Navigating the AI Era: Conceptual Models of Labour Transformation and Sectoral Resilience

Vusi S. Mncube[1]

[1]DR V S Mncube Foundation NPC/Atlantic International University

Publication Date: 2025/10/06

Abstract: This study introduces two new conceptual frameworks—the Displacement–Augmentation Continuum (DAC) and the Sectoral Impact and Resilience Model (SIRM)—to examine the complex interaction of artificial intelligence/machine learning (AI/ML) technologies with human labour. Grounded in interdisciplinary literature, empirical trend analysis, and policy analysis, the study dismisses the naive binary models that dichotomise labour as displaced or augmented, along with the deterministic sectoral risk approaches. DAC reconceptualises work transformation along a continuum, identifying five stages ranging from total displacement to human-led AI collaboration, and stresses that most transformations involve shifts in human–machine interaction rather than job displacement per se. The SIRM model maps sectoral exposure to automation against adaptive capacity, producing a dynamic matrix that guides differentiated policy responses. Rooted in task-based economic theory, sociotechnical systems thinking, and resilience theory, these models provide an integrative view of both micro-level task change and macro-sectoral restructuring. These frameworks offer policymakers, educators, and business leaders, effective tools for influencing the AI-driven future of work.

Keywords: *Artificial Intelligence (AI), Machine Learning (ML), Human Labour, Displacement-Augmentation Continuum (DAC), Sectoral Impact and Resilience Model (SIRM), Future Work.*

How to Cite: Vusi S. Mncube (2025) Navigating the AI Era: Conceptual Models of Labour Transformation and Sectoral Resilience. *International Journal of Innovative Science and Research Technology*, 10(9), 2553-2564.
https://doi.org/10.38124/ijisrt/25sep1465

I. INTRODUCTION

The rapid convergence of artificial intelligence (AI) and machine learning (ML) into core economic and social systems is reshaping the nature of work for humans in all industries. From manufacturing and healthcare to supply chains and creative services, AI/ML technologies are no longer peripheral technologies; they're now transformative drivers reshaping jobs, professions, and even occupational categories. This relentless shifting of Labour drives fundamental questions about work, productivity, justice, and the evolving role of humans in the fast-paced automated economy. While existing research has explored various areas of automation, such as displacement of Labour (Frey and Osborne 2017), enabling human work (Brynjolfsson and McAfee 2014), and economic and social impact of smart technology (Susskind 2020), there is still the vacuum in balanced models that fully embrace the diversity and richness of AI/ML's impact. Existing models oversimplify the dynamics between technology and work to one of displacement versus augmentation, failing to recognize the complex and industry-specific forces that inform how these dynamics manifest.

This paper introduces two conceptual models—the Displacement–Augmentation Continuum (DAC) and the Sectoral Impact and Resilience Model (SIRM)—to respond to this question. The DAC model provides a dynamic perspective of how human work is altered on a continuum from total displacement to thoughtful augmentation, capturing the multi-faceted nature of Labour transformation. Complementary to this, the SIRM model provides a cross-sectional perspective of sectoral vulnerability and resilience to automation, mapping the adaptive capacity of various sectors.

Together, these models constitute a solid, operational model for policymakers, academics, and business leaders to navigate the complexities of workforce transformation, design fair Labour policies, and forecast future change in the global division of Labour. By recognising the heterogenous strategic and structural responses to AI/ML-fueled transformation, these models aim to deliver more sage and just decision-making amidst technological turmoil.

II. METHODS AND THEORETICAL FRAMING

➢ *Conceptual Modeling as Methodological Approach*

The approach in this paper is conceptual modeling methodology, a qualitative and theory-building approach suitable for synthesising complex phenomena not well represented in current frameworks (Jabareen, 2009). Conceptual models are invaluable instruments for surfacing new relations, explaining under-theorised dynamics, and

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25sep1465

guiding empirical inquiry and policy response.

Contrary to the employment of quantitative evidence or predictive models, conceptual models synthesise theoretical frames, empirical evidence, and inter-disciplinary literature to construct interpretive frameworks. To this end, the Displacement–Augmentation Continuum (DAC) and the Sectoral Impact and Resilience Model (SIRM) were constructed to achieve a more dynamic and policy-driven understanding of AI/ML's interaction with human labour.

➢ *Model Building Process*

- *Step 1: Literature Synthesis*

The first step was a systematic integration of more than 60 academic research studies, policy documents, and sectoral reports on AI/ML, automation, labour economics, and future of work futures. Major themes derived were:

- ✓ Task evolution over time (task-based modeling).
- ✓ Sectoral vulnerability to automation (occupational risk models).
- ✓ Societal responses to technological change (policy readiness frameworks).
- ✓ Conceptual integration gaps between micro and macro domains.

- *Step 2: Thematic Pattern Identification*

From synthesis of literature, the following emerging trends were established:

- ✓ The inadequacy of binary displacement-augmentation classifications.
- ✓ The need for continuum-based models that address the fluid development of tasks.
- ✓ Inconsistencies in the manner sectors develop according to internal and external capabilities.

These findings formed the conceptual framework of DAC and SIRM.

- *Step 3: Iterative Refining Through Triangulation*

The evolving model structures were tightened through triangulation against:

- ✓ Real-world case studies (e.g., automation in manufacturing vs. augmentation in healthcare).
- ✓ Sectoral trend studies (e.g., WEF Future of Jobs reports).
- ✓ OECD, ILO, and World Bank policy reports.

➢ *Building on Prior Scholarship and Literature*

The accelerated rise of artificial intelligence (AI) and machine learning (ML) technologies has prompted profound scholarly debates about their impact on human Labour. This chapter provides a critical synthesis of existing research, structured into three key sections. The below section examines the multifaceted ways AI/ML are reshaping nature, scope, and value of human work. Additionally, this section reviews dominant paradigms and predictive models that attempt to forecast Labour market transformations under technological disruption. Lastly, the limitations of current frameworks are identified and the need for a more holistic conceptualisation of labour transformation is proposed, laying the foundation for the models introduced later in this study.

➢ *The Impact of AI/ML on Human Work*

The diffusion of artificial intelligence (AI) and machine learning (ML) technologies is a tipping point in human Labour history. Automation has indeed been a source of economic change for centuries—a process that started with industrial mechanization and was amplified by computerisation in the late 20th century—but the present surge of AI/ML is distinguished by a qualitatively new dynamic. These technologies now not only perform mundane physical Labour but also increasingly advanced intellectual tasks such as processing data, making decisions, and creating content (Brynjolfsson & McAfee, 2014; Chui et al., 2016).

A succession of seminal studies has attempted to quantify the impact of AI/ML on employment. Frey and Osborne (2017) estimated that approximately 47% of jobs in the United States were at significant risk of computerisation. However, subsequent research has refined these estimates by moving from an occupation-based analysis to a task-level approach. Arntz et al. (2016) found that few jobs are fully automated, but many are partially exposed to automation risk. While this task-based framework has advanced our understanding, it also presents several limitations. For instance, it assumes the stability of tasks over time and overlooks the evolutionary nature of AI systems, which are increasingly capable of learning and automating complex tasks. Moreover, it fails to capture the psychosocial and structural consequences of automating core components of job consequences that can threaten the viability of entire occupations, even if only certain tasks are replaced.

