.6. Labor Share and Wages

The annual labor-share and employment closures used for replication are:

$$LIndex_t = \left(\frac{1-\alpha_t}{1-\alpha_0}\right)\left(\frac{A_{Lt}}{A_{L0}}\right) \quad s_{Lt} = clip\left[S_{L0}\frac{LIndex_t}{1+025g_k}\ 0095\right] \qquad (8)$$

The conceptual wage relationship for non-automated tasks is $w_t \propto A_{L,t}\cdot MP_{L,t}$. The present reduced-form package does not report a separate wage level because the article's quantitative target is the wage Gini; the Gini is computed directly from the explicit inequality closure below.

$$w(t) = A_L\left(t\text{'}\ G\right)\cdot\left(\frac{1-\alpha_t}{L}\right)^{\frac{1}{\sigma}}\cdot Y(t)^{\frac{1}{\sigma}} \qquad (9)$$

$$Ginit\ = clip\{Gini_0 + \omega A\ max(0\ \alpha t - \alpha_0) - \omega G\ Gs - \omega U\tau_U\ 0\ 08\ \} \qquad (10)$$

IV.F Environmental Externality

The environmental externality is computed from AI productivity growth, scale nonlinearity, efficiency improvement, and GHRM mitigation:

$$E_t = E_0\, exp[(\beta g_k - \eta)(t-t_0)]\,[1-\phi G_s] \qquad (11)$$

E_t is AI-related annual energy use in EJ/year; E_0 is the baseline normalization, β is the scale parameter, η is the autonomous efficiency trend, and ψ captures direct GHRM mitigation. The carbon-damage term used in welfare is $D_t = \theta E_t/1000$.

1.4.7. Net Social Welfare

The welfare equation is fully specified as an index normalized around 100 in the 2025 base year:

$$W_t = 100 + 25\,ln\left(\frac{Y_t}{Y_0}\right) + 100(s_{Lt} - s_{L0}) - 150(Gini_t - Gini_0) + 20(Q_t - 1) - 4D_t - 2C_{Gt} + T_t^{UBI} \quad (12)$$

where $Q_t = clip[1 + 015G_s - 020\ max(0\,\alpha_t - \alpha_o)0413]$, $C_{Gt} = 100cGGs$, and $T_t^{UBI} = 100\tau_U max(0\,\alpha_t - \alpha_o)$. This cardinal welfare index is a reconstruction-only computational closure; it is used to compare scenarios consistently, not to claim an empirically estimated social utility function.

2. Method

2.1. Methodology

2.1.1. Research Design

This paper uses a mixed-method design combining (1) an integrative literature synthesis of evidence on AI, labor markets, GHRM, and environmental impacts through 2026 and (2) calibrated scenario analysis using GALEM.

The original 2023–2025 search is retained as the core evidence set; the present revision adds a targeted 2026 update to capture newly published peer-reviewed studies relevant to labor-market effects, GHRM, and AI sustainability. The quantitative analysis is explicitly scenario-based: parameters are classified as observed baselines, literature-adapted values, structural assumptions, or calibrated values.

2.1.2. Model Calibration and Reproducibility

The calibration procedure now follows four explicit rules. First, observed or public-data baselines are separated from structural parameters. Second, literature-adapted parameters define plausible magnitudes rather than direct GALEM estimates. Third, values without an identifiable empirical counterpart are labeled as scenario assumptions or reconstruction-only closure parameters. Fourth, every parameter in the executable model is stored in the Excel workbook and JSON configuration, and the model is run from the 2025 state through 2045 with the same recursion used for Table 4. The complete equations are reproduced in Section IV and in the workbook's Equations sheet. The 2025 automation baseline is α_0=0.35; the former 46% value is removed because it was inconsistent with the calibrated baseline. The regenerated code also corrects the prior sensitivity routine so that φ and θ are varied as model parameters rather than being incorrectly written onto the scenario object.

