The Impact of AI Machine Learning on Human Labor in the Workplace: A Systematic Review of Emerging Trends, Challenges, and Opportunities

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Abstract: As the world continues to witness advancements in Artificial Intelligence (AI) and Machine Learning (ML) technologies, global effects on the job market start to be dramatically realized. This systematic review consolidates empirical as well as theoretical literatures to examine how AI/ML reshapes human work across industries-adhering to emerging trends, structural issues, and emerging opportunities. Based on insights from peer-reviewed articles, industry reports, and empirical research, the study reveals a two-way dynamic of displacement and augmentation: as automation disproportionately impacts routine and low-skilled jobs, AI is simultaneously augmenting professional work and enabling new forms of labor such as gig work and human-AI collaboration. Main challenges include skills polarization, digital inequality, and psychosocial stress, especially in developing regions with inadequate digital infrastructure. Conversely, the review identifies paths of innovation, reskilling, and entrepreneurship empowerment via AI. The study integrates several theoretical frameworks—Technological Determinism, Socio-Technical Systems Theory, and Skill-Biased Technological Change—to conceptualize these innovations. Furthermore, two conceptual models—the AI/ML-Driven Labor Market Transformation Model and the Sectoral Impact and Resilience Model—are introduced to illustrate labor transformation across sectors and skill levels. The review concludes by suggesting a framework for future research, policymaking, and employment adaptation policies for the AI age.

Keywords: *Artificial Intelligence (AI), Machine Learning (ML), Human Labor, Skills Gap, Displacement, Inequality.*

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I. INTRODUCTION

The modern workplace is vulnerable to core changes with the constantly increasing pace of technological progress, namely Artificial Intelligence (AI) and Machine Learning (ML). These developments have contributed to enhanced productivity and efficiency in decision-making and process optimization (Brynjolfsson & McAfee, 2014). But as the future of AI/ML lies in greater efficiency and innovation, their larger entry into the labor force is also a reason for disruption, fueling concerns about job displacement, skill obsolescence, and long-run sustainability of human-dependent employment (Chui et al., 2016; Frey & Osborne, 2017).

The pace of technological change is now outpacing the capability of the labor force to adapt, leading to structural unemployment, skills mismatch, and new socio-economic inequalities. As the OECD (2021) points out, the emergence of AI not only will displace jobs but also redefine required skill sets, changing the fundamental nature of work itself. As Sytsma and Sousa (2023) also observe, such developments have far-reaching implications for workforce planning and inclusive policy design.

This systematic review examines the complex impact of AI and ML on human labor in the work environment by uncovering principal trends, analyzing workforce challenges, and unveiling new job and skills development prospects. Acknowledging the uneven distribution of technological impact, the study investigates both global and regional experiences with specific interest in Africa, where structural labor vulnerabilities, youth-dominant populations, and infrastructural shortcomings interact with the AI revolution in unique ways.

To support more holistic analysis, this study introduces two new conceptual frameworks: the Displacement–Augmentation Continuum (DAC), outlining the evolving human work–machine system interplay; and the Sectoral Impact and Resilience Model (SIRM), enabling sector-

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specific exposure, adaptability, and long-term resilience to AI-induced developments. The models provide theoretical support for understanding heterogeneous impacts of AI/ML on labor ecosystems.

In addition, this review is grounded in underlying theoretical paradigms such as Technological Determinism, Socio-Technical Systems Theory, and Skill-Biased Technological Change that enable closer inspection of the manner in which intelligent systems reshape labor institutions, workers' identity, and socio-economic equality. The study relies on a systematic literature review for the period 2015-2025, and exclusively on the work-related dimensions of AI/ML adoption across both advanced and emerging economies. Technical applications outside the scope of human labor transformation are excluded.

The findings provide actionable knowledge to policymakers, labor unions, educators, and researchers interested in managing the future of work amidst a period of intelligent automation.

II. LITERATURE REVIEW

Artificial Intelligence (AI) and Machine Learning (ML) have increasingly been at the forefront of workplace transformation, affecting job design, labor needs, and skills development across numerous industries. Current studies recognize how AI adoption is transforming labor relations and calls for a better understanding of the beneficial, in addition to adverse, effects (Lane & Saint-Martin, 2021; Mäkelä & Stephany, 2024).

Several studies have examined the effect of these technologies on the labor market in various countries. For instance, the study of AI and ML's effect on workforce skills and economic mobility in Nigeria and Ghana by Muhammad et al. (2023) discovered a shift in demand to complementary skills, creating a skills gap exacerbated by the educational systems lagging behind rapid technological advancements. Mäkelä & Stephany (2024), after analyzing 12 million U.S. jobs between 2018 and 2023, discovered that the demand for substitute skills such as customer service had declined while AI-complementary skills like digital literacy had increased. Eloundou et al. (2023), in their study evaluating the large language models (LLMs) in the U.S. labor market, found that about 80 percent of the workforce had at least one of their tasks affected, with 19% having over 50% of their tasks impacted. With technological advancements occurring rapidly and constantly, including the envisioned machine learning, more impact is likely to be seen on the labor market in the future, requiring effective responses from industry leaders and policymakers. This literature review mainly encompasses conceptual and theoretical frameworks applicable to this study, as well as emerging trends in this space, including related challenges and opportunities.

➢ *Clarifying Basic Constructs: Operationalizing Key Concepts in the Conceptual Framework*

- *Artificial Intelligence (AI)*

Kühl et al. (2021) tell us that Artificial Intelligence (AI) started to begin in the year 1956 at the Dartmouth Conference when John McCarthy first used the term "Artificial Intelligence" to start considering it as an area of work. McCarthy (1956) defined AI at that time as engineering and science aimed at creating intelligent machines. Undeniably, AI has evolved since the decades after the mid-20th century to be the interdisciplinary and core discipline it stands today in technology and research, particularly in areas such as information systems (Lindner, 2022; Kühl et al. (2021).

Artificial Intelligence (AI) has evolved over the years to be understood as the simulation of human intelligence in machines (Russell & Norvig, 2020). de Zúñiga et al. (2024) provide an academic definition of AI in their publication as the material everyday ability of non-biological equipment to carry out work, address problems, communicate, interact, and behave reasonably, as is done by biological human beings. In their theoretical framework, de Zúñiga et al. (2024), propose two dimensions, namely the level of performance (performing tasks, making decisions, and making predictions), and the level of autonomy (the level of human input, interaction, or supervision involved). These dimensions suggest a certain level of interaction between the machine and human beings to potentially alleviate possible biases among other issues. Dobrev (2012) argues that the so-called “intelligence” should not be equated with knowledge, suggesting that even a newborn can be considered an intellect. This highlights the necessity for the machines to be guided by human beings who are likely to be more informed than the machines, even with the machine's ability to learn.