In addition, Arntz et al.'s framework does not account for sectoral variation, particularly in the informal and digitally underdeveloped economies common in the Global South. Scholars such as Ayana et al. (2024), Omotubora and Basu (2024), Mollema (2024), and Adams (2021) have called for "contextualised" or "decolonised" approaches to AI adoption that consider local Labour dynamics, cultural norms, and power asymmetries in the global diffusion of technology. These shortcomings underscore the need for conceptual frameworks that move beyond binary understandings of AI's impact. Instead of viewing work as either automated or preserved, the reality unfolds along a spectrum—a Displacement–Augmentation Continuum (DAC)—in which AI simultaneously displaces certain human tasks while augmenting others, depending on skill intensity, job function, and sectoral conditions (Autor, 2015; Brynjolfsson, Hitt, & Brynjolfsson, 2018). This continuum helps illuminate why some workers experience enhanced productivity and job enrichment, while others face erosion of task relevance and deskilling.

Another prominent dimension in the AI-work debate is job creation. Studies such as those by the World Economic Forum (2018, 2020), Danso and Hanson (2023), and Autor (2015) emphasize that AI technologies not only destroy jobs

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25sep1465

but also create new ones, especially in high-skill domains. However, many of these analyses fail to acknowledge that this transition is rarely equitable. AI tends to replace low-skill, routine Labour while generating high-skill, specialized roles, thereby widening inequality between workers who can adapt and those who cannot. As Brynjolfsson and McAfee (2014) note, automation's replacement of manual and repetitive tasks shifts Labour demand toward higher-order thinking, technical fluency, and adaptability—capacities often constrained by educational and infrastructural limitations in regions such as Sub-Saharan Africa.

Acemoglu and Restrepo (2018, 2020) proposed a task displacement theory to explain how automation removes some work functions while generating new demand for complementary roles. Their work offers a compelling macroeconomic account of technological transitions, stressing that the outcomes of automation are shaped by institutional arrangements, economic incentives, and policy responses. However, the theory underplays the temporal gap between displacement and reemployment—a critical phase during which workers often experience income loss, skill decay, or shifts into precarious employment. For low- and medium-skilled workers, particularly in regions lacking robust social safety nets, this transition can produce long-term socio-economic insecurity (ILO, 2021; Berg et al., 2018).

While Acemoglu and Restrepo (2018, 2020) provide insightful theoretical bases, their employment of data from developed economies limits the generality of their findings. In addition, their model pays insufficient attention to the agency of Labour institutions, such as unions and civic Organisations, which may shape the nature and distributional effects of technological change. Empirical observations from countries that have managed to shield themselves from the destabilising effect of automation—such as Singapore's Skills Future program or Sweden's bargaining responses to automation—firmly establish the critical role institutions play in buffering Labour markets from technology shocks (ILO, 2019; OECD, 2020). These observations substantiate that the trajectory of AI is not technologically fixed but is heavily mediated by social and political choices.

Moreover, the adaptive capacity of different Labour sectors—their ability to absorb, adapt to, or be reformed by AI shocks—remains under researched in recent literature. Adaptive capacity in high-technology sectors like finance and ICT comes through their exposure to infrastructure and learning systems. They are contrasted with Labour-intensive sectors like agriculture, domestic work, or informal trade that lack structural readiness to benefit from AI in a positive manner (UNDP, 2022; World Bank, 2023). This cross-industry disparity necessitates a more systematic approach of understanding the AI effect across industries. The Sectoral Impact and Resilience Model (SIRM), introduced in this study, is proposed as a framework to assess not only which sectors are vulnerable but also which are most equipped to adapt or transform.

Bessen (2019) argues that automation can, in some contexts, increase Labour demand by improving productivity. His study suggests that firms adopting automation may see expansions in employment where AI enhances human labour rather than replacing it. While this is a valuable corrective to overly pessimistic views, it risks assuming a neutral or benign outcome from productivity gains. In practice, automation may increase labour market polarisation by expanding high-skill roles while contracting mid- and low-skill ones. Moreover, the assumption that productivity gains translate directly into equitable employment growth overlooks how firms often reinvest those gains into further automation, rather than rehiring displaced workers. Bessen also underestimates the challenges of reskilling, particularly in settings where access to formal education is limited or where educational institutions are not aligned with future labour demands.

While the existing literature presents valuable insights into AI-driven labour dynamics, it often fails to capture the multidimensional, context-sensitive nature of technological change. Many models either overstate AI's displacement potential or understate the structural inequalities that mediate labour outcomes across different regions and sectors. This review underscores the need for spectrum-based conceptual tools that better reflect the realities of hybrid labour futures. The Displacement–Augmentation Continuum (DAC) and the Sectoral Impact and Resilience Model (SIRM) proposed in this study offer more granular and integrative frameworks to evaluate not just what types of work are affected by AI, but how, why, and under what conditions resilience, exclusion, or transformation occurs. These models foreground the temporal, institutional, and sectoral mediators of labour transformation, reframing the discourse on the future of work in the AI era with a more inclusive, empirical, and policy-relevant perspective.

➢ *Theoretical Foundations*

The models draw on a variety of intersecting theoretical traditions:

- Sociotechnical Systems Theory (Trist ,1981): Emphasises the co-evolution of human systems and technology, which underlies the continuum logic of DAC.
- Task-Based Economic Theory (Autor ,2013; Acemoglu & Restrepo, 2018): Underlies the task-level granularity of task shifts and human–machine complementarities in DAC.
- Resilience Theory (Holling ,1973; Folke, 2006): Informs SIRM by showing how systems absorb shocks and accommodate them—tech disruption here.
- Institutional Theory: Explains sectoral difference by referring to governance, norms, and policy infrastructure difference, all present in SIRM.

➢ *Existing Paradigms and Predictive Models*

The dynamic interaction among Machine Learning (ML), Artificial Intelligence (AI), and the Labour Market has precipitated a sequence of conceptual models aimed at predicting, explaining, and guiding labour transformations. However, most of the literature resorts to either binary displacement-augmentation or fixed sectoral risk models, both of which, although seminal, are restrictive in their ability

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25sep1465

to explain the complex, dynamic, and reciprocal features of labour systems in today's times.

- *Binary Displacement-Augmentation Models:*

Binary frameworks have a propensity to characterise labour outcomes in basic, binary terms: employees either become unemployed due to automation or have their productivity boosted through man–machine collaboration. One of the earliest interventions in the discussion is found in Brynjolfsson and McAfee (2014), where they pose the "race against the machine" and the "race with the machine" as two competing narratives. The former issues a warning about mass obsolescence of jobs, while the latter argues that with the necessary skills and resilience strategies, human beings can survive alongside intelligent systems.

