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Abstract

Artificial intelligence (AI) has quickly become a technology that shapes both environmental systems and the way labor market's function. This chapter examines these two sides together, because AI can support sustainability goals while also creating new risks. On the environmental side, AI helps with predictive maintenance, improves circular-economy practices, strengthens the integration of renewable energy, and offers better tools for forecasting climate-related threats. Still, these gains come with clear costs. Data centers require large amounts of electricity and water, and the production of advanced hardware relies on resource-intensive supply chains. In some cases, efficiency improvements even trigger rebound effects that offset the environmental benefits. The labor market is also undergoing a noticeable shift. AI speeds up automation in routine tasks, which puts pressure on workers in administrative and mid-skill occupations. At the same time, it opens new roles in areas such as AI ethics, algorithm auditing, and human-machine collaboration. These developments do not affect all groups equally. Differences in digital skills, gender, region, and socioeconomic background can widen existing inequalities. For this reason, the idea of a "just transition" has become central, emphasizing policies such as reskilling programs, income-support mechanisms, and more inclusive innovation strategies. The chapter also discusses governance challenges. While frameworks like the EU AI Act, the OECD Principles, and various responsible AI guidelines try to set clearer rules, countries still take very different approaches, especially on issues such as data control and cross-border information flows. These differences reflect broader geopolitical tensions and influence how benefits and burdens are distributed. Overall, the chapter highlights the need for evidence-based policies that align ecological sustainability, fair labor outcomes, and balanced global governance.

Keywords

Artificial Intelligence, Sustainability, Labor Markets, Digital Divide, Innovation

Introduction

Artificial intelligence (AI) was first described in 1956 as "the science and engineering concerned with creating intelligent machines" (McCarthy, 2007). This description still matters, but the field has grown far beyond what early researchers imagined. Today, AI is widely viewed as a general-purpose technology with the ability to reshape productivity, influence social and ecological systems, and even alter the way institutions operate (Brynjolfsson & McAfee, 2017; Trajtenberg, 2018). Unlike earlier waves of technological change, AI brings together prediction, optimization, and a degree of autonomous decision-making in the same system. It is steadily changing how societies allocate resources, design labor regulations, and approach sustainability problems (Acemoglu & Restrepo, 2019; Ng et al., 2021).

Within the framework of the United Nations Sustainable Development Goals (SDGs), this multi-layered influence creates both opportunities and difficult tensions (Malmio, 2024). AI can support climate action by improving forecasting models (SDG 13), help industries use resources more efficiently (SDG 9), and raise productivity in ways that align with decent work and economic growth (SDG 8) (Vinuesa et al., 2020). At the same time, large AI models come with clear environmental costs. Data centers rely heavily on electricity and water, which raise concerns for responsible consumption and production (SDG 12) (Strubell et al., 2019; Henderson et al., 2020).

AI is also reshaping how we talk about inequality in labor markets. Demand for advanced digital skills continues to grow, but pressure on routine and mid-skill jobs is increasing as well, widening gaps in employment and income (Webb, 2020). Beyond these distributional effects, artificial intelligence is transforming labor markets through both automation and augmentation dynamics. While routine tasks are increasingly automated, many non-routine and cognitive tasks are complemented rather than replaced, leading to the reconfiguration of job roles and skill requirements. This shift places greater emphasis on adaptability, continuous learning, and the ability to work alongside intelligent systems, thereby redefining employability in the digital era (Felten et al., 2021). Despite a growing research base, discussions about AI and sustainability often follow separate paths. Many prior works focus on efficiency gains and emission reductions, but the environmental footprint of computational systems receives far less attention (OECD, 2022). Similarly, work on automation highlights job loss but rarely addresses how these effects differ across regions, industries, and social groups (Frey & Osborne, 2017; Webb, 2020). Another problem is the lack of studies that investigate environmental and labor impacts together. When these issues are treated in isolation, it becomes harder to see the trade-offs. AI may help meet environmental targets while at the same time increasing social inequality. Conversely, efforts to prioritize equity can sometimes undermine ecological goals (Vinuesa et al., 2020).