Various researchers have presented different definitions of AI, to a great extent based on their focus and discipline. But there is a general sense that AI means machines performing tasks that otherwise would require human intelligence, like learning, reasoning, problem-solving, etc. There is also a general growing acknowledgment that AI technology can involve autonomy where machines operate independently with limited human intervention. However, despite this agreement among scholars, there is no single universal definition of AI for various reasons. Initially, the multi-disciplinary origin of researchers suggests that they dissect AI to bring into relief numerous facets depending on the area of specialization. McCarthy (1956) perceived AI, for example, as engineering and science aimed at making intelligent machines and explicitly marked it from the engineering angle. On the contrary, Russell and Norvig (2021) also observe that AI can be described as thinking and acting humanly and thinking or acting rationally and conceivably forming this definition through a human psychological viewpoint. Second, just like AI capability and technology is on the increase, so is its definition in light of how the scholars' view of it may change. For example, de Zúñiga et al. (2024) AI definition is centered on "what the machine does nowadays," i.e., "the concrete real-world ability of non-human machines. to execute tasks, solve

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problems, communicate, interact, and act logically like people." Thirdly, some definitions will likely be utilitarian in nature, while others will tend to be philosophical depending on scholars. For instance, theorists and philosophers may assume that AI is human intelligence or consciousness or human thinking, while engineers and technical businesspeople can affirm that AI is systems doing something in a particular manner and efficiently adaptively, which is a pragmatic view. Finally, some definitions of AI might be too sweeping and broad, e.g., AGI, while others are very narrow and task-oriented, e.g., chatbots, image recognition, etc.

- *Machine Learning (ML)*

Machine Learning (ML) is generally regarded as an AI subcategory where machines are trained on data patterns without explicit programming (Goodfellow et al., 2016). The ML was invented as far back as 1950 by Alan Turing who posed a research question: could machines think? This sparked an interest that led to further work by Samuel (1959), creating the first ML algorithm through a checkers game. This exercise resulted in developing what has generally been considered as a universal definition of ML, although there have been different reiterations over the years based on its evolution and the disciplines of various scholars. Samuel (1959) defined ML as the capacity of computers to learn without being explicitly programmed, focusing on adaptive algorithms. The diagram below presents the timeline of the scholarly evolution of ML as a subset of AI over the years:

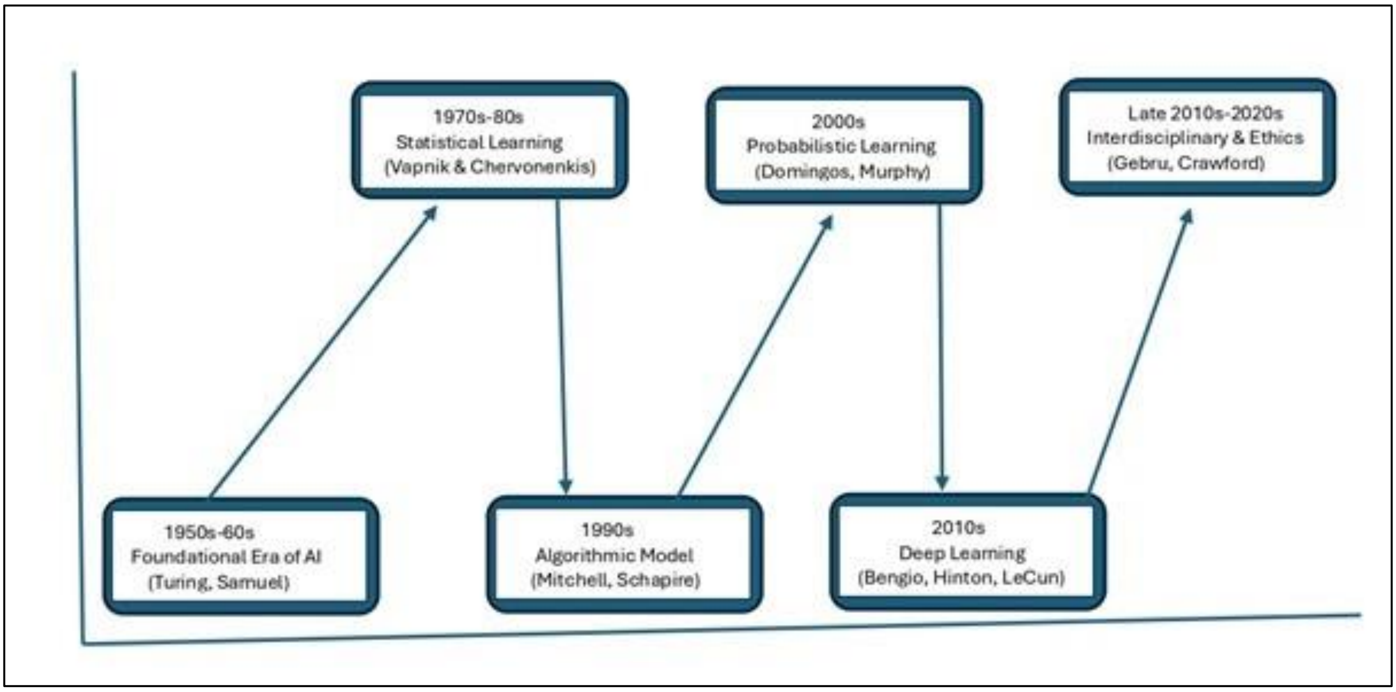

Fig 1 Evolution of Machine Learning: A Scholarly Perspective

- ✓ *Description of the Diagram 1 - Evolution of Machine Learning: A Scholarly Perspective*

Machine Learning (ML) evolved from a niche artificial intelligence subfield to a global, multidisciplinary leader of multiple industries such as healthcare, finance, education, transportation, and creative arts. Its scholarly development echoes changes in computational paradigms, data availability, and society's progressively more complex problems.

- ✓ *Foundational Era: Symbolic AI and Learning by Rules (1950s–1960s)*

The roots of ML trace their origins back to early AI studies to simulate human thought. Alan Turing's (1950) proposal of machine intelligence provided the philosophical basis. The initial ML program, designed by Arthur Samuel (1959), was taught to play checkers through experience — establishing the principle of learning from data.

- ✓ *Statistical Foundations and Pattern Recognition (1970s–1980s)*

Scholars incorporated probability theory and statistics into learning algorithms. Vapnik & Chervonenkis developed VC-dimension, mathematizing ML generalization theory. Decision trees and nearest neighbors models appeared. The Algorithmic Revolution and Theoretical Maturity (1990s) ML became a distinct academic discipline, emphasizing algorithm efficiency and theoretical performance. Mitchell (1997) formalized ML as improvement from experience. Methods such as SVMs and boosting became popular.

- ✓ *Data Explosion and Probabilistic Learning (2000s)*

The web and information explosion propelled ML to large-scale, probabilistic models. Murphy (2012) emphasized learning under uncertainty. Domingos (2012) outlined five paradigms of ML styles, advocating unification. Deep Learning and Computational Breakthroughs (2010s) Neural networks, motivated by GPU computing, led to image and

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speech recognition breakthroughs. LeCun et al. (2015) outlined the fundamentals of deep learning.

✓ *Interdisciplinary Expansion and Ethical Reflections (Late 2010s–2020s)*

ML's scope stoked concerns about fairness, and transparency as well as human implications. Scholars like Gebru et al. (2018) and Crawford (2021) advocated for ethical AI and prudent innovation.

The definition of ML has mainly developed based on the above-explained evolution of research and models in this regard. There are several other studies that have provided definitions of ML. For instance, Zhang and Zhou (2017) explore how ML has been used to extract meaningful patterns from complex and large amounts of data, forming a core of intelligent systems. The processing of data is seen as critical to enable effective learning of the machines, as argued by Halevy et al. (2009) that for many tasks effective ML occurs when simple algorithms with massive data are used compared to complex algorithms with less data. They insist that the former outperforms the latter in this regard. Generally, as far as the definition of ML is concerned, most scholars agree that it is about systems that improve performance through experience, basically involving learning from data. The essence of this notion was captured by Mitchell (1997) who highlighted that "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E." This definition has been widely quoted, probably because it has been regarded as clear, practical, and general, forming the basis of the understanding of the ML process in today's context. It must be noted, though that scholars have presented different definitions based on their various perspectives and priorities. For example, Mitchell (1997) emphasizes task performance improvement from experience, while Bishop (2006) highlights probabilistic models and inference, and LeCun et al. (2015) emphasize deep representative learning, etc. It might be argued that these scholars are talking about the same "elephant" but describing different parts based on their academic lens.