Though impactful, such polarities underestimate the range of transformations that many occupations experience. Arntz et al. (2016) contend that jobs within occupations will be reorganised more likely than the total occupation being displaced. In addition, they do not account for hybrid jobs and task re-composition—cognitive, social, and technical task blending that redefine professions over the passage of time (Autor, 2015). They are likely to ignore the ways in which the power dynamics, institutional settings, and global value chains condition the speed and nature of displacement or supplementation (Acemoglu & Restrepo, 2019).

- *Sectoral Risk Models and Task-Based Automation Probabilities:*

Industry models, such as those created by the McKinsey Global Institute (Manyika et al., 2017), provide forecasts of automation probability for various industries and tasks. Such models use large-scale task taxonomies in order to forecast the magnitudes to which various industries—such as manufacturing, transportation, and customer service—are exposed to automation. Similarly, Frey and Osborne's (2017) influential paper places an estimate of up to 47% of US jobs at "high risk" of automation, although later criticisms called for over-reliance on task-level statics and a neglect of context sensitivity.

Even though helpful in highlighting aggregate exposure patterns, these models are apt to overlook some of the important moderating variables such as labour regulation, diffusion lags in technology, policy heterogeneity at the regional level, and cultural readiness for automation. Notably, they categorise industries as largely homogeneous blocks, bypassing the in-sector heterogeneity of skill combinations, task contexts, and innovation trajectories (Chiacchio, Petropoulos, & Pichler, 2018). Moreover, these models tend not to incorporate feedback processes, e.g., how job destruction in an industry might stimulate demand elsewhere (e.g., robot maintenance services or data infrastructure growth).

- *Institutional and Policy Readiness Models:*

A second stream of frameworks is generated by multilateral institutions like the OECD, World Economic Forum (WEF), and International Labour Organisation (ILO). These models encompass macroeconomic considerations, education systems, and digital infrastructure readiness to assess countries' preparedness for the Fourth Industrial Revolution. The OECD Skills for Jobs database, for instance, monitors skill mismatches and shifting demand in Labour markets (OECD, 2019), while the WEF Future of Jobs Reports (WEF 2020, 2023) emphasise reskilling pathways and organisational adaptability.

While more integrated, such models have a macro-level view that can conceal specific, sectoral shifts. They also assume a linear readiness trajectory and relatively smooth technology adoption curve, hence overestimating nonlinear shocks, policy resistance, and resilience gaps between developing and developed economies (UNCTAD, 2021). The presumption that education reform or digital infrastructure would be able to counterbalance the threats of automation does not hold against power imbalances in international labour markets, particularly the Global South, where platform work and informal workplace particularly acute complexities on the landscape of automation (De Stefano, 2016).

➢ *Shortcomings Across Paradigms*

In recent years, numerous critical shortcomings across these paradigms include:

- Temporal rigidity: Numerous models are incapable of capturing nonlinear tasks, skill, and role evolution over time. Task transformation does not take place at a single moment in time but consists of extensive stretches of task hybridisation.
- Contextual insensitivity: Very few models capture the influence of sociopolitical aspects, including worker agency, union dynamics, and state intervention, on labour outcomes.
- Insufficiency in modeling interdependence: Most existing models are insufficient to embody the interdependencies between regional economies, supply chains, and labour markets that dynamically adjust to automation shocks.
- Overemphasis on resilience and adaptability: Not much emphasis is put on how adaptive capacity—via policy, training systems, or firm-level mechanisms—can mitigate risks or create new opportunities for inclusion.

These shortcomings propose the need for more dynamic, integrative, and forward-looking conceptual frameworks—frameworks that recognize the multi-speed, multi-path nature of AI/ML diffusion, labour market change, and sectoral transformation. Our suggested frameworks, the Displacement–Augmentation Continuum (DAC) and the Sectoral Impact and Resilience Model (SIRM), aim to fill these gaps by incorporating technological, institutional, and behavioral dynamics into an integrated analytical framework. These models not only address transition spectrums and sectoral diversity but also incorporate feedback loops, resilience-building approaches, and inclusive adaptation potential.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25sep1465

Table 1 Comparative Summary of Current Models on AI/ML and Labour Market Dynamics

Model Type	Key Features	Representative Works	Main Limitations
Binary Displacement–Augmentation	- Jobs are displaced or augmented. - Individual job outcomes are emphasised.	Brynjolfsson and McAfee 2014; Autor 2015	- Simplifies transitions to overly elementary forms. - Hybrid roles and task reconfiguration are neglected. - Structural forces are not addressed.
Sectoral Task Risk Models	- Probabilistic risks automation. - Sector-level analysis at the task level.	Frey and Osborne 2017; Manyika et al. 2017	- Makes assumptions on static tasks. - Ignores adaptability. - Homogenises sectors.
Institutional Readiness Models	- Preparedness at National-level. - Policy, infrastructure, and skills analysis.	OECD 2019; WEF 2020; WEF 2023; ILO 2021	- Too macro in perspective. - Linear progress assumed. - Lack of differentiation in resilience.
Task-Centric and Hybrid Role Models	- Breaks down occupations into tasks. - Accounts for task recomposition.	Arntz et al. 2016; Acemoglu and Restrepo 2019	- Insufficient in capturing sectoral dynamics. - Generally static or ahistorical.
Policy-Driven Simulation Models	- Scenario analysis and forward projections. - Coupling with education/labour policy.	UNCTAD 2021; EPRS 2023	- Rarely involve feedback mechanisms. - Fail to capture informal and precarious labour systems adequately.

Source: Translated by Authors from Seminal Literature on AI/ML and Labour Economics (2014–2024)

While these earlier models and examinations have significantly expanded our understanding of technological impacts on labour, considerable conceptual gaps remain. There are requirements for more integrative and adaptive frameworks to manage concerns about technological determinism, labour heterogeneity, sectoral dynamics, and ethical concerns. To these ends, the present section suggests two conceptual frameworks—the Displacement–Augmentation Continuum (DAC) and the Sectoral Impact and Resilience Model (SIRM)—intended to give a more comprehensive, advanced grounding for articulating labour change in the age of AI and machine learning.

- *Towards a Holistic Conceptualization of Labour Transformation*

The critical gaps identified in existing analytical approaches—including excessive technological determinism, inadequate attention to labour and sectoral heterogeneity, and insufficient ethical sensitivity—underscore the need for more dynamic, integrative frameworks to understand AI/ML-driven labour transformation. While past models have provided important insights, they often remain constrained by static, binary categorisations and insufficient responsiveness to evolving socio-technical realities.

More recent work by Acemoglu and Restrepo (2018) and Susskind (2020) continues to highlight that technological effects on jobs are not uniform or binary but rather evolve on multifaceted, time-variable paths where displacement and complementarity exist side by side. There are, however, few conceptual models that fully capture this dynamic range. To address this gap, the present study introduces the Displacement–Augmentation Continuum (DAC), a new theory that aims to map the evolutionary path of human work roles in relation to smart systems. DAC positions displacement and augmentation as interdependent points on a continuum along task complexity, co-adaptive technology interfaces, and time-dependent changes in skill requirements.