This chapter brings these discussions onto a shared ground by placing them at the crossroads of sustainability research, labor economics, and technology governance. Its contribution unfolds in three main parts. First, it emphasizes that AI is not just a neutral tool but a system with real energy requirements, material dependencies, and emissions. Second, it shifts the discussion of AI's labor-market effects away from simple productivity narratives and toward questions of fairness, social justice, and the conditions needed for a just transition. Third, it highlights how regulatory and ethical frameworks shape AI's dual nature: its potential to support sustainable development and its ability to create new risks (European Commission, 2021; OECD, 2022).

The study proceeds as follows. Section 2 reviews theoretical foundations from sustainability studies, labor-market analysis, and political economy. Section 3 explores the environmental implications of AI, including both benefits and unintended consequences. Section 4 turns to labor-market changes such as automation, job creation, and changing task structures. Section 5 focuses on inequality and the policies required for a fair transition. The discussion section brings these insights together, offers policy recommendations, and identifies areas where further research is needed.

1. Theoretical and Conceptual Foundations

1.1. Innovation and Sustainability Theories

Research on innovation and sustainability offers a helpful lens for understanding how AI reshapes organizational routines and the wider social and ecological systems in which firms operate (Vargas-Hernández et al., 2023). One of the central ideas in this field is the dynamic capabilities view (DCV). It describes how firms identify emerging opportunities or threats, invest in the right areas, and adjust their internal processes to remain competitive in environments that shift quickly (Teece et al., 1997; Teece, 2007). When AI enters the picture, these capabilities often stretch beyond traditional organizational boundaries (Hanelt et al., 2025). Amazon provides a well-known example. The company uses AI-driven logistics not only to detect shifts in customer demand but also to fine-tune inventory management and redesign its distribution networks. Over time, this has pushed the company toward a supply chain structure that is both more energy-efficient and lower in emissions. These kinds of cases show that dynamic capabilities today rely as much on digital learning systems as on managerial insight (Hossain et al., 2025).

The socio-technical transitions framework adds another additional perspective to this discussion (Geels, 2002; Geels & Schot, 2007). It situates AI within long-term sustainability transitions and examines how novel technologies interact with established systems and the broader social and political landscape. AI-based tools, such as smart energy grids, have the potential to challenge fossil-fuel-centric infrastructures by making it easier to absorb renewable energy. Yet this shift is rarely straightforward. Existing institutions, outdated regulations, and legacy infrastructures often slow down or complicate the adoption of such innovations. Tesla's Autopilot illustrates this tension well. While the technology supports lower-emission mobility, its wider adoption still depends on road infrastructure, legal standards, and the public's willingness to trust partially autonomous driving systems (Laurell & Sandström, 2022).

The circular economy (CE) perspective introduces a further dimension by focusing on reducing waste and keeping materials in circulation for longer (Geissdoerfer et al., 2017). AI plays a supportive role here through predictive maintenance. AI also improves how materials are traced in recycling networks and helps identify inefficiencies in resource flows. Still, rebound effects remain a challenge: when efficiency improves, consumption sometimes rises, neutralizing environmental gains. This makes it important for both theory and practice to acknowledge that while AI can strengthen circularity, it can also indirectly stimulate higher demand, which may run counter to sustainability goals.

1.2. Labor Market and Technological Change Theories

AI is changing work routines in many fields, and labor economists have been analyzing this shift for years. An important line of reasoning is offered by the skill-biased technological change perspective, which suggests that emerging technologies typically boost the output of more qualified workers while taking over activities that are repetitive or physically oriented (Autor et al., 2003; Acemoglu & Autor, 2011). Generative AI tools such as ChatGPT reflect this dynamic clearly. They can draft text, review documents, analyze data, and organize information, which generally benefits workers and other professionals with advanced training (Ritala et al., 2024). At the same time, administrative tasks involving translation, data entry, or basic customer support are becoming progressively easier to automate.