- *Automation*

Autor (2015) defines automation as the application of machines to perform work without the involvement of humans. This has been identified as a major threat, especially for low-skill and mundane jobs, which automation has been replacing over the past few years and is likely to render some skills obsolete, resulting in economic exclusion for a large segment of workers. Frey and Osborne (2017) in their study highlight that about 47% of US jobs are at high risk of being automated, especially as machine learning evolution continues. Contrary to this finding, Arntz et al. (2016) suggest that only 9% of jobs across OECD countries are automatable because of task variety within occupations, arguing that task-based analysis offers a more nuanced view than occupation-level analysis. However, there is general agreement among many scholars globally that automation will have dire consequences for low-skill jobs, as noted in studies such as Acemoglu and Restrepo (2020), Brynjolfsson and McAfee (2014), Bessen (2019), Manyika and Miremadi (2016), Marguerit (2025), etc. Ozgul et al. (2024) indicate that high-skilled workers performing analytical, non-routine tasks are increasingly vulnerable to automation. This suggests that even at high-skill levels, certain occupations remain vulnerable to automation. However, Marguerit (2025) argues that augmenting AI correlates with positive wage effects and job creation, especially for high-skilled sectors. It must be noted that while automation brings risks in terms of displacements, most studies have hailed the business benefits associated with it in terms of productivity and efficiency, calling for interventions to be put in place to address the challenges that accompany it. The studies include Zhang and Tao (2024), Kumara et al. (2024), World Economic Forum (2022), Akhtar (2024), Zhang and Zhang (2024), and Zhang and Wang (2024).

- *Human Labor – Nature of Human Work in the AI and Machine Learning Age*

The very character of human work has undergone a radical shift from mechanical and repetitive to cognitive and creative higher-level work. In the AI and ML times, the transformation raises critical concerns about the character, value, and fate of human work. Labor in the past has been more than an economic role; it is a defining part of identity, social interaction, and meaning (Arendt, 1958). The integration of smart systems into the workplace negates this foundation, particularly as machines become more competent at tasks traditionally tied to human beings. With AI and ML systems dominating routine work and decision-making positions, human labor is being transformed into the line of complementarity and substitution. On the one side, intelligent systems can enhance productivity in labor and liberate human beings from repetitive tasks so that labor can be diverted to more important or higher-value activities (Brynjolfsson & McAfee, 2014). On the other side, displacement of workers, particularly those with middle-skill jobs—gives rise to anxieties regarding joblessness, underemployment, and the degrading of enormous chunks of the labor force (Autor, 2015). Moreover, the philosophical dimension of labor in a post-AI future cannot be ignored. With intelligent machines assuming increasing amounts of work without human input, concerns are raised regarding the social arrangements centered on wage labor, i.e., access to wages, social mobility, and personal satisfaction. This recalls Marxist critiques, where alienation and exploitation may be worsened, not merely by capitalist modes, but by algorithmic surveillance and control (Srnicek & Williams, 2015). Second, the concept of "human-in-the-loop" systems grasps a hybrid model where labor is reorganized more than it is displaced. Human judgment is still supreme here, most obviously in such domains as healthcare, education, and law. Yet even in these fields, the compulsion to adapt to data-driven work processes can erode the independence and discretion with which expert labor has traditionally been invested (Susskind & Susskind, 2015).

Briefly, the meaning of human labor in the AI/ML era is not static but dynamic; neither is it irrelevant nor antiquated. What the future is for work remains in the balance based on how societies, institutions, and people manage changing

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frontiers between machines and human abilities. There needs to be emphasis on human-centered design, equitable access to reskilling, and wise regulation of work-augmenting technologies.

➢ *Regional Perspectives: The Case of African Labor Markets in the Age of AI*

While the international discourse around AI and ML in the workplace generally concerns developed economies, there is a unique convergence of opportunity and challenge in Africa. The continent is open to both the risk of losing jobs through automation and the potential of bypassing the old industrial process through digital revolution.

Labor markets in the majority of African countries are characterized by widespread informality, limited access to digital infrastructure, and a large youth population. These are the factors that determine the impact of AI adoption on employment. For example, whereas AI can automate routine clerical tasks in formal economies, in Africa it can destabilize informal service work or accelerate digitization in agriculture, health, and education through mobile-based solutions (World Bank, 2021).

Furthermore, Africa's demographic dividend, possibly the world's largest workforce—desperately requires digital capabilities and education systems to adapt to AI-age standards. Failure of proactive policy could exacerbate existing inequalities. Nevertheless, interventions for specific aims, such as Kenya's AI-enabled diagnostics for health or Nigeria's AI-enabled monitoring for agriculture, are instances of utilizing the technology for solving local challenges while creating new forms of employment (UNDP, 2023). The African case highlights the imperative of policy, infrastructure, and inclusive innovation.

In the evolution of AI and ML, the future of work in the continent will be built on technologically guided strategic alignment with human capital development fueled by equity, resilience, and sensibility to context.

➢ *Conceptual Framework: The AI/ML-Driven Labor Market Transformation*

This conceptual framework illustrates how AI/ML technologies shape labor market dynamics, illustrating the interactions between AI adoption, skill demand, job displacement, and policy response.