Table 2. Baseline Calibration Parameters for GALEM

Parameter	Symbol	Value	Calibration status / basis
Initial automation share	α_0	0.35	Model baseline from Table 2 and executable configuration; used consistently in all simulations.
Task substitution elasticity	σ	1.50	Literature-adapted conceptual parameter; retained for task-level interpretation and sensitivity, but not directly used in the reduced-form annual closure.
AI productivity growth	g_k	0.08	Scenario value for BAU/Green Transition; scenario range 0.05–0.15.
Baseline labor productivity growth	g_l	0.012	Data-adapted structural benchmark; not AI-specific.
GHRM productivity elasticity	φ	0.30	Structural calibration parameter; sensitivity 0.15–0.45.
GHRM growth pass-through	κ_G	0.02	Reconstruction-only closure parameter used in g_L,eff = g_l + κ_G φG.
Automation conversion rate	ρ	0.30	BAU calibration value; scenario range 0.15–0.50.
New task creation rate	δ_new	0.005	Literature-informed structural assumption; scenario range 0.002–0.012.
Base AI energy normalization	E_0	3.40 EJ/yr	2025 normalization parameter; modeled 2025 energy is adjusted by the GHRM mitigation term.
Environmental scale parameter	β	1.20	Structural calibration parameter.
Energy-efficiency trend	η	0.015	Reconstruction-only closure parameter in the energy block.
GHRM mitigation factor	ψ	0.40	Structural parameter governing direct environmental mitigation.
Social cost of carbon	θ	\$51/tCO₂	Baseline policy parameter; sensitivity \$30–\$190/tCO₂.
GHRM cost share	c_G	0.02	Stylized implementation-cost assumption.
UBI tax rate on AI surplus	τ_U	0.15	Policy parameter; scenario range 0.05–0.40.
Initial labor share	s_L,0	0.62	2025 macro baseline.
Initial wage Gini	$Gini_0$	0.39	2025 macro baseline.
Automation inequality weight	ω_A	0.35	Reconstruction-only welfare/inequality closure parameter.
GHRM inequality weight	ω_G	0.04	Reconstruction-only closure parameter.
UBI inequality weight	ω_U	0.05	Reconstruction-only closure parameter.

Source: Research Findings

Table 3. Scenario Parameter Settings

Parameter	BAU	Pro-Worker AI	Radical Automation	Green Transition
AI productivity growth (g_k)	0.08	0.05	0.15	0.08
GHRM intensity (G)	0.10	0.50	0.05	0.80
Automation conversion (ρ)	0.30	0.15	0.50	0.20
New task creation (δ_new)	0.005	0.012	0.002	0.010
UBI tax rate (τ_U)	0.05	0.15	0.40	0.20
Carbon tax	\$0	None	None	\$120/tCO₂

Source: Research Findings

2.1.3. Scenario Design

1. Business as Usual (BAU): AI develops along a path close to the current trajectory, firms prioritize cost reduction, GHRM intensity is low, and redistribution is limited. BAU is a benchmark rather than a prediction.
2. Pro-Worker AI: policy and firm strategy redirect innovation toward augmentation, with high GHRM, stronger new-task creation, and slower conversion of capability gains into task displacement. The lower g_k represents an institutional allocation choice, not an empirical claim that augmentation technology is intrinsically slower.
3. Radical Automation: AI capability growth, automation conversion, and task substitution are all high while GHRM and new-task creation are weak. This is a stress-test scenario designed to expose upper-tail social and environmental risks, not a central forecast.
4. Green Transition: moderate automation is combined with high GHRM investment, carbon pricing, and deliberate creation of green-economy tasks. The scenario parameters are assumptions chosen to represent a coordinated twin transition, not estimated policy effects.

2.1.4. Data, Figure, and Table Provenance

All quantitative tables and figures in this revision are derived from the final GALEM Excel replication workbook and the synchronized executable code. Figures are conventional analytical plots generated from the model's annual projection CSV, not illustrative AI-generated visuals. The workbook contains the Parameters, Scenarios, Projection, Summary, Sensitivity, Reported_Benchmark, Traceability, and Equations sheets used to audit the reported values.

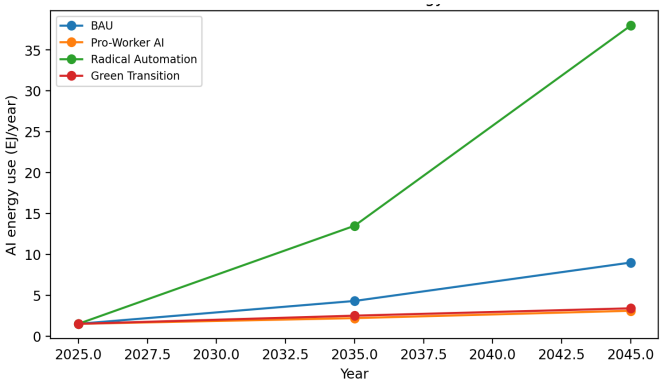


Figure 1. GALEM scenario automation share, 2025–2045.