In addition, as sectoral analyses have more often experienced differentiated vulnerability to automation risks (Chiacchio, Petropoulos, and Pichler, 2021), the empirical frameworks of most studies have not fully theorised about the processes by which sectors are resilient or not. Existing approaches tend to discount such significant mediating factors as institutional support mechanisms, innovation ability, regulatory conditions, and labour market flexibility. As a corrective, this study proposes the Sectoral Impact and Resilience Model (SIRM). SIRM complements DAC by adding sector-level trajectories to broader socio-economic contexts. Drawing on platform labour precarity studies (De Stefano, 2015) and labour rights under algorithmic management (Wood et al., 2019), SIRM reveals that sectoral resilience is not technologically fixed but dynamically shaped by policy architecture, welfare regimes, and responsiveness in the education system.

Together, DAC and SIRM offer an integrated, multidimensional approach that escapes rigid "job loss versus job creation" binaries. They offer a robust conceptual anchor for studying labour market change under AI/ML-one that remains attuned to temporal change, sectoral heterogeneity, and social intermediation. By placing labour futures in co-adaptive and policy-responsive contexts, DAC and SIRM aim to contribute to both academic research and practical interventions in industries, policymaking, and societies undergoing the AI era.

➢ *Application Logic and Policy Relevance*

Both models are constructed to serve as:

- Analytical Tools: For academic analysis and comparative sectoral study.
- Diagnostic Instruments: For finding risk areas and policy gaps in the labour force.
- Strategic Frameworks: To guide human capital development, education reform, and AI regulation.

In their cumulative application, they offer multi-scalar vision—from the micro-scale of individual tasks to the macro-scale of the general labour system—making them especially useful to policymakers, educators, development agencies, and labour market planners.

Building upon the conceptual frameworks developed in Chapter 3, the next chapter undertakes a comparative analysis of how AI and ML technologies are transforming human work across different sectors and contexts. Chapter 4 expands the discussion by applying the Displacement–Augmentation Continuum (DAC) and the Sectoral Impact and Resilience Model (SIRM) to real-world patterns and empirical findings. Through this analysis, the nuanced dynamics of labour transformation—ranging from task-level reconfigurations to broader systemic shifts—are critically examined to deepen understanding and practical application.

➢ *Comparitive Analysis: Expanding the Discussion of AI/ML and Human Work*

- *Moving Beyond Binary Labour Displacement Models*

Conventional AI and automation impact models have a tendency to describe the transformation of labour in a binary way: the work either is displaced or increased. The binary description is good for parsimony but simplifies the problem and ignores the intricate nature of emergent processes of work tasks and adaptation of human labour's role.

The Displacement–Augmentation Continuum (DAC) is a more nuanced view by placing job transformations along a continuum. This continuum encapsulates the chronological evolution of tasks—from full human displacement to partial automation, to strategic augmentation where AI systems complement human capabilities. Unlike static models for example Frey and Osborne (2017), DAC takes into account:

- Job role transition states,
- The interplay between machine capability and human flexibility,
- The non-linear dynamics of technology adoption across industries.

This enables stakeholders to transition away from forecasting job losses and towards workforce transition management.

➢ *Transcending Sectoral Blindness in Automation Risk Models*

Most sectoral risk models—McKinsey, PwC, and the World Economic Forum included—are founded on automation probability scores. As good as these methods are:

- They rely on homogeneous sectoral behavior,
- They are not taking into account institutional readiness and adaptation capacity,
- They do not recognize inter-sectoral spillovers or mechanisms for resilience.

The Sectoral Impact and Resilience Model (SIRM) offers a correction by merging two axes:

- Automation Impact Intensity – To what degree AI/ML innovations reshape essential processes within a given sector.
- Sectoral Resilience Capacity – To what degree a sector can relearn, adjust, and absorb change based on policy incentives, R&D expenditure, and labour mobility.

This placement allows for a matrix analysis of sectoral exposure and guides nuanced policy interventions. For example:

- Protectionist and transition interventions can be applied to high-impact, low-resilience industries (such as administrative routine work).
- High-impact, high-resilience industries (such as health technology, finance) can have proactive upskilling and incentives for innovation.

➢ *Micro and Macro Dimension*

The integration of DAC and SIRM's complementarity is their defining feature. Where DAC follows the occupational or individual-level career of work, SIRM maps the structural context within which that career unfolds. This two-lens approach enables:

- Cross-scalar insights—from task positions to policy systems.
- A connection between task-specific automation discourse and systemic labour policy design.
- Greater utility to both academic researchers and government or private sector policymakers.

➢ *Innovation Summary*

The innovation summary illustrates how the DAC & SIRM enhances traditional models based on five dimensions: framing of labour impact, sectoral analysis, temporal dynamics, policy responsiveness, and integration levels. This summary is presented in Table 2 below:

Table 2 Comparison of Traditional Labour Impact Models and the DAC & SIRM Frameworks across Key Dimensions.

Dimension	**Traditional Models**	**DAC & SIRM Contribution**
Framing of Labour Impact	Binary (displacement or augmentation)	Spectrum-based (DAC)
Sectoral Analysis	Static risk scores	Resilience-integrated dynamic mapping (SIRM)

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25sep1465

Temporal Dynamics	Largely absent	Core to DAC continuum logic
Policy Responsiveness	Generic guidelines	Tailored recommendations by sector type and task flow
Integration of Levels	Task or sector (not both)	Cross-scalar (micro + macro)

Collectively, DAC and SIRM establish a richer, policy-responsive, and dynamic framework for understanding and navigating labour transformations in the AI/ML era.

While the exponential growth of AI/ML technologies has driven global debate about the future of work, existing frameworks fail to capture the complex, non-linear relationships of shifts in labour. This chapter extends the analytical framework through the application of the Displacement–Augmentation Continuum (DAC) and the Sectoral Impact and Resilience Model (SIRM) to critically examine trends, sectoral variations, and systemic dynamics. By adopting this comparative approach, the chapter places the vulnerabilities of traditional binary schemes and sectoral risk strategies in perspective, offering a more dynamic, policy-focused understanding of human labour's changing context.

➢ *Conceptual Models*

The Displacement–Augmentation Continuum (DAC) and the Sectoral Impact and Resilience Model (SIRM) conceptual models presented in this paper are two complementary frameworks for understanding the shifting dynamics between human work and AI/ML technology. They present a twin-lens framework, observing change at both the task and sectoral levels.