The routine-biased automation hypothesis (Autor, 2015) refines this idea by suggesting that automation spreads most quickly in areas where work is repetitive and easy to formalize. AI systems carry this logic beyond manufacturing and into service sectors. Legal technology platforms now assist with contract review, while AI tools in accounting help identify irregularities in financial records. These developments primarily affect mid-skill cognitive roles. Human capital theory (Becker, 1993) reinforces this insight by emphasizing that workers' ability to adapt depends on their education and commitment to continuous learning. Because AI increasingly requires a mix of domain expertise and digital competence, many occupations are facing new skill demands. Healthcare illustrates this well: as AIsupported diagnostic tools grow more common, clinicians must not only maintain medical expertise but also exercise sound judgment, empathy, and the ability to interpret algorithmic recommendations.

Task-based models (Acemoglu & Restrepo, 2018) offer yet another perspective by examining how specific tasks are distributed between humans and machines. This approach helps explain why AI seldom eliminates an entire occupation. Rather than replacing jobs completely, it reorganizes them by shifting certain tasks to algorithms while leaving others under human responsibility.

1.3. Political Economy of AI

Beyond its functional implications, the political economy of AI highlights how technology is embedded in larger structures of power and inequality. The concept of algorithmic capitalism (Srnicek, 2017; Zuboff, 2019) frames AI as part of a system that extracts value from data. In this system, predictive analytics turn user behavior into a commodity (Helbing, 2018). AI-driven algorithms monetize user attention and support business models that depend heavily on constant surveillance.

The idea of data colonialism (Couldry & Mejias, 2019) extends this critique by pointing out global inequalities. It argues that companies in the Global North extract, process, and sell data from populations in the Global South, creating dependencies like those seen in historical resource colonialism. Google's AI-enabled agricultural applications illustrate these issues. They collect crop data from farmers in Africa and Asia, raising key questions about data ownership, control, and how economic value is shared (Zuboff, 2022).

The platformization of work (Vallas & Schor, 2020) further emphasizes how AI-powered gig platforms are changing labor markets. Companies like Uber and Deliveroo show how algorithmic management controls work allocation, pricing, and performance evaluation. AI systems determine driver routes, affect customer ratings, and adjust wages, creating job insecurity even as they provide new opportunities for flexible work. These developments reveal AI's complex nature. While technology lowers barriers to job market entry for some, it also reinforces existing power imbalances in employment relations.

1.4. Integrative Theoretical Perspectives on AI

Overall, the framework presents AI as a technology shaped by two transition pathways. It can support sustainability-oriented changes, but it can also make existing social and environmental inequalities worse. This tension matches a broader agreement in the literature that technological innovation acts as a "double-edged" force. It improves productivity and efficiency, but it can also increase inequality and environmental stress (Schot & Kanger, 2018). In this sense, the sustainability potential of AI relies not just on its technical abilities but also on the institutional structures, governance arrangements, and distributional dynamics in which it operates.

Addressing this duality requires combining insights from various fields. Innovation theory explains how technological capabilities develop and spread. Labor economics highlights the redistributive effects of automation and changes in skills. Critical political economy shows how algorithmic systems shape power relations and creates new ways to extract value across global production networks. As policy-focused research increasingly points out, only a thoughtful and reflective approach can balance growth driven by innovation with fairness. This allows researchers and policymakers to recognize the trade-offs involved in technological advancement and to develop governance structures that enhance AI's role in creating sustainable, inclusive, and ethically sound futures (Zuboff, 2019; Pasquale, 2020).

2. AI and Global Sustainability Developments

2.1. Environmental Impacts

The environmental impact of AI has become a key factor in assessing technology's overall contribution to sustainability. Life-cycle perspective is important because AI systems involve several stages, including hardware production, model training, system deployment, and end-of-life disposal (Elahi et al., 2023). Each stage brings unique ecological challenges. Life-cycle assessments indicate that these impacts go well beyond the operational phase. The extraction of rare-earth minerals for semiconductor manufacturing, the production of GPUs, and the high electricity demands of large data centers lead to significant carbon emissions, considerable water consumption, and increasing electronic waste.