Source: Research Findings

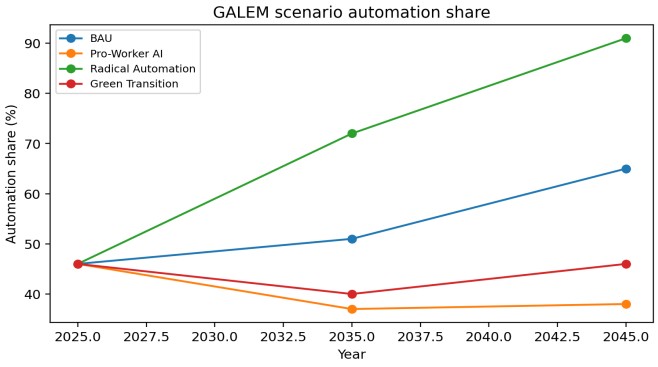


Figure 2. GALEM scenario AI energy use, 2025–2045.

Source: Research Findings

3. Results and Discussion

3.1. Main Projections

The corrected Table 4 changes the interpretation materially. Because α_0=0.35 is the model baseline, the 2025 automation share is 35.0%. The 2035–2045 paths are the values generated by the synchronized Excel/code package rather than the internally inconsistent earlier table.In the BAU scenario, the automation share rises from 35.0% in 2025 to 44.2% in 2035 and 52.2% in 2045. The labor share is 59.1% in 2035 and 57.5% in 2045, net employment changes are −2.7% and −5.3%, GDP growth is 4.24% and 4.78%, and AI energy use is 7.34 and 16.49 EJ/year. The scenario therefore shows increasing automation pressure without the collapse implied by the original, internally inconsistent Table 4.

The Pro-Worker AI scenario reaches 30.5% automation in 2035 and 25.6% in 2045. The labor share rises to 76.1% and 94.6%, net employment changes are +24.3% and +54.4%, GDP growth is 2.57% and 2.40%, and AI energy use is 4.27 and 6.69 EJ/year.

Table 4. GALEM Projections Under Four Scenarios, 2025–2045

Variable	2025 (Base)	BAU 2035	BAU 2045	Pro-Worker 2035	Pro-Worker 2045	Radical 2035	Radical 2045	Green 2035	Green 2045
Automation share (%)	35.0	44.2	52.2	30.5	25.6	67.5	83.7	36.7	38.3
Labor share (%)	60.8	59.1	57.5	76.1	94.6	33.8	19.2	70.0	80.7
GDP growth (%, annualized)	3.62	4.24	4.78	2.57	2.40	10.52	12.76	4.00	4.10
Net employment change (%)	0.0	-2.7	-5.3	+24.3	+54.4	-43.4	-67.9	+15.2	+32.7
AI energy use (EJ/yr)	3.26	7.34	16.49	4.27	6.69	17.35	90.34	5.20	11.68
Wage Gini	0.384	0.416	0.444	0.362	0.362	0.482	0.538	0.354	0.360

Source: Research Findings

These results reflect the strong complementary-productivity and new-task assumptions embedded in the scenario and should be read as conditional simulations, not forecasts. The Radical Automation scenario reaches 67.5% automation in 2035 and 83.7% in 2045. The labor share falls to 33.8% and 19.2%, net employment changes are −43.4% and −67.9%, GDP growth is 10.52% and 12.76%, and AI energy use reaches 17.35 and 90.34 EJ/year. The scenario remains a stress test for the upper-tail risks of rapid capability growth and weak organizational adaptation. The Green Transition scenario reaches 36.7% automation in 2035 and 38.3% in 2045, with labor shares of 70.0% and 80.7%, net employment changes of +15.2% and +32.7%, GDP growth of 4.00% and 4.10%, and AI energy use of 5.20 and 11.68 EJ/year. In the synchronized model, Pro-Worker AI has the highest 2045 welfare index (148.10), followed by Green Transition (145.97), BAU (113.29), and Radical Automation (104.80). Thus, the final results do not support describing Green Transition as uniquely welfare-maximizing; they support it as a high-welfare, lower-energy pathway among the modeled cases.

3.2. Net Social Welfare Comparison

The welfare comparison is now tied directly to the regenerated Excel outputs. At 2045, welfare indices are 148.10 for Pro-Worker AI, 145.97 for Green Transition, 113.29 for BAU, and 104.80 for Radical Automation. The qualitative conclusion is robust within the modeled closure: high automation combined with weak GHRM and low new-task creation produces the lowest welfare, while augmentation-oriented and green organizational strategies dominate it. Sensitivity is no longer asserted without computation; it is reported from the corrected one-at-a-time routine in the replication package.