➢ *The Displacement–Augmentation Continuum (DAC)*

The DAC model maps the future of work under AI/ML along a single spectrum of autonomy, with three strategic zones:

- Displacement Zones (Full & Partial Displacement) Work in this zone is increasingly automated, from total substitution (e.g., toll booth collection, routine data entry) to highly automated with minimal human oversight (e.g., algorithmic trading, radiologic image interpretation). Policy emphasis: social protection, re-skilling pathways, and transition support.
- Co-Creation Zones (Hybridization & Task Redesign) Since routine tasks are automatable, human work shifts to higher-value, creative, or relational tasks. AI and humans collaborate on decision-making—legal research augmented by NLP tools, or semi-automated customer service with human escalation. Policy focus: human–AI teaming grants, upskilling programs, and redesign incentives.
- Augmentation Zones (Symbiosis & Augmented Intelligence) AI systems complement, rather than replace, human judgment, allowing true symbiosis. Examples are AI-assisted surgery, strategic planning, and leadership assistance tools that enhance empathy and creativity. Policy emphasis: R&D funding, lifelong learning credits, and innovation ecosystems.

Together, these areas show that AI-driven labour change is not a zero-sum game but a dynamic spectrum—one requiring differentiated policies to protect workers displaced, empower hybrid jobs, and stimulate human-centered innovation.

➢ *Representational Figure: The Displacement–Augmentation Continuum (DAC)*

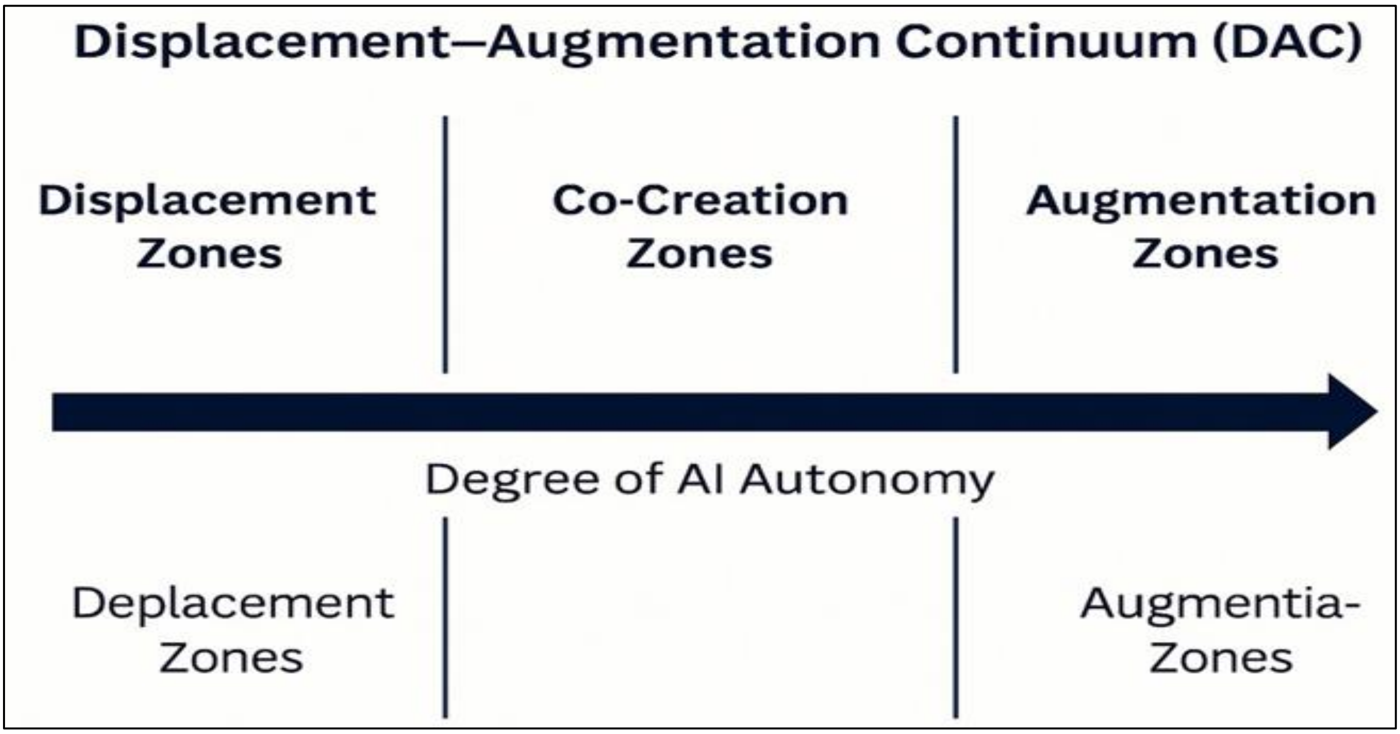

Fig 1 Displacement-Augmentation Continuum (DAC)

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25sep1465

Figure 1 illustrates the Displacement-Augmentation Continuum (DAC) model, mapping the future of work with AI/ML on a single continuum of autonomy, splitting labour activities into three strategic areas: Displacement Zones (Full & Partial Displacement), Co-Creation Zones (Hybridization & Task Redesign), and Augmentation Zones (Symbiosis & Augmented Intelligence). This model stresses the dynamic nature of the labour transformation process under AI/ML, with different policy imperatives at different stages—social protection and re-skilling in the domains of displacement, incentives to human-AI collaboration in the domains of co-creation, and R&D assistance in the domains of augmentation.

➢ *The Sectoral Impact and Resilience Model (SIRM)*

SIRM is a 2×2 matrix where sectors are graphed on two axes:

- X-axis: AI/ML Impact Intensity – the level to which AI/ML is transforming a sector's core activities.
- Y-axis: Sectoral Resilience Capacity – the adaptive resilience of the sector through workforce ability, innovation readiness, and institutional facilitation.

Table 3 AI/ML Sectoral Impact and Policy Response

Quadrant	Description	Policy Implications
Transformative Innovation Zones	High impact, high resilience (e.g., fintech, health tech)	Scale up innovation; facilitate lifelong learning.
Vulnerable Disruption Zones	High impact, low resilience (e.g., clerical admin, logistics)	Reskilling programs; improving digital infrastructure; social protection.
Stable Adaptation Zones	Low impact, high resilience (e.g., education, local governance)	Encourage experimentation; facilitate incremental innovation and adaptability.
Insulated Zones	Low impact, low resilience (e.g., agriculture in developing economies)	Invest in futureproofing and shock-readiness.

Table 3: Sectoral classification along AI/ML impact and resilience capacity, to be used as a reference point for sector-based policy formulation and assistance.

The SIRM approach enables the stakeholders to move beyond the application of a single solution for all sectors by prioritizing interventions based on each sector's location on the impact–resilience axis.