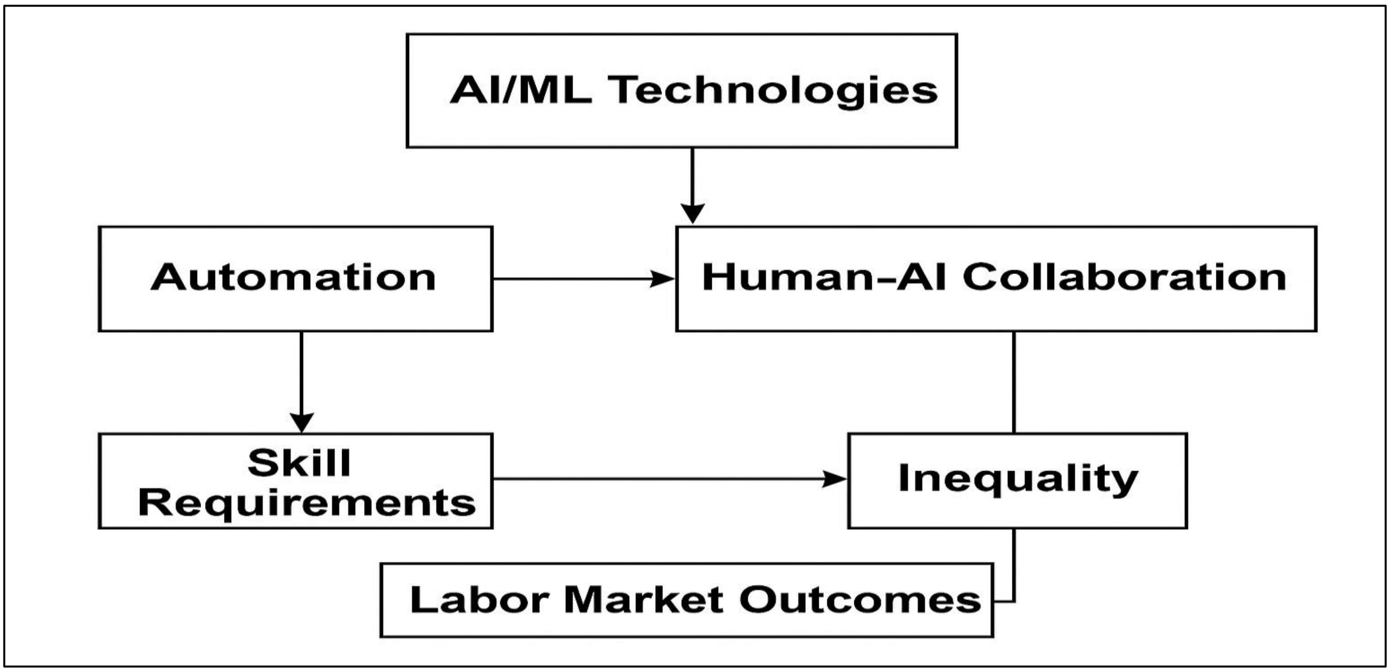

Fig 2 AI/ML-Driven Labor Market Transformation Model

- *Conceptual Model Description*

This theoretical framework illustrates the multi-dimensional influences of AI and machine learning (AI/ML) technologies on labor market outcomes. In the middle, the framework positions AI/ML Technologies as the principal driver, separating into two primary channels: Automation and Human–AI Collaboration.

✓ Automation provokes Skill Requirements change, making some skills redundant and introducing new ones.
✓ The change of the skills setting has an immediate effect on Labor Market Outcomes, on the level of employment, the quality of employment, and on remuneration.
✓ While doing so, Human–AI Collaboration seems to have a complementary force, re-inventing work procedures and creating novel hybrid jobs. However, this transition can also reinforce inequality if access to upskilling and retraining is uneven.
✓ Skill Requirements and Inequality separately and in combination affect final Labor Market Outcomes, highlighting the complex interplay of technology, worker skills, and social equity.

This model provides a unifying lens through which to consider the socioeconomic ripple effects of intelligent

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systems, observing the double-edged sword of disruption and opportunity in the future of work.

Finally, the entire system is embedded within the broader local context of a specific region e.g. African Context, which includes infrastructural capacity, education systems, degrees of economic development, and sociopolitical conditions. These context factors play an essential role in determining how ML impacts labor and determine the ability for adaptive strategies to flourish.

➢ *Theoretical Background*

The multifaceted and dynamic impact of artificial intelligence (AI) and machine learning (ML) on human work has to be accounted for with a solid theoretical base. This review adopts a multi-theoretical framework bringing together Technological Determinism, Socio-Technical Systems Theory, and Skill-Biased Technological Change (SBTC). Together, these theories provide an integrated overview of the drivers, mediators, and implications of AI/ML adoption in the work setting.

- *Technological Determinism*

Technological Determinism posits that technological change is the primary force behind social and structural change (Smith & Marx, 1994). In AI and ML, the theory focuses on the way intelligent systems are now regarded as autonomous entities that shape labor markets, break up traditional employment relationships, and reconfigure human work roles in the workplace. Smith and Marx (1994) argue that technology has an autonomous course of development regardless of social control, thereby creating revolutionary change in economic and institutional systems. Determinist in its outlook is also the work of Winner (1986), who opines that technologies possess inherent political and social features that influence power structures and organizational hierarchies.

- *Socio-Technical Systems Theory*

While Technological Determinism suggests one-way technological influence, Socio-Technical Systems Theory focuses on a two-way approach that recognizes the mutual influence between technical and human components in organizational settings (Trist, 1981). In this theory, optimum workplace performance is not brought about by technological innovation but by optimizing both social systems (for instance, people, communication, values) and technical systems (for instance, tools, procedures, algorithms) simultaneously. Appelbaum (1997) points out that successful integration of AI/ML in the workplace depends on human adaptability, cooperative design, and context fit. The model is particularly useful in understanding the failures of integration as well as symbiotic possibilities of human-AI systems.

- *Skill-Biased Technological Change (SBTC)*

Skill-Biased Technological Change (SBTC) presents an economics of labor perspective, one which focuses on technological progress's role in shaping the incidence of skills and wages within the labor market. Emerging technologies, Acemoglu and Autor (2011) argue, will supplement high-skilled labor (e.g., analytical, creative, and managerial tasks) but replace routine, manual, or low-skill work. This creates increasing demand and pay for high-skilled labor, reestablishing labor market polarization and inequality. The latest research introduces an added layer of complexity to the theory, that the ever-evolving developments in AI can one day start replacing some of the higher-skill cognitive tasks in the near future, thus challenging the classical SBTC paradigm in new words (Bloom et al., 2023).

- *Critical Evaluation of the Theoretical Framework*

While Technological Determinism offers a compelling macro-level view of the role of technology in bringing about change in society, it has been faulted for simplifying human agency and institutional mediation (Wyatt, 2008). In characterizing technology as an autonomous force, it risks adopting a deterministic stance that dismisses socio-political forces in favor of considering design and deployment of technology. Socio-Technical Systems Theory fills this lacuna by pointing to co-construction of technology and society. But its application at work can be complex, requiring complex knowledge of organizational behavior and thinking about systems—competencies not necessarily inherent in the implementation of workplace technology. Similarly, SBTC provides strong explanatory power for labor market polarization but too frequently is too economically narrow in its analysis, all too often overlooking the cultural and psychological dimensions of technological displacement. Considered alone, no single theory alone gives us a complete picture, yet together they comprise a multidimensional system that accounts for the structuring drivers as well as human-mediated processes that shape AI and ML's impact on work.

- *Integrative Perspective*

By integrating these three theories, this systematic review is in a strong position to explore the multifaceted impacts of AI and ML on human work. Technological Determinism accounts for the overall, often disruptive character of technological progress; Socio-Technical Systems Theory clarifies the organizational and human-centered processes of change; and SBTC accounts for the uneven labor market adaptation to technological change. This combined framework offers a richer description of emergent trends, challenges, and opportunities viewed through multiple workplace settings. Additionally, by using these theories in a combined framework, this study is able to leverage the complementary nature of these models in addressing critical perspectives associated with each theory covered by the alternative theory in the combination.

- *Theoretical Framework*

This theoretical model integrates three main theories to guide the analysis of the impact of AI and Machine Learning on human labor in the workplace: Technological Determinism, Socio-Technical Systems Theory, and Skill-Biased Technological Change (SBTC). Each theory provides a different explanation for the transformative impact of AI/ML:

✓ Technological Determinism views AI/ML as macro-level change drivers, explaining technology as a force that

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independently determines transformation in society (Smith & Marx, 1994).

- ✓ Socio-Technical Systems Theory concentrates on the interaction between people and technology within organizational settings and argues that successful outcomes radiate when both systems evolve together (Trist, 1981).
- ✓ Skill-Biased Technological Change (SBTC) focuses on how AI/ML technologies are high-skilled labor-biased and hence contribute to wage inequality and labor force polarization (Acemoglu & Autor, 2011).