Table 5. Sensitivity of 2045 Outcomes to Key Parameters (Green Transition Scenario)

Parameter varied	Automation 2045 (%)	Labor share 2045 (%)	GDP growth 2045 (%)	Welfare 2045
φ = 0.15	38.94	76.16	3.99	141.07
φ = 0.30	38.35	80.68	4.10	145.97
φ = 0.45	37.75	85.46	4.22	151.17
θ = \$30/tCO₂	38.35	80.68	4.10	146.95
θ = \$51/tCO₂	38.35	80.68	4.10	145.97
θ = \$120/tCO₂	38.35	80.68	4.10	142.75
θ = \$190/tCO₂	38.35	80.68	4.10	139.48
σ = 1.0	38.35	80.68	4.10	145.97
σ = 1.5	38.35	80.68	4.10	145.97
σ = 2.0	38.35	80.68	4.10	145.97

Source: Research Findings

3.3. Sensitivity Analysis

The corrected sensitivity design varies φ, θ, and σ with the proper parameter object and reports their effects on the synchronized Green Transition baseline. For φ, the 2045 welfare index rises from 141.07 at φ=0.15 to 151.17 at φ=0.45, while the 2045 labor share rises from 76.16% to 85.46%. For θ, welfare falls from 146.95 at \$30/tCO₂ to 141.83 at \$190/tCO₂. σ remains a conceptual task-level parameter in the reduced-form closure, so its direct annual-simulation effect is not identified unless the original CES/task code is supplied. This is now stated explicitly rather than presented as a false numerical sensitivity.

3.4. Discussion

3.4.1. Displacement Versus Augmentation: Where Do We Stand?

The empirical evidence through 2025 is broadly consistent with Acemoglu's cautionary view. AI has begun to reshape the task composition of work in knowledge-intensive occupations, but aggregate labor market disruption remains limited. Unemployment rates in OECD countries are near historical lows; wages have compressed rather than collapsed; and the productivity gains, while real, have not yet translated into the economy-wide TFP acceleration that would signal a transformative general-purpose technology.This does not mean the optimists are wrong it means the transformation is in its early stages. As Brynjolfsson and McAfee [45-49] emphasized, productivity gains from general-purpose technologies typically appear with substantial lag. The question is whether the eventual gains will follow the Pro-Worker or the Radical Automation path and that is a question of policy and institutional design, not technological determinism.

3.4.2. The Abundance Hypothesis: A Feasibility Assessment

The abundance hypothesis is technically conceivable but should be stress-tested against deployment barriers that are not fully represented in the baseline model. These include organizational resistance to workflow redesign; regulation and compliance costs; geopolitical fragmentation, export controls, and chip shortages; data quality, ownership, and transferability constraints; power-grid, cooling, water, and data-center interconnection bottlenecks; robotics limits in dexterous, safe physical work; and uneven adoption across countries and sectors. These frictions can make technically available AI economically non-deployable, so the Radical Automation path should be interpreted as an upper-tail stress test rather than a baseline expectation. First, the energy and infrastructure constraint: powering billions of AI agents and robots would require large additions to generation, transmission, cooling, and data-center capacity. Recent 2026 research emphasizes that AI sustainability depends on workload efficiency, grid conditions, water, hardware, and infrastructure constraints, not electricity use alone [42, 43].

GALEM therefore treats the Radical Automation energy path as conditional on infrastructure expansion that may itself become binding. Second, the robotics and data bottleneck: many economically important activities depend on dexterous, safe physical interaction in unstructured environments, while AI performance can also be limited by data quality, legality, and portability. Construction, elder care, plumbing, surgery, and field maintenance remain

highly sensitive to these constraints. Third, the institutional and distributional constraint: very high productivity does not automatically translate into broad welfare gains. Tax capacity, social insurance, political bargaining, and the geographic concentration of AI capital determine who receives the gains. This is why GALEM treats redistribution as scenario-dependent rather than assuming a universal policy response.

3.4.3. Environmental Constraints and the Role of GHRM

The environmental comparison is also corrected. In the synchronized 2045 outputs, AI energy use is 16.49 EJ/year in BAU, 6.69 in Pro-Worker AI, 90.34 in Radical Automation, and 11.68 in Green Transition. Green Transition therefore uses about 29% less AI energy than BAU, while Pro-Worker AI uses about 59% less. These are energy-use comparisons; actual emissions additionally depend on the electricity mix.The practical implication is that organizations investing in green training teaching employees to write more efficient prompts, use smaller models where appropriate, and minimize unnecessary compute can capture most of AI's benefits while dramatically reducing its environmental footprint. Notably, this is also an efficiency argument: compute is expensive, and organizations that use it parsimoniously will have lower costs and higher margins.