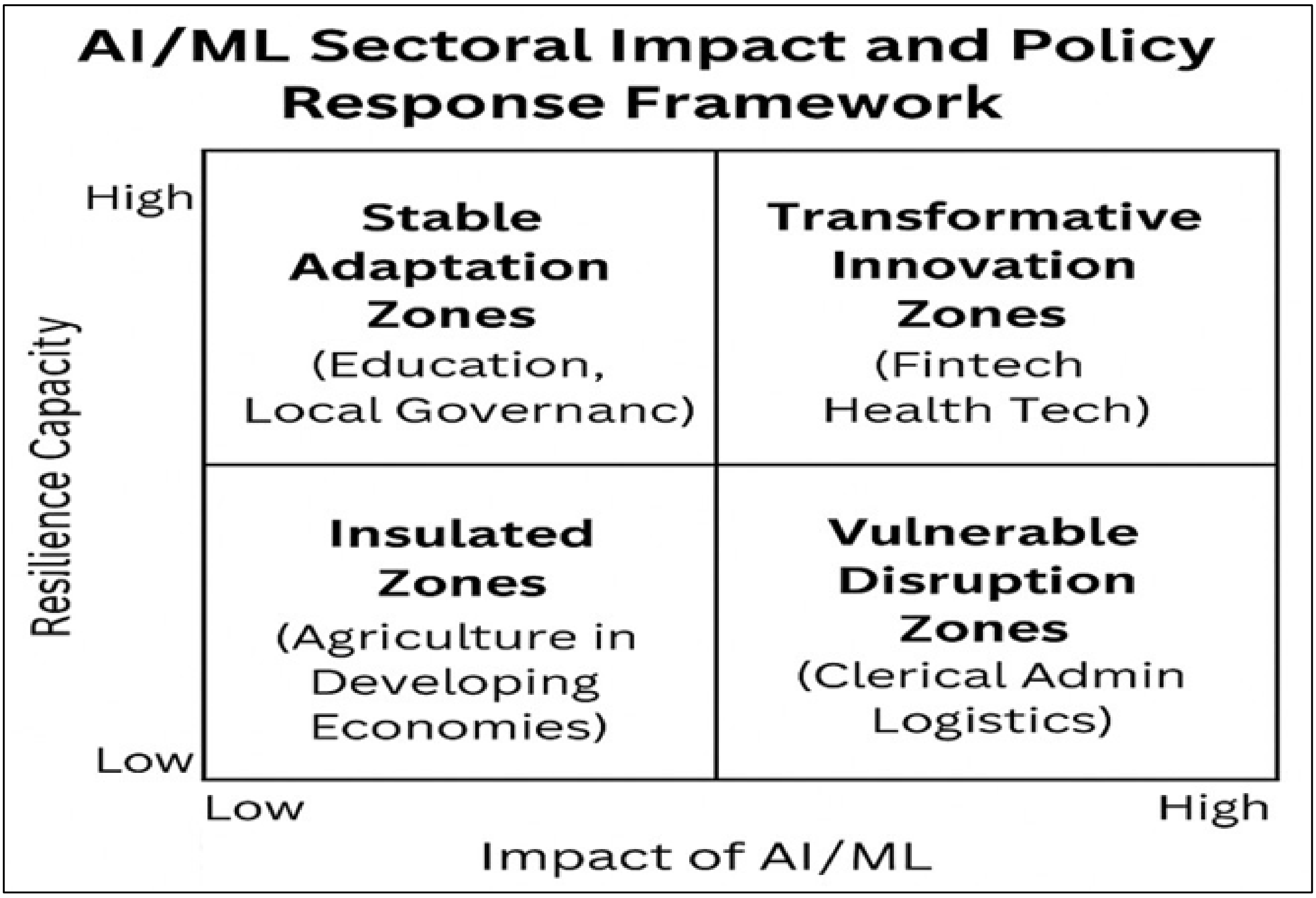

Fig 2 AI/ML Sectoral Impact and Policy Response Framework

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25sep1465

Figure 2 shows the AI/ML Sectoral Impact and Policy Response Framework, designed to map sectors according to the level of AI/ML disruption and their inherent resilience capacity. The horizontal axis is employed to indicate the extent of AI/ML impact on activities by sectors, and the vertical axis is employed to indicate adaptive capacity in the event of change of sectors. The sectors are categorized into four strategic types: Transformative Innovation Areas (high impact, high resilience), Vulnerable Disruption Areas (high impact, low resilience), Stable Adaptation Areas (low impact, high resilience), and Insulated Areas (low impact, low resilience). Each group implies different policy needs, ranging from innovation stimulation to base resilience improvement. This framework offers a dynamic way of linking sectoral strategy with the realities of technological change.

➢ *Synergistic Combination of DAC and SIRM*

Together, when used, DAC and SIRM provide an integrated, multi-dimensional framework for analysis of labour transformation in the age of AI/ML:

- Integration at the micro–macro level: DAC operates at the occupational and task level, while SIRM operates at the sectoral structural change level, thereby offering a systemic view of labour transformation.
- Policy directing: DAC leads the retraining and task creation endeavors, while SIRM facilitates determining sectors needing priority investment, policy change, or regulatory adjustments.
- Strategic foresight: Both methodologies may be utilized to plan future landscapes, workforce development strategy, and scenarios on future employment trends, providing valuable tools for strategic long-term planning.

III. DISCUSSION

The intersection of human Labour and artificial intelligence/machine learning (AI/ML) systems is among the most profound changes in modern economic history. The theoretical models developed in this research—the Displacement–Augmentation Continuum (DAC) and the Sectoral Impact and Resilience Model (SIRM)—offer an extensive and multifaceted foundation for understanding and managing this change.

➢ *Reconsidering Labour in the Age of Intelligent Systems*

DAC is in direct opposition to the standard narrative of automation-induced job displacement. Instead of depicting AI/ML as a phenomenon leading to outright job replacement, DAC emphasizes that AI/ML propels a task-level restructuring in which human tasks are reassigned instead of eliminated. This continuum posits several key observations:

- Most jobs evolve, rather than vanish—the nature of human work adapts, with a shift in emphasis to tasks engaging higher-level cognitive faculties.
- Human value lies increasingly in judgment, ethics, empathy, and creativity, in which AI/ML is not yet capable of full autonomy.
- Technological disruption needs to be viewed as a transition, rather than a destination; disruption is a process that opens up new potential for human agency, especially in non-routine tasks.

These results suggest that the future of work is not post-human, but post-mechanical—redefining human work in terms of creativity, ethical decision-making, and problem-solving of complicated problems, rather than routine, repetitive tasks.

➢ *Sectoral Responses and Vulnerabilities*

The SIRM model develops this argument by showing that AI/ML's impact on sectors is unevenly distributed. It illustrates the following:

- Resilience is multi-dimensional: It is not just technological resilience that sectors need to withstand disruptions, but also institutional and cultural resilience.
- Disruption zones threaten utter economic displacement unless there are concerted, sector-specific policy responses.
- Innovation districts hold the promise of policy experimentation, i.e., universal learning credits or adaptive regulation, that can shelter vulnerable sectors while enabling innovation.

The model emphasizes the necessity of selective policy actions rather than a pan-cyclic strategy. Policymakers must react to interventions in terms of sectoral conditions, combining investment in technological innovation with protection for exposed workers and labour market reforms.