The following diagram illustrates how these theories intersect to form the theoretical framework of this systematic review:

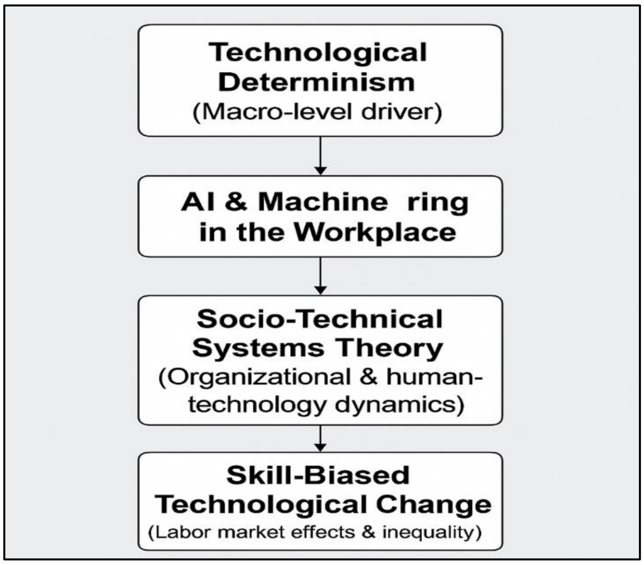

Fig 3 Theoretical Framework

The above diagram illustrates the theoretical process by which technological determinism as a macro driver initiates the implementation of AI and machine learning in modern workplaces. It then uses socio-technical systems theory to elaborate on the interplay between technological and human elements, leading finally to the model of skill-biased technological change, which examines the resultant change in the labor market and inequality.

➢ *Brief Outline of Emerging Trends*

Implementation of AI and ML in the organization is a double sword—carrying the promise of enhanced productivity and innovation but also with risks of job displacement, inequality, and disruption to the workforce. The literature continues to highlight the imperative of workers being provided with complementary capabilities and a culture of adaptability (Eloundou et al., 2023; Mäkelä & Stephany, 2024). Addressing the ethical, social, and practical concerns of AI implementation will be necessary to ensure an inclusive, equitable, and sustainable future of work.

- *Workforce Adaptation and Skill Transformation*

The widespread application of AI throughout business processes has called for employees to acquire new skill sets. Data analysis, AI literacy, and coding are highly required technical skills, with growing emphasis on soft skills such as flexibility, creativeness, and moral thinking (Mäkelä & Stephany, 2024; Hussain, 2023). In the opinion of Lane and Saint-Martin (2021), AI does not eliminate the need for human labor but changes it, building a demand for occupations that supplement smart systems.

- *Human-AI Collaboration*

Contrary to worry about job replacement through AI, research shows that AI typically becomes a complementary function and not a replacement. Brynjolfsson et al. (2023) demonstrated the ways in which generative AI systems can benefit workers by advancing their performance, especially for lower-skilled labor, by advancing productivity and accelerating on-the-job learning. All such trends apply to other functions as well, reflecting AI as an augmenting factor that adds to human judgment (Sytsma & Sousa, 2023).

- *Problems of AI and ML*

Job displacement and inequality are perhaps one of the oldest concerns in AI literature, with mass job displacement being a significant issue. Eloundou et al. (2023) highlight that AI/ML threatens more than 80% of jobs in the United States, with as much as 19% facing more than half of their activities under threat. This disruption could disproportionately affect lesser-skilled labor and further accelerate existing economic and social gaps, particularly if access to training and tools with AI remains unbalanced (Resh et al., 2025; Muhammad et al., 2023).

✓ *Redundancy and Displacement*

Low-skilled workers are most vulnerable to automation, especially in repetitive task domains (Frey & Osborne, 2017). Skill mismatches and obsolescence exist as curricula lag behind necessary AI-age skills (World Economic Forum, 2020). Other issues relate to challenges such as digital inequality, where access to computer resources and AI training is unequal, especially in developing nations (UNDP, 2021). Additional this era also faces regulatory and organizational challenges where governments and slow-to-adopt companies are behind policy adaptation to protect labor and promote virtuous AI utilization (Cath et al., 2018). This tendency exacerbates the negative impact of AI/LM on human labor.

✓ *Quality of Work Life*

New studies also suggest a decline in job satisfaction and happiness due to AI-related monitoring and automation technologies. Psychosocial impacts include job insecurity, loss of identity, and increased stress due to insecure job opportunities (Susskind, 2020). The Institute for the Future of Work (2024) found that performance-monitoring or repetitive-task automation technologies can lead to increased stress, reduced autonomy, and job insecurity. These findings are aligned with broader criticisms of how automation might devalue human work in some occupational groups (The Guardian, 2024).

✓ *Human Challenges in AI*

Integration of human challenges such as resistance to change, technical ineptness, and low trust levels in AI systems are significant barriers to successful AI uptake. Ghasemaghaei et al. (2025) emphasized that there is a need to break these barriers using specialized training programs and improving organizational change management practices.

- *Opportunities of AI and ML*

✓ *Strategic Skill Development*

Scholarly journals highlight the strategic role of training and education in the workforce preparedness for AI adoption. Emphasis on lifelong learning and cross-functional competencies has been seen as key to mitigating risks of job displacement and enabling workers to shift to new roles (Hussain, 2023; Lane & Saint-Martin, 2021). Industry-academia connection has also been recommended towards matching educational curricula to emerging needs in the job market (Mäkelä & Stephany, 2024). Upskilling and Reskilling Public-private partnerships and artificial intelligence-based training platforms are likely to expand the reskilling possibilities (OECD, 2019).

✓ *Improving Human-AI Collaboration*

Successful human-AI collaboration presents promising prospects for workforce improvement. Brynjolfsson et al. (2023) and Resh et al. (2025) advocate for architectures that promote human-AI synergies by including ethics, transparency, and user-centric design in AI systems. Such architectures can be especially successful in careers such as healthcare, legal services, and customer care, where contextual judgment and empathy are still important. Human-AI Joint Work AI doing drudgery work allows humans to focus on imagination, empathy, and critical thinking (Wilson & Daugherty, 2018).

✓ *Other Opportunities*

The other opportunities that are evident with AI and ML include the creation of new job roles like AI trainers, data ethicists, and prompt engineers (Manyika et al., 2017). Additionally, Remote and Flexible Work AI technologies facilitate new flexible work patterns (Brynjolfsson et al., 2020), and Entrepreneurial Enablement AI technologies enable small businesses and startups, democratizing innovation (Cockburn et al., 2018).

III. RESEARCH DESIGN AND METHODOLOGY

This study employs the systematic literature review (SLR) method to investigate the evolving role of Artificial Intelligence (AI) and Machine Learning (ML) in human work in the global workplace. Drawing on an enormous corpus of policy and academic literature, this method allows for the incorporation of significant variables such as skill requirements, automation, labor displacement in the labor market, and policy reactions, all of which are significant in understanding the transformative role of AI/ML in shaping labor trends. The systematic review process is well known for its rigor in finding, evaluating, and synthesizing studies, especially in multifaceted and multidisciplinary topics. Snyder (2019) proposes that the SLR methodology is suitable for condensing existing evidence and determining literature gaps. In addition, the framework presented by Tranfield et al. (2003) emphasizes systematicity, transparency, and replicability, which are basic to the credibility and replicability of this study.

➢ *Data Sources and Search Strategy*

Data collection consisted of an extensive search of prominent research and academic databases like Google Scholar, ResearchGate, Scopus, AJOL (African Journals Online), AOSIS Academic Journals, and other valid international repositories. Boolean operators (AND, OR) and advanced search options were utilized to search for relevant studies. Search terms included but were not restricted to: "AI/ML advancement", "Automation", "AI/ML impact on human labor", "Workforce transformation in the age of AI," and "Human work of the future in the AI/ML era." These terms have been carefully selected to capture a broad range of interdisciplinary literature encompassing both the technology and the wider societal effects of AI/ML.