Research highlights the extent of these environmental issues. Training a single large natural language processing (NLP) model can produce up to 284 tons of CO_2-equivalent emissions, roughly the same as the lifetime emissions of about five average American cars (Strubell et al., 2019).

2.2. Resource Optimization and the Circular Economy

Beyond its direct environmental impact, AI also plays a key role in optimizing resources within the CE model. Predictive analytics help develop maintenance strategies that extend the life of machinery and consumer goods. Siemens provides a clear example of this method. The company uses AI-based monitoring systems in its turbines to predict potential failures, which reduces downtime and minimizes material waste (Bressanelli et al., 2022).

AI also improves the efficiency of waste sorting and recycling. Computer-vision algorithms now classify and separate materials with greater accuracy, which boosts recovery rates for plastics, metals, and glass (Bhattacharjee & Bhave, 2025). In closed-loop supply chains, AI enhances traceability and transparency by enabling firms to track material flows throughout production, use, and end-of-life stages. However, realizing these benefits relies heavily on support from institutions, such as extended-producer-responsibility policies and incentives for circular product design. Without such regulatory support, optimization tools may end up reinforcing rather than changing traditional linear production models.

2.3. Climate-Change Mitigation and Adaptation

AI plays a role in both reducing climate impact and adapting to its effects. On the reduction side, machine-learning systems improve how we use renewable energy by making solar and wind forecasts better. This leads to more stable integration into the energy grid (Rolnick et al., 2022). AI also improves energy management for buildings, which helps lower energy use in cities. For adaptation, AI boosts resilience against climate-related risks. Smart agriculture systems powered by AI assist farmers in using less fertilizer and water while enhancing their crops' resilience to drought and pests (Chlingaryan et al., 2018). Likewise, AI-based disaster-risk platforms analyze satellite images and sensor data to predict floods, wildfires, and hurricanes. This allows for earlier and more focused interventions (Rolnick et al., 2022). However, these innovations also raise concerns about governance and fairness. Corporate-controlled agricultural platforms often gather large amounts of data from smallholder farmers, creating new dependencies and weakening their control over data (Bronson & Knezevic, 2016). Thus, while AI can improve adaptive capacity, it may also reinforce existing inequalities in control and benefit distribution.

Even with its potential, AI’s impact on sustainability involves several ongoing tensions. First, efficiency gains can lead to rebound effects. Here, lower costs from optimization result in increased overall consumption, ultimately causing higher emissions. For instance, AI-driven logistics reduce transportation costs but also increase demand for quick delivery services. Second, the idea of “AI for Good” risks becoming greenwashing. Companies might highlight improved efficiency from AI while downplaying the rising energy demands that come with data-heavy computing (Crawford, 2021). Third, the uneven global spread of AI’s costs and benefits raises significant issues around fairness and inclusion. Advanced economies and large companies capture most of the economic gains from AI. In contrast, the environmental downsides-like high energy use, water consumption, and data extraction-often impact marginalized communities and the Global South more heavily (Couldry & Mejias, 2019). This imbalance complicates AI’s role in achieving the United Nations Sustainable Development Goals (SDGs), especially those focused on fairness, inclusion, and equitable development results.