➢ *Ethical and Existential Implications*

Apart from workforce planning, the DAC and SIRM models also present essential philosophical as well as ethical challenges:

- What does it mean to labour in a world where machines are able to "think"? This question challenges our most basic assumptions regarding work, purpose, and identity in the AI era.
- How do we preserve dignity, purpose, and autonomy in technologically advanced Labour systems? The increased integration of AI has pushed worker alienation and autonomy issues to the fore.
- Can we ensure that AI serves all sections of society, and particularly the most vulnerable, without exacerbating existing inequalities?

The DAC model indirectly suggests that AI innovation should embrace value-sensitive design wherein systems are developed with human flourishing and well-being at their core. Similarly, the SIRM model underscores that ethical governance, and social inclusion must be prioritized, particularly in domains that are susceptible to rising inequality or exclusion.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25sep1465

➢ *Contribution to Scholarship and Practice*

This research adds in the following notable ways to scholarship and policy design:

- New conceptual frameworks that integrate task-based and sectoral approaches, producing a more refined understanding of AI/ML impacts on work.
- Cross-disciplinary synthesis, bringing together the evidence of labour economics, AI ethics, public policy, and futures research.
- Actionable policy suggestions for governments, educators, unions, and employers, including guidance on how to steer through the AI/ML transition and future-proof against labour market shocks.

In summary, DAC and SIRM offer a paradigm shift in how we think about the impact of AI on work. Rather than depicting AI as a threat to the presence of work, these models view AI as a structural mirror, reflecting the social decisions we are making regarding the future of work, organisation of labour, and human–machine collaboration.

IV. CONCLUSION AND STRATEGIC RECOMMENDATIONS

➢ *Conclusion*

With AI and ML technologies swamping the world's job markets, human work is experiencing complex, non-linear transformations. Two integrative frameworks employed in this study—the Displacement–Augmentation Continuum (DAC) and the Sectoral Impact and Resilience Model (SIRM)—together overcome simplistic, dualistic narratives of automation. DAC maps the evolution of work from open displacement to phased expansion, and finally to full human–machine symbiosis, while SIRM positions industries on an active grid of impact intensity and adjusting capacity. Both models demonstrate that AI/ML's ultimate effect on work is neither predetermined nor linear but is mediated by policy choices, institutional adaptability, workforce skills, and moral engineering. By combining micro- and macro-perspectives, this research formulates a policy-relevant theory for labour transformation in the intelligent-systems era.

➢ *Strategic Recommendations*

To translate these findings into practice, we propose five targeted measures:

- *Redefine Workforce Development*

✓ Align reskilling on the DAC continuum with an emphasis on cognitive flexibility, adaptive learning, and high-level socio-emotional skills.
✓ Embed lifelong learning in education and company training, utilizing micro-credentials tied to new task profiles.

- *Deploy Sectoral Diagnostics via SIRM*

✓ Plot sectors to chart high-risk "Vulnerable Disruption Zones" and high-opportunity "Transformative Innovation Zones."
✓ Trigger investments in digital infrastructure, R&D, and labour mobility for low-resilience sectors. – Pilot regulatory sandboxes in innovation districts to accelerate safe experimentation.

- *Institutionalize Ethical AI Governance*

✓ Impose transparency and accountability on AI development, including value-sensitive design principles.
✓ Safeguard workers from digital precarity, surveillance, and algorithmic bias through enforceable rights and standards.

- *Foster Cross-Sectoral Policy Coordination*

✓ Establish national AI adaptation councils that convene labour, technology, education, and industry interests.
✓ Develop future-of-work observatories to monitor trends, evaluate interventions, and exchange best practices.

- *Promote Research, Discussion, and Scenario Planning*

✓ Empirically test DAC and SIRM across different economies, occupations, and institutions.
✓ Conduct multi-stakeholder foresight exercises to stress-test policy directions under other technological trajectories. – Publish open-access toolkits and datasets to catalyze innovation and criticism.

➢ *Constraints and Future Studies*

While DAC and SIRM capture fundamental dynamics of AI/ML-Labour relations, the following limitations require future research:

- Quantitative calibration: Continuum phases and resilience levels' empirical parameterization remains an open issue.
- Heterogeneity of Labour markets: Firm sizes, informal economies, and cultural environments vary across different locations, requiring adaptation of both models.
- Feedback effects: Endogenous responses—e.g., wage hikes or regulatory pushbacks—must be integrated into future model iterations.

Future studies will need to combine large-scale survey data, case studies, and agent-based simulations to build on these frameworks and test their predictive validity across a range of contexts.

Rather than fear the fate of work, societies can take control through conscious policymaking, institutional collaboration, and value-oriented AI development. By placing AI/ML in the role of tools to augment human flourishing—amplifying creativity, dignity, and solidarity—DAC and SIRM stage inclusive, robust, and human-centric futures amidst intelligent systems.

➢ *Implications for Theory, Application, or Policy*

The conceptual models developed in this paper—the Displacement–Augmentation Continuum (DAC) and the Sectoral Impact and Resilience Model (SIRM)—offer three main categories of implications:

- *Implications for Theory*

This work contributes to the theoretical understanding of technology–labour relations by moving beyond binary narratives (e.g., replacement vs. augmentation) and introducing a continuum-based and sector-sensitive framework. The DAC model challenges deterministic framings by capturing the fluidity of labour transitions in the AI era, while the SIRM model contextualises these transitions within organisational and macroeconomic resilience factors. Together, these models offer a multi-scalar lens for analysing sociotechnical change, opening up new directions for conceptual work in labour studies, digital transformation, and socio-technical systems theory.

➢ *Implications for Application*

For practitioners and organisational leaders, these models can serve as diagnostic tools to:

- Assess job roles and sectors based on their position along the DAC,
- Identify workforce exposure and readiness to AI augmentation or displacement,
- Guide strategic responses such as re-skilling, organisational redesign, and investment in resilience-building mechanisms.

By visualising impact trajectories, the models assist in scenario planning and strategic workforce adaptation, especially in sectors where digital disruption is unevenly distributed.

➢ *Implications for Policy*

The framework underscores the need for nuanced, sector-specific policy responses to AI-induced labour transformation. Rather than blanket approaches to automation or digital literacy, policymakers can:

- Support resilience-building in vulnerable sectors, especially in the Global South;
- Develop targeted upskilling and safety-net interventions based on SIRM's resilience axes;
- Inform ethical and inclusive AI governance that incorporates social and labour dimensions, not just technical or economic efficiency.

This paper thus advocates for an integrated policy approach that recognises technological, organisational, and human variables as interconnected pillars in navigating the AI era.

➢ *Authors' Notes on Prior PublicationsS*

This manuscript is original, unpublished, and not under consideration elsewhere. The models introduced were developed by the author and have not appeared in prior publications. No funding or institutional affiliations supported this work.

ACKNOWLEDGMENTS

The author thanks colleagues and independent reviewers who provided critical feedback on earlier drafts of this work. Gratitude is extended to the broader research community in AI, labour policy, and digital ethics whose scholarship made this synthesis possible.