➢ *Inclusion and Exclusion Criteria*

Inclusion of books from the period 2005-2025 allowed for the incorporation of more recent advances in addition to the historical record. The inclusion criteria were peer-reviewed journal articles, policy briefs, and conference papers focusing on studies on the deployment and development of AI/ML in labor market environments as well as wider socio-economic and ethical concerns literature. Only English-language publications were considered. Conversely, the exclusion criteria were non-empirical sources (e.g., opinion pieces or blog posts), duplicate studies, and literature unrelated to AI/ML's impact on labor. Non-English publications were excluded.

➢ *Review Process and Data Management*

To ensure rigor, the data were screened and selected for this study based on a structured and transparent method aligned with the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines as noted in Page et al. (2021). The process involved a multi-stage selection process: Initial retrieval of 250 sources from the search process; De-duplication using Zotero reference management software; Screening of abstracts and full texts against pre-defined criteria; Final selection of 46 studies deemed relevant for close examination. The screening and selection process was conducted by two reviewers without being involved in deciding each other's to ensure minimal bias and maximize reliability, according to best practice guidelines by Higgins et al. (2022).

➢ *Data Analysis*

The selected literature was examined thematically, a qualitative method used to identify, examine, and record patterns in data. Informed by the process proposed by Braun and Clarke (2006), the analysis involved familiarity with content, coding of main ideas, and construction of themes that capture the multifaceted impact of AI/ML on work. Themes were inductively constructed from data, sensitized to emerging trends, concerns, opportunities, and policy implications in various sectors and geographies.

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IV. FINDINGS

➢ *Emerging Trends in AI/ML and Labor Transformation*

AI and ML have had a contradictory effect on the job market, displacing existing opportunities while offering new ones. On the one hand, ML-driven automation takes away routine, repetitive, and low-skill work (Autor, 2015; Frey & Osborne, 2017). Work involving data entry, customer support, and simple manufacturing is highly automated, resulting in structural unemployment for workers without AI-complementary skills. Conversely, ML has raised professional tasks and enhanced combination human-AI models, particularly in choice-based sectors like healthcare, finance, and education (Brynjolfsson & McAfee, 2014; Davenport & Ronanki, 2018). Workers using AI frameworks exhibit enhanced productivity and decision-making ability, marking a shift from job replacement to job reformation and complementarity (Brynjolfsson et al., 2023; Sytsma & Sousa, 2023). The relationship between various variables triggered by the AI/ML revolution, creating labor dynamics, is illustrated in Figure 4 below:

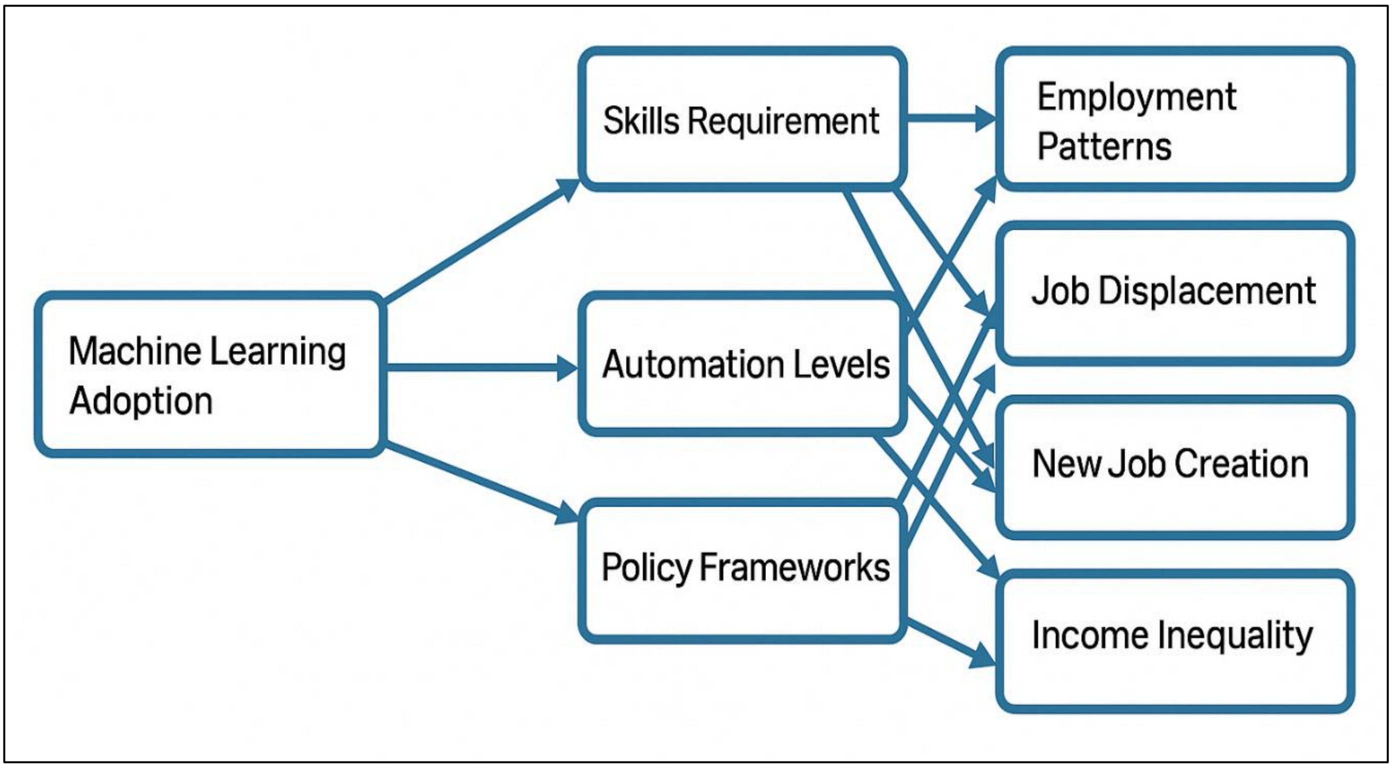

Fig 4 Impact of Machine Learning on Labor Market Dynamics

Figure 4: Impact of Machine Learning on Labor Market Dynamics synthesizes these emerging transformations, mapping AI's effects along three major pathways: displacement, augmentation, and hybridization. Sectors such as transportation and logistics are experiencing high automation due to advancements in robotics and predictive algorithms, whereas professions requiring empathy, ethical judgment, and nuanced decision-making remain less automatable (Chui et al., 2016).

- *Key Emergent Patterns Include:*

✓ Automation of Repetitive Tasks: Clerical, data entry, and low-skilled manufacturing jobs are more automated, with significant efficiency gains but large potential risks of job displacement.
✓ Hybrid Human-AI Work Models: AI remakes work processes by reassigning mental tasks (e.g., diagnosis, financial advice) between humans and machines (Brynjolfsson et al., 2023).
✓ AI-Supported Roles: In sectors such as healthcare and law, AI supports human decision-making through real-time interpretation of data, thereby redefining the need for skills (Sytsma & Sousa, 2023).
✓ Platform Economy Expansion: AI promotes gig economy and freelance virtual work economies, disrupting the traditional employment models (De Stefano, 2016).
✓ Sector-Specific Adoption: As shown in Figure 4, adoption intensity and labor outcomes vary across sectors, influenced by factors like data availability, regulatory maturity, and skill levels (McKinsey Global Institute, 2017).