Figure 1

AI- Driven Sustainability: A Multi-Level System and Its Impact Pathways

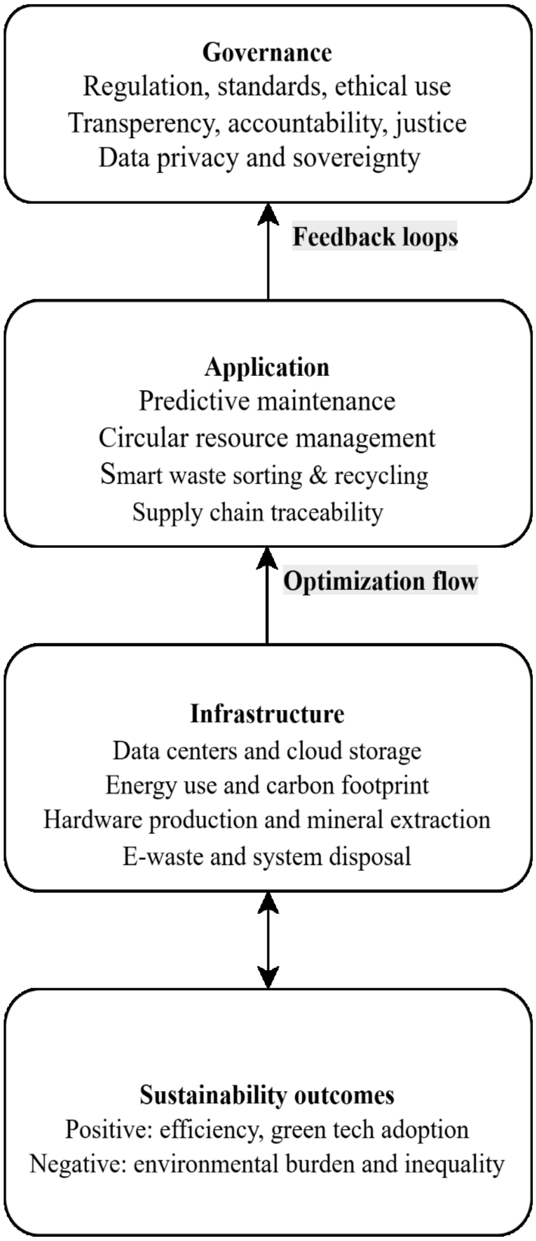

Figure 1 shows the relationship between AI and sustainability through three connected layers. The first layer, AI infrastructure, represents the resource-intensive foundations of AI systems, including data centers, energy consumption, and hardware production, all of which generate direct environmental impacts such as greenhouse gas emissions and resource depletion. The second layer, AI applications, illustrates how AI-enabled solutions contribute to sustainability by enhancing resource efficiency and supporting circular economy practices, including predictive maintenance, advanced recycling systems, and supply chain traceability. The third layer, AI governance, encompasses the regulatory frameworks, institutional arrangements, and ethical principles that guide the development and deployment of AI in addressing sustainability challenges. This includes policies related to renewable energy integration, risk management, and data governance. The arrows connecting these layers indicate feedback loops, suggesting that the environmental effects of AI are not linear but depend on how technological capabilities are aligned with governance mechanisms and societal priorities. Overall, the figure highlights the dual nature of AI in sustainability, pointing to both its potential to improve environmental performance and the risks associated with unequal distribution of environmental costs and benefits.

3. AI-Induced Transformation of Labor Markets

Artificial intelligence is increasingly recognized as a general-purpose technology that reshapes labor markets not only through automation but also by transforming the content and organization of work. Recent evidence shows that AI exposure varies significantly across occupations and primarily operates through task-level changes, where some activities are automated while others are augmented, leading to shifts in skill demand, job design, and employment structures (Eloundou et al., 2024).

3.1. Automation and Employment Displacement

AI-driven automation has raised concerns about replacing human jobs with machines. Meta-analyses of industry studies show that the level of job loss differs greatly between sectors. Manufacturing, logistics, and administrative services are the most affected areas. Here, AI-enabled robots and machine learning systems carry out routine tasks more effectively than people (Frey & Osborne, 2017; Acemoglu & Restrepo, 2018). In contrast, health care, education, and creative sectors have lower risks of job replacement but greater potential for job enhancement (Hearn and McCutcheon, 2020). This uneven exposure to automation reflects differences in skill requirements, increasing demand for digital, analytical, and socio-emotional skills.

Comparisons between countries further highlight this trend. More recent evidence from OECD (2023) suggests that this exposure has increased, with approximately 27% of jobs now considered at high risk of automation and over 30% expected to undergo substantial task transformation, reflecting the growing impact of artificial intelligence and digital technologies on job structures. Emerging economies are even more vulnerable due to the high number of routine jobs. However, differences in regulations, wage structures, and demographics affect these outcomes. For example, Germany’s strong apprenticeship program helps lessen job displacement, while Southeast Asian economies are more at risk because of inadequate reskilling opportunities. These patterns highlight the need for continuous reskilling and upskilling.