All correspondence should be addressed to Name: Vusi S. Mncube, Affiliation: Dr V S Mncube Foundation NPC, Address: 5th Floor, 27 Owl Street, Milpark, Johannesburg, 2001, South Africa, ORCID 0009-0008-0854-2062

➢ *Author Biography*

Dr. V.S. Mncube is a business executive, researcher, and thought leader with expertise in financial services, IT, and community development. He has led transformative projects, published in both business and theology, and mentors future leaders. Holding multiple advanced degrees, he contributes globally as a speaker, policy adviser, and certified mentor with Oxford Brookes University.

REFERENCES

[1]. Adams, R. (2021). Can artificial intelligence be decolonized? *Interdisciplinary Science Reviews, 46*(1–2), 176–197. https://doi.org/10.1080/03080188.2020.1840225
[2]. Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review, 108*(6), 1488–1542. https://doi.org/10.1257/aer.20160483
[3]. Acemoglu, D., & Restrepo, P. (2020). Automation and the economy. *Journal of Economic Perspectives, 34*(3), 3–30. https://doi.org/10.1257/jep.34.3.3
[4]. Arntz, M., Gregory, T., & Zierahn, U. (2016). The risk of automation for jobs in OECD countries: A comparative analysis. *OECD Social, Employment and Migration Working Papers, 189*. https://doi.org/10.1787/5jlz9h56dvq7-en
[5]. Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives, 29*(3), 3–30. https://doi.org/10.1257/jep.29.3.3
[6]. Ayana, G., Dese, K., Nemomssa, H. D., Habtamu, B., Mellado, B., Badu, K., ... Kong, J. D. (2024). Decolonizing global AI governance: Assessment of the state of decolonized AI governance in Sub-Saharan Africa. *Royal Society Open Science, 11*(8), 231994. https://doi.org/10.1098/rsos.231994
[7]. Bessen, J. E. (2019). AI and jobs: The role of demand. *NBER Working Paper No. 24235*. https://doi.org/10.3386/w24235
[8]. Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.
[9]. Brynjolfsson, E., Rock, D., & Syverson, C. (2018). Artificial intelligence and the modern productivity paradox. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda*

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25sep1465

(pp. 23–57). University of Chicago Press. https://doi.org/10.7208/chicago/9780226583926.003.0002
[10]. Chiacchio, F., Petropoulos, G., & Pichler, D. (2018). Estimating the exposure of occupations to automation: A task-approach. *European Economic Review, 108*, 114–147. https://doi.org/10.1016/j.euroecorev.2018.06.001
[11]. Chiacchio, F., Petropoulos, G., & Pichler, D. (2021). Sectoral task risk and automation. *Journal of Industrial Economics, 69*(1), 1–33. https://doi.org/10.1111/joie.12247
[12]. Chui, M., Manyika, J., & Miremadi, M. (2016). Where machines could replace humans—and where they can't (yet). *McKinsey Quarterly*. https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/where-machines-could-replace-humans-and-where-they-cant-yet
[13]. Danso, W. B., & Hanson, E. (2023). Artificial intelligence disruption and its impacts on future employment in Africa: A case of the banking and financial sector in Ghana. *Journal of Social Economics, 18*(1), 20082. https://doi.org/10.26634/jse.18.1.20082
[14]. De Stefano, V. (2015). The rise of the just-in-time workforce: On-demand work, crowdwork, and Labour protection in the gig economy. *Comparative Labour Law & Policy Journal, 37*(3), 471–504. https://doi.org/10.2139/ssrn.2591155
[15]. De Stefano, V. (2016). Platform work: Uber, taxi drivers, and algorithmic control. *European Journal of International Law, 27*(2), 285–303. https://doi.org/10.1093/ejil/chw020
[16]. European Parliamentary Research Service. (2023). *Artificial intelligence and future of work: Study*. https://www.europarl.europa.eu/thinktank/en/document/EPRS_STU(2023)739206
[17]. Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerization? *Technological Forecasting and Social Change, 114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019
[18]. Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics, 4*, 1–23. https://doi.org/10.1146/annurev.es.04.110173.000245
[19]. International Labour Organisation. (2019). *Skills for a greener future: A global view*. https://www.ilo.org/global/publications/books/WCMS_724412/lang--en/index.htm
[20]. International Labour Organisation. (2021). *World employment and social outlook 2021: The role of digital labour platforms in transforming the world of work*. https://www.ilo.org/global/research/global-reports/weso/2021/WCMS_767763/lang--en/index.htm
[21]. Jabareen, Y. (2009). Building a conceptual framework: Philosophy, definitions, and procedure. *International Journal of Qualitative Methods, 8*(4), 49–62. https://doi.org/10.1177/160940690900800406
[22]. Manyika, J., Chui, M., Miremadi, M., Bughin, J., George, K., Willmott, P., & Dewhurst, M. (2017). *A future that works: Automation, employment, and productivity*. McKinsey Global Institute.
[23]. Mollema, T. (2024). Decolonial AI as disenclosure. *Open Journal of Social Sciences, 12*(2), 574–603. https://doi.org/10.4236/jss.2024.122032
[24]. Organisation for Economic Co-operation and Development. (2019). *OECD skills for jobs 2019*. OECD Publishing. https://doi.org/10.1787/9ee00155-en
[25]. Organisation for Economic Co-operation and Development. (2020). *OECD skills for jobs 2020*. OECD Publishing. https://doi.org/10.1787/2b8ef9d6-en
[26]. Omotubora, A., & Basu, S. (2024). Decoding and reimagining AI governance beyond colonial shadows. In *Handbook on public policy and artificial intelligence* (1st ed., chap. 17). Edward Elgar. https://doi.org/10.4337/9781803922171.00025
[27]. Susskind, R. (2020). *A world without work: Technology, automation, and how we should respond*. Metropolitan Books.
[28]. Trist, E. L. (1981). The concept of sociotechnical systems. In A. M. van de Ven & W. F. Joyce (Eds.), *Perspectives on Organisation design and behavior* (pp. 19–75). Wiley.
[29]. United Nations Development Programme. (2022). *Human development report 2022: Uncertain times, unsettled lives: Shaping our future in a transforming world*. https://hdr.undp.org/en/2022-report
[30]. United Nations Conference on Trade and Development. (2021). *Digital economy report 2021*. https://unctad.org/webflyer/digital-economy-report-2021
[31]. World Bank. (2023). *World development report 2023: Migration and development*. https://doi.org/10.1596/978-1-4648-1719-2
[32]. World Economic Forum. (2018). *The future of jobs report 2018*. https://www.weforum.org/reports/the-future-of-jobs-report-2018
[33]. World Economic Forum. (2020). *The future of jobs report 2020*. https://www.weforum.org/reports/the-future-of-jobs-report-2020
[34]. Wood, A. J., Graham, M., Lehdonvirta, V., & Hjorth, I. (2019). Good gig, bad gig: Autonomy and algorithmic control in the global gig economy. *Work, Employment and Society, 33*(1), 56–75. https://doi.org/10.1177/0950017018785616