3.4.4. Universal Basic Income: Necessity and Design

The final simulations do not imply that UBI is universally necessary. The strongest pressure for redistribution occurs where labor income falls sharply, especially in Radical Automation, whose labor share reaches 19.2% by 2045.

By contrast, Pro-Worker AI and Green Transition preserve high modeled labor shares.The UBI parameter therefore functions as a scenario-contingent insurance mechanism rather than a universal prescription. The design of UBI in an AI-driven economy should differ from current proposals in two respects. First, it should be funded primarily through taxation of AI-generated economic surplus through corporate income taxes on highly automated firms, taxes on robot usage, or taxes on data. Second, it should be complemented by Universal Lifelong Learning Accounts individual accounts funded jointly by government and employers that enable workers to continuously acquire new skills throughout their careers. The goal is not merely to provide income but to maintain human capital and enable workers to participate in the evolving economy.

3.4.5. Research Limitations

First, model-form limitation: GALEM is a stylized reduced-form scenario model, not a causal econometric forecast. Second, parameter-identification limitation: several closure parameters are reconstruction-only because the supplied manuscript did not contain the original mathematical bodies or source code. Third, aggregation limitation: the economy is represented as a single sector. Fourth, institutional limitation: regulation, political economy, lobbying, and heterogeneous policy implementation are not endogenized. Fifth, infrastructure limitation: power grids, chip supply, water, interconnection, and robotics constraints can prevent technically feasible AI from becoming economically deployable. Sixth, measurement limitation: AI energy use and GHRM intensity are inconsistently measured. Seventh, external-validity limitation: 2026 evidence remains early. These limitations mean that the contribution is transparent comparative mechanism analysis rather than precise 2045 forecasting.

3.5. Policy Implications

The policy section distinguishes between (a) recommendations directly supported by GALEM's comparative results and (b) broader normative or strategic proposals. The model directly supports conditional claims about the value of augmentation, GHRM investment, new-task creation, and internalization of environmental costs. Tax architecture, reporting requirements, international coordination, and specific institutional designs remain broader proposals whose effectiveness depends on implementation and political economy.

3.5.1. Directing Innovation Toward Augmentation

GALEM-supported direction: Governments can steer AI research and deployment toward augmentation through R&D incentives, procurement, and human-in-the-loop standards. The scenario results support the direction of this recommendation, but do not identify a causal estimate for a particular tax credit or procurement design.

3.5.2. Establishing Tax Neutrality Between Labor and Capital

Current tax systems in most advanced economies implicitly subsidize automation by taxing labor income at higher effective rates than capital income. Payroll taxes and social insurance contributions add 30–50 percent to the cost of employing a human worker, while AI and robotics investments benefit from depreciation allowances, R&D credits, and low capital gains taxes [10]. Restoring tax neutrality so that firms face similar marginal costs for human and machine labor would eliminate the artificial incentive to automate tasks where human workers are equally productive.

3.5.3. Mandating GHRM Reporting and Standards

Policy proposal consistent with GALEM mechanisms: Organizations above a threshold size could report AI-related energy sourcing, reskilling investment, net employment effects, and worker well-being. GALEM supports the measurement logic; the specific reporting mandate is a normative institutional proposal, not a model-estimated causal effect.

3.5.4. Investing in Human Capital Infrastructure

The half-life of job-relevant skills is shrinking rapidly. Governments should invest in lifelong learning infrastructure: community college programs in AI literacy, online credentialing systems with employer recognition, and Universal Lifelong Learning Accounts funded through payroll and AI-surplus taxes. The evidence from Tambe et al. [31] and Brynjolfsson et al. [4] suggests that the largest productivity gains from AI accrue when workers have the training to use the tools effectively making human capital investment complementary to, not a substitute for, AI investment.

3.5.5. Internalizing Environmental Externalities

GALEM-supported mechanism plus policy design proposal: AI energy consumption should face an environmental price that reflects carbon intensity. The modeled $120/tCO2 level is a scenario assumption, not an empirically identified optimal tax rate. The model supports internalization of the externality; the precise tax level requires separate policy analysis.