3.2. Creation of New Occupational Niches

While AI displaces some jobs, it also creates new job opportunities. The demand for AI ethics specialists, algorithm auditors, and human-machine interaction designers has grown quickly (Bessen, 2018). These roles focus on making sure algorithms are fair, accountable, and easy to understand, reflecting society's concerns about bias and transparency. Furthermore, hybrid professions, like medical AI interpreters, show how AI enhances rather than replaces human expertise by helping patients understand algorithmic outputs. Tasks that involve creativity, empathy, and judgment are still important alongside AI systems (McAfee, & Brynjolfsson, 2017). The challenge lies in helping workers who lose jobs in routine sectors transition to these new roles, which often need higher digital skills and ongoing learning. This shift requires hybrid skill sets combining technical and domain-specific knowledge, along with continuous learning.

3.3. Platformization and Gig Work

AI has changed job relationships by creating platform-based labor markets. Gig economy companies like Uber, Deliveroo, and Upwork use algorithmic management systems to assign tasks, set pay, and assess performance in real time. These platforms offer flexible job options for workers, but they worsen job insecurity by breaking down traditional employment ties, shifting risks onto workers, and limiting collective bargaining (Vallas & Schor, 2020). Platform work increasingly demands digital adaptability and the ability to navigate algorithmic systems.

The lack of transparency in these algorithms creates power imbalances. Workers often do not know how their ratings, pay, or job assignments are decided. Research shows that these systems reinforce existing social biases, penalizing marginalized groups more harshly (Rosenblat, 2018). Therefore, platformization shows both the potential of AI for innovative job allocation and its impact on making employment more unstable.

3.4. Global Variations

The impact of AI on the labor market differs greatly by region. Advanced economies have strong institutional support, including active labor market policies and vocational education systems that help people improve their skills. For example, Scandinavian countries have set up digital reskilling programs that match their national AI strategies. In contrast, many emerging markets face structural issues like limited broadband access, underfunded education systems, and weaker regulatory oversight. These differences increase the global skill gap. Advanced economies are more likely to capture the productivity and high-value gains associated with AI adoption, whereas emerging economies face greater vulnerability in terms of labor market disruption, institutional adaptation challenges, and uneven workforce transitions (ILO, 2025). These differences underline that AI's impact depends on countries' capacity for skill development and workforce adaptation.

4. Inequality, Governance, and Geopolitical Dimensions of AI

AI adoption does not happen evenly; instead, it increases existing inequalities within and between societies. The digital divide is especially noticeable between the Global North and South. High-income countries lead in AI patents, venture capital investments, and data infrastructure. Many low- and middle-income countries primarily use imported applications (UNCTAD, 2021). This imbalance risks reinforcing historical patterns of dependency between central and peripheral regions. Even within countries, rural and urban divides continue. Major cities with advanced digital ecosystems attract AI-related jobs. In contrast, less developed areas miss out on the benefits of digital change (Zhang, 2023). These gaps highlight the need for policies that promote equal access to AI resources, including investments in broadband, open data platforms, and affordable digital literacy programs.

Beyond infrastructure, AI-related job markets reveal gender and diversity inequalities. Women are underrepresented in AI-heavy jobs due to obstacles in STEM education, workplace cultures, and biased hiring practices (West et al., 2019). Algorithmic systems often reflect social biases found in training data, which reinforces racial and gender discrimination (Buolamwini & Gebru, 2018). Additionally, occupational segregation continues, with women mainly in clerical and administrative roles that can be easily automated. They are also underrepresented in fast-growing fields like engineering and data science. Addressing these issues requires a two-pronged approach: targeted educational initiatives that widen diversity pipelines and algorithmic fairness measures that reduce bias in AI systems.

The conversation about a *just transition* focuses on redistributive measures to lessen the inequalities caused by AI adoption. National reskilling and upskilling programs show how lifelong learning can help workers adapt. Experiments with universal basic income (UBI) in Finland and Kenya offer more evidence that income guarantees can support workers during disruptions, though discussions about costs and work incentives are still ongoing (Standing, 2017). Additionally, inclusive innovation strategies that promote locally designed AI solutions, especially in emerging economies, might lessen dependence on foreign technologies and build local capabilities. These steps can ensure that AI-driven changes are both efficient and fair.