- *Description of Figure 4 Model:*

As already established, the above conceptual framework describes the dynamic relationship between the adoption of machine learning (ML) and its effect on labor market outcomes. The adoption of ML technologies is the central change driver in the middle of the framework. The driver influences a series of mediating variables including:

✓ Skill Requirements – Adoption of ML reshuffles the skill requirements and is likely to increase the need for

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technical and digital skills while decreasing the importance of repetitive or clerical tasks.
- ✓ Automation Levels – The extent to which tasks are automated determines the rate and magnitude of job disruption and transformation.
- ✓ Policy Frameworks – Active labor policies and regulatory measures are capable of mitigating the impact of ML, deciding whether change leads to common growth or escalates inequality.

- *These Intervening Factors, in Turn, Influence Core Labor Market Outcomes:*

- ✓ Employment Patterns – Shifts in employment structure, sectors, and types of employment.
- ✓ Job Displacement – Job displacement of conventional jobs, particularly those that are at risk of automation.
- ✓ New Job Creation – The establishment of new jobs and new industries based on ML innovations.
- ✓ Income Inequality – Variation in the distribution of profits and losses due to ML between socioeconomic classes.

➢ *Challenges to Human Labor in the AI Era*

One of the major challenges created by AI/ML is the transformation in skill requirements and resulting inequality. Increasing demands are made for digital literacy, critical thinking, and data skills (Hussain, 2023; Mäkelä & Stephany, 2024). The shift has the capacity to expand the skills gap, particularly among low- and middle-income countries whose education system is misaligned with emerging labor market demands (Muhammad et al., 2023).

As Figure 4 demonstrates, the nature and degree of labor disruption vary by industry. Industries like manufacturing and agriculture are witnessing direct displacement, while others are witnessing subtler role redefinitions. These patterns confirm the Skill-Biased Technological Change (SBTC) hypothesis that argues AI discriminately benefits high-skilled workers, which intensifies labor market polarization (Acemoglu & Autor, 2011).

- *Challenges Identified Are:*

- ✓ Job Displacement: As much as 47% of American jobs are susceptible to automation, most severely impacting routine-based positions (Frey & Osborne, 2017).
- ✓ Expanding Skills Gap: The gap between required and present skills is expanding, especially in digitally deprived economies.
- ✓ Digital Inequality: Unequal access to AI resources and training spurs global and regional inequalities (UNDP, 2023).
- ✓ Psychosocial Stress: Increased surveillance, algorithmic control, and job insecurity fuel work anxiety (Susskind, 2020).
- ✓ Organizational Resistance: Trust issues, poor change management, and limited infrastructure hinder AI adoption across most firms (Ghasemaghaei et al., 2025).

➢ *Issues Beyond Job Displacement*

Deploying AI/ML poses complex issues beyond job displacement. These include: -

- Infrastructural and digital disparities, particularly in African labor markets (World Bank, 2021). –
- Psychosocial effects, such as increased stress, employment insecurity, and eroded work identity (Susskind, 2020; Institute for the Future of Work, 2024). –
- Resistance at the organizational level, with many companies struggling with change management, technical readiness, and employee trust (Ghasemaghaei et al., 2025).
- These findings suggest that successful AI deployment entails not just technical setup but organizational transformation and human-centered change strategies, as posited by Socio-Technical Systems Theory (Trist, 1981; Appelbaum, 1997).

➢ *Opportunities for Human Innovation and Progress*

Although AI deprives us of some occupations, it provides opportunities for innovation and human-AI collaboration at the same time. Technologies like generative AI-based ChatGPT and Copilot enable even non-experts to participate in sophisticated work, accelerate productivity, and learn (Brynjolfsson et al., 2023). Moreover, entirely new professions like AI ethicists, explainability analysts, and machine trainers have emerged (Manyika et al., 2017). Figure 2.2 illustrates sectors that are positively affected by augmentation rather than displacement. For instance, the education sector sees AI as a tutor or administrative assistant, while in retail, AI enables personalized marketing and logistics planning.

- *Opportunities Are:*

- ✓ New Job Creation: AI has given rise to new professions in AI governance, prompt engineering, and machine oversight.
- ✓ Skill Development Initiatives: Public-private partnerships and AI-based platforms allow for upskilling and lifelong learning.
- ✓ Entrepreneurial Empowerment: SMEs leverage AI for product innovation and predictive analysis (Cockburn et al., 2018).
- ✓ Flexible Work Models: AI enables remote work, adaptable working hours, and balance between work and life.

➢ *Regional Insights: Africa's Unique AI Trajectory*

Africa is unique with its youth populations, high informality, and infrastructure deficiencies. While these environments are risky, they are also promising grounds for digital leapfrogging (World Bank, 2021). Figure 4 puts these differences in regional perspective, suggesting low-resilience, highly informal sectors such as informal retail or subsistence agriculture are most at risk of displacement, but others such as mobile health or AI-driven agriculture have potential for innovation.

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- *Major Findings Are:*

- ✓ Informality and Innovation: AI impacts differ with variation in infrastructure, labor informality, and institutional preparedness.
- ✓ Potential for Digital Leapfrogging: Mobile diagnostics and agri-AI leapfrog over traditional systems (UNDP, 2023).
- ✓ Demographics and Risk Amongst Youth: Over 60% of Africa's population is below the age of 25; scalable skilling programs are essential not to fall into demographic crises.

➢ *Theoretical Insights*

The new convergence of AI/ML technologies with human labor is best explored by recourse to foundational theoretical frameworks that are able to capture both structural dynamics and dynamic tensions at play. The present study appropriates three major theories—Technological Determinism, Socio-Technical Systems Theory, and Skill-Biased Technological Change (SBTC)—each of which offers unique explanatory value to the nature of labour change in the age of AI.

Technological Determinism is the argument that technological progress has a straight and often unidirectional effect on social and economic institutions. From this argument, AI and ML are not instruments but autonomous forces that transform labor markets by altering work procedures, reducing human decision-making requirements, and substituting traditional categories of jobs (Mumford, 1964; Chandler, 1980). The findings of this review substantiate this reading, especially in sectors such as manufacturing, logistics, and customer service, where algorithmic systems have assumed work previously considered to be uniquely human. Determinate readings are insufficient, however, as they systematically underestimate the agency of workers and institutions in shaping technological directions.

Socio-Technical Systems Theory, on the other hand, emphasizes the co-evolution of technology and human systems, arguing that successful innovation requires two-way adaptation between social structures and technical components (Trist & Bamforth, 1951; Bijker et al., 1987). The theory explains why AI/ML deployment yields different results in different sectors and regions. In adaptive organizational cultures, training regimes, and policy structures, AI is an adjunct to human effort—enabling augmentation, upskilling, and job enrichment. The Displacement–Augmentation Continuum (DAC) outlined in this review takes direct inspiration from this principle, mapping how the dynamic between automation and human effort changes in response to contextual determinants such as leadership vision, regulatory preparedness, and digital literacy.

At the same time, Skill-Biased Technological Change (SBTC) provides a powerful perspective with which to analyze the reshaping of labor demand toward high-skilled employees, often at the cost of routine and manual labor (Autor et al., 2003; Acemoglu & Restrepo, 2019). As illustrated within this review, AI/ML implementation disproportionately favors higher-cognitive, higher-analytical, and higher-digital-skilled individuals—exacerbating wage polarization and limiting upward mobility for lower-skilled employees. The Sectoral Impact and Resilience Model (SIRM) developed in this study contributes to SBTC by illustrating the manner in which entire sectors differ in their experience of skill-biased displacement and resilience. For instance, while industries such as ICT and finance possess high absorptive capacity and skill adaptability, industries such as agriculture and low-end manufacturing are more vulnerable to structural exclusion.