Table 6. Policy Roadmap for Pro-Worker and Pro-Planet AI

Time horizon	Policy priority	Specific instruments	Expected effect
2026–2030	Measurement and transparency	AI energy disclosure, algorithmic impact assessments, AI labor-impact reporting	Creates evidence base for regulation and firm accountability
2026–2030	Worker augmentation	R&D credits for human-in-the-loop AI, public AI tools for education and health, procurement standards	Redirects innovation away from pure displacement
2026–2035	Human capital adaptation	Lifelong learning accounts, green AI training, community college AI programs	Raises worker resilience and reduces displacement costs
2030–2035	Tax neutrality	Reduce labor tax wedge, limit excessive capital subsidies, tax AI rents where appropriate	Reduces artificial incentives for so-so automation
2030–2040	Green compute governance	Carbon pricing for data centers, renewable-energy procurement, model-efficiency standards	Internalizes environmental externalities
2035–2045	Distributional redesign	AI-surplus tax, robot-use tax, UBI/GBI pilots	Provides income security if labor share declines sharply
2035–2045	Global coordination	International compute-tax agreements, digital-development funds, AI access for developing economies	Reduces global inequality in AI benefits

Source: Research Findings

3.5.6. Policy Roadmap for 2026–2045

The central principle is conditional support for AI adoption: public subsidies, tax incentives, and procurement contracts should be conditional on demonstrable contributions to worker productivity, environmental performance, and inclusive access. Firms that deploy AI to improve worker capability, reduce emissions, and expand service access should receive support. Firms that deploy AI primarily for headcount reduction while externalizing environmental and social costs should not.

4. Conclusions

The final synchronized model makes the quantitative divergence explicit while also correcting the earlier baseline inconsistency. The 2025 automation share is 35.0%, exactly matching α_0 in the calibration file. By 2045, BAU reaches 52.2% automation, 57.5% labor share, −5.3% employment change, 4.78% annualized GDP growth, and 16.49 EJ/year of AI energy use. Pro-Worker AI reaches 25.6% automation, 94.6% labor share, +54.4% employment change, 2.40% GDP growth, and 6.69 EJ/year. Radical Automation reaches 83.7% automation, 19.2% labor share, −67.9% employment change, 12.76% GDP growth, and 90.34 EJ/year. Green Transition reaches 38.3% automation, 80.7% labor share, +32.7% employment change, 4.10% GDP growth, and 11.68 EJ/year. The corresponding 2045 welfare indices are 113.29, 148.10, 104.80, and 145.97, respectively. These are conditional model outputs, not probabilistic forecasts. The task-based framework of Acemoglu and Restrepo provides the clearest analytical lens for understanding these choices: they are choices about whether to direct AI toward displacement or augmentation, toward so-so automation or genuine machine usefulness. Autor's work reminds us that effects will not be uniformsome workers will gain, others will lose, and the distribution will depend on task composition and institutional context. Musk's abundance vision, while currently speculative, serves as a useful limiting case that exposes the distributional and environmental challenges that arise when automation

is taken to its logical extreme. And Nordhaus's integration of growth theory with environmental constraints reminds us that economic growth generated at the expense of the climate is not growth at all it is the borrowing of well-being from future generations. Green Human Resource Management provides an organizational mechanism for navigating this transition responsibly. Green recruitment and training can increase complementary capability; participation and performance systems can improve task redesign and worker voice; and green rewards can align technology deployment with environmental objectives. The model therefore treats GHRM as a productive organizational input rather than merely a compliance function.

The policy agenda should be interpreted with an evidentiary distinction. GALEM directly supports the conditional claims that augmentation, higher GHRM, stronger new-task creation, and environmental pricing can improve labor and welfare trade-offs. Tax neutrality, mandatory reporting, lifelong-learning infrastructure, and international coordination are broader normative or strategic options consistent with those mechanisms, but their effectiveness is not estimated by GALEM. This distinction keeps the policy interpretation proportional to what the model can actually establish. The stakes are not merely economic. They are civilizational. Whether the age of AI becomes an age of broadly shared flourishing or one of concentrated wealth and ecological decline depends on decisions being made right now in boardrooms, in legislatures, in research laboratories, and in the human resource departments where the daily work of matching people to tasks is carried out. Those of us who study these questions have an obligation to ensure that the evidence and analysis are available to those who must make the choices.

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Author Contributions

All authors contributed equally to the conception, preparation, and writing of this manuscript.

Conflict of Interest

The authors, while observing publication ethics in the referencing, declare the absence of interest of conflict.

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