AI governance shows a complex landscape shaped by ethical discussions, institutional actions, and geopolitical competition. Responsible AI principles-fairness, accountability, transparency, and human focus-have become global standards (Jobin et al., 2019). Additional frameworks, like the ethics-of-care perspective, emphasize the relationships and context of AI's societal effects. In practice, algorithmic accountability remains crucial, with increasing demands for explainability, auditability, and impact assessments that mirror environmental assessment methods.

Institutional responses differ widely across regions. The EU’s AI act is the most thorough effort to categorize AI systems by risk and regulate high-risk applications with strict rules (European Commission, 2021). The OECD AI principles focus on inclusive growth and transparency. The ILO has provided guidelines to protect decent work in digital settings. National strategies vary: the United States supports light regulation to encourage innovation, China emphasizes state-led development and control, and the EU highlights ethical considerations. These differences show a mix of regulations that complicate global cooperation.

Discussions on data sovereignty and global governance further reveal the complex nature of AI regulation (Roberts et al., 2023). Countries like India and Brazil have enacted data localization laws, while the EU’s GDPR has established new global standards for privacy and data protection. This fragmentation reflects clashing viewpoints: one supports open data flows to drive innovation, while the other favors national control for security and development. On the geopolitical stage, organizations like ISO, IEEE, and the UN act as platforms for setting standards, but the dominance of advanced economies raises worries about including the Global South in creating these norms.

At the macroeconomic and geopolitical level, AI is often seen as a catalyst for productivity. Recent estimates suggest that generative AI alone could add between $2.6 trillion and $4.4 trillion annually to the global economy across a wide range of use cases, with even greater gains expected as these technologies become embedded in broader software systems (McKinsey, 2023). Studies at the firm level show efficiency improvements in logistics, finance, and healthcare. However, overall productivity effects are inconsistent due to hurdles in implementation and the slow spread of complementary skills (Brynjolfsson et al., 2021). Beyond productivity, AI is changing global value chains. Automation lessens the need for low-cost labor, promoting reshoring and nearshoring in industries like electronics and textiles (Antràs, 2020). Meanwhile, AI-driven resilience strategies, such as real-time supply chain monitoring and predictive forecasting, have gained importance in response to disruptions like the COVID-19 pandemic.

As a result, AI heightens strategic competition and power imbalances on the geopolitical front. The rivalry between the U.S. and China is prominent, with both countries heavily investing in AI for economic, military, and strategic goals (Lee, 2018). Competition includes setting standards, recruiting talent, and accessing data. This dynamic affects global governance and technological sovereignty. Multilateral organizations like the OECD and G20 encourage cooperation but differing national interests create obstacles to agreement. This situation increases the risk of a fragmented AI landscape with competing groups and unequal advantages. Such fragmentation threatens not only job quality and sustainability but also the larger aim of establishing inclusive and collaborative global governance structures.

Discussion

The findings of our study examine the mixed and systemic role of AI in shaping global sustainability and labor markets. In terms of sustainability, AI holds great promise. It can improve resource efficiency, support CE practices, and aid in climate change mitigation and adaptation. However, these benefits come with significant ecological costs, including the energy demands of data centers, the resource extraction needed for hardware, and the rebound effects that may undermine efficiency gains.

In labor markets, AI brings about dual transformation. It automates routine tasks and displaces employees in fields like manufacturing, logistics, and administrative services. At the same time, it creates new jobs in areas such as AI ethics, algorithm auditing, and human-machine collaboration. These changes deepen existing inequalities, as workers in vulnerable sectors often do not have the resources to move into high-skill jobs. The rise of algorithmic management in platform-based work further illustrates how AI changes labor relations, increasing job insecurity and positioning AI as both a technological advancement and a driver of institutional change.

Responses to these challenges are fragmented and inconsistent. The European Union's AI Act represents a significant regulatory effort focused on risk classification and human-centered safeguards. In contrast, other regions, particularly the United States and China, follow different paths that prioritize innovation or state control. This regulatory divergence reflects broader geopolitical tensions and complicates the goal of establishing coordinated global governance. Discussions about data sovereignty, privacy, and cross-border information flows show how contentious AI governance has become, particularly given the strong influence of advanced economies in creating global standards. These dynamics highlight the uneven distribution of benefits and challenges associated with AI's integration into sustainability and labor markets. There is a strong need for better alignment between ethical commitments, institutional capabilities, and global governance frameworks.

In the context of Türkiye, the implications of artificial intelligence for sustainability and labor markets reflect both emerging opportunities and structural constraints. Türkiye’s relatively young and dynamic workforce provides a favorable basis for digital transformation; however, sectoral concentration in manufacturing, services, and informal employment increases vulnerability to task-based automation. National policy initiatives and investments in AI ecosystems indicate a growing institutional awareness of these challenges. At the same time, gaps in advanced digital skills, regional inequalities, and limited diffusion of high-technology applications constrain the inclusive adoption of AI. From a sustainability perspective, Türkiye’s commitments to green transformation create an important policy window, yet the integration of AI into these agendas remains uneven. Therefore, the Turkish case illustrates how the impact of AI is shaped by technological capabilities, institutional readiness, human capital development, and the alignment between digital and sustainability strategies.

Several policy implications arise from this context. Governments should take an integrated approach that incorporates AI into national sustainability strategies while ensuring these strategies align with climate goals, circular economy principles, and social inclusion efforts. Expanding reskilling and lifelong learning systems is vital to prepare workers with the necessary hybrid skills-mixing digital literacy, ethical judgment, and creativity-for an AI-dominated economy. Additionally, supportive measures like wage insurance, conditional transfers, or pilots for universal basic income may be needed to mitigate the effects of job displacement and sustain social stability. Companies should embrace “Green AI” principles by openly reporting the energy and carbon footprints of their operations and prioritizing renewable energy in their data infrastructures. Corporate responsibility should go beyond efficiency to include algorithmic audits and fairness assessments. Internationally, organizations like the OECD, ILO, and UN need to enhance collaboration to align standards, close capacity gaps in the Global South, and link AI governance to existing sustainability goals, such as the Paris Climate Agreement and the 2030 Agenda for Sustainable Development.

These findings suggest several paths for future research. Long-term studies are necessary to track how AI affects employment trends, labor displacement, and reskilling results over time-issues that cannot be fully understood through short-term analyses. Standardized reporting on the energy and resource use of AI applications would facilitate more meaningful comparisons across sectors and help develop sustainable computing practices. More empirical research is also needed to assess how ethical AI principles are applied in organizations and to determine their effectiveness in reducing bias and enhancing accountability. Importantly, research should expand its geographical focus to include viewpoints from the Global South, where issues like data colonialism, agricultural adaptation, and changes in informal labor are critical yet often overlooked in mainstream discussions.

This discussion confirms that AI is not automatically a transformative solution nor an unavoidable threat. Instead, it exists in a contested space where ecological, social, and political outcomes depend on governance decisions, institutional structures, and collective priorities. The challenge is not just to speed up AI adoption but to guide it intentionally towards futures that are environmentally sustainable, socially equitable, and globally inclusive.

Conclusion

This chapter shows that artificial intelligence helps sustainability and changes labor markets, but it does so in uneven and often conflicting ways. While it improves resource efficiency, supports circular-economy practices, and aids climate actions, it also creates major environmental pressures due to energy use and hardware production. In labor markets, technology opens up new opportunities for skilled work, but it also increases risks for routine jobs, widening social and economic gaps.

These mixed results indicate that AI's impact is not set in stone. Effective governance, clear environmental rules, and strong social-protection systems will determine whether this technology leads to more inclusive and sustainable futures. Coordinated policies for reskilling, fair digital labor practices, and responsible data use are vital. Ultimately, AI's direction relies on the choices we make together and the commitments from institutions, not just on technology itself.

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