These conceptual lenses together offer a multi-dimensional view of how AI/ML shapes the world of work—neither as a linear force, but as a complex socio-technical process. They also underscore the need for mindful policy interventions, skill building strategies in an inclusive form, and relentless institutional flexibility to reap the benefits of AI while keeping human agency and employment equity intact.

V. DISCUSSION

➢ *Synthesizing Evidence and Conceptual Insights*

The systematic review draws attention to the multi-dimensional impact of AI and ML on the personality, shape, and fate of human work. Whether it is automation-led replacement or AI-enabled augmentation, evidence converges in favor of an iterative process of change driven by technological potential, sectoral specificities, and institutional setting. Mutual dynamics between findings and conceptual typification are articulated by way of two conceptual models built within this research. Figure 2: AI/ML-Driven Labor Market Transformation Model is a theoretical trajectory of how intelligent systems affect labor markets via automation and upgrading, and consequence, the level of employment, inequality, and the nature of work. This is complemented by Figure 4: Impact of Machine Learning on Labor Market Dynamics, which brings together empirical trends by sector and geography and demonstrates how skills transformation, policy environments, and rates of take-up mediate labor outcomes. Together, these models reveal the shifting workplace architecture of the AI era — not a simple human-to-machine substitution, but an evolving redistribution of tasks, roles, and identities. They also reveal the increasing importance of AI-complementary skills, the precariousness of routine jobs, and the new hybrid human-machine work arrangements in industries.

➢ *Building Theoretical Insights*

The findings corroborate and build on three theoretical models guiding this study. First, Technological Determinism manifests in the data where AI proves to act as a prime force of social and economic change, reshaping job environments beyond the control of people. This determinism is nevertheless moderated by situational factors such as policy readiness and education frameworks. Second, the Theory of Skill-Biased Technological Change (SBTC) is validated by the evidence of increasing labor polarization — AI

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technologies favor disproportionately skilled workers and replace routine and low-skill occupations. It is best evidenced in the widening skills gap and digital divide between high-income and low-income areas. Third, Socio-Technical Systems Theory elucidates the cause of variance in AI adoption successes between organizations. Successful implementation not only depends upon technical readiness but also aligning AI with people's capabilities, faith, company culture, and helping systems. Psychosocial consequences enumerated — distress, employment uncertainty, loss of identity — amplify this human-centered necessity.

➢ *Introducing the DAC and SIRM Models*

For the purpose of enhancing analysis and providing a forward-looking perspective, this study introduces two novel conceptual models:

- *The Displacement–Augmentation Continuum (DAC) Model*

The DAC model develops a continuum model for viewing work shifts within the context of AI/ML. Displacement, where technological automation renders certain tasks or jobs obsolete, is on one end; augmentation, where intelligent systems enhance human abilities, is on another. Jobs are located on the continuum based on task routinization, technology maturity, and organizational flexibility. This model moves beyond binary job classifications as either "at risk" or "secure" and, instead, emphasizes transitional strategies — such as upskilling, job redesign, and human-AI collaboration — that can shift laborers along the augmentation continuum.

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

The SIRM model inserts a meso-level analytical framework, assessing sectoral exposure to AI disruption against resilience capacity (adaptability, innovation, policy support). This results in a quadrant-based chart that differentiates sectors as being vulnerable, adaptive, resilient, or insulated. SIRM is especially useful for organizational managers and policymakers in identifying interventions. For instance, finance and healthcare can simultaneously be resilient and susceptible due to professional training and standards. In contrast, African informal sectors can be low in institutional backing and high in vulnerability and require urgent policy and capacity-building interventions.

- *Diagrammatical Representation of DAC and SIRM Models*

The Displacement-Augmentation Continuum (DAC) model, which is the theoretical model depicted, illustrates the continuum of the effects of AI/ML on human work from full automation and displacement to enhancement and hybrid human-AI job creation. The DAC model brings together evidence presented in the findings chapter of this paper, according to which transformations in the labor market are generally not binary in nature. Instead, they correspond to overlapping areas of disruption, adaptation, and synergy with repercussions for skill development strategies and policy responses (Brynjolfsson et al., 2023; Autor, 2015).

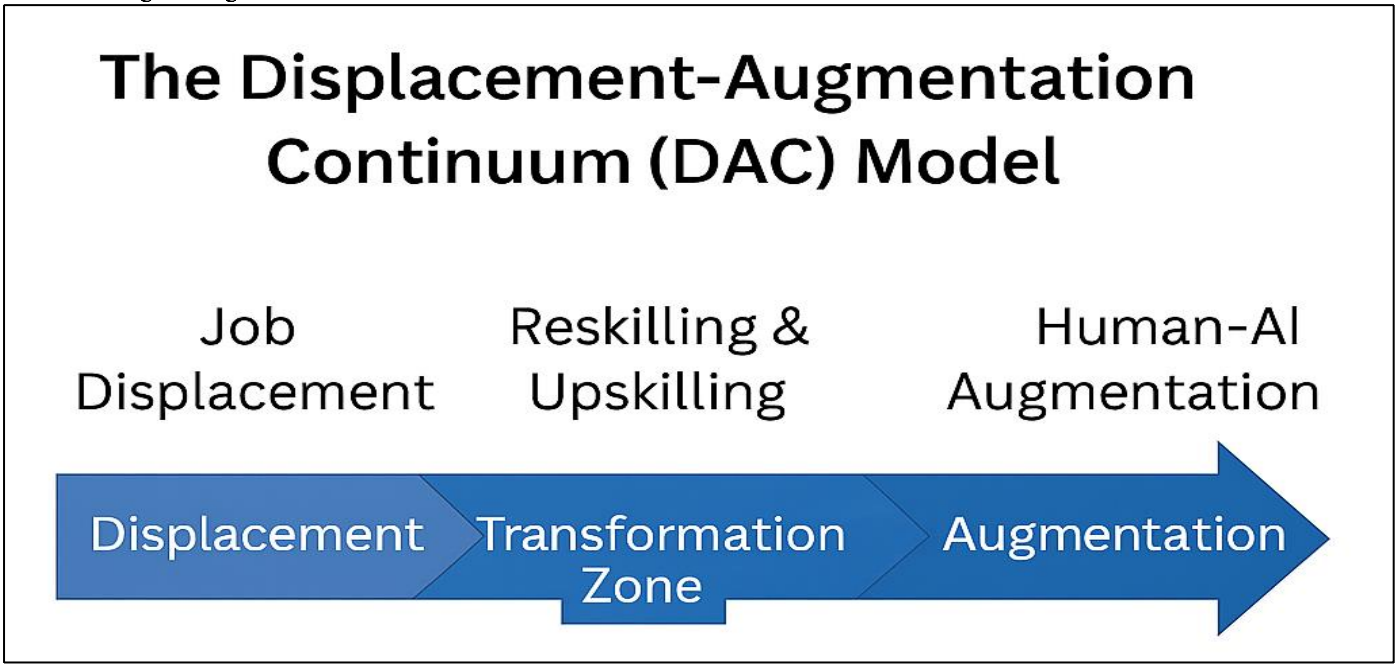

Fig 5 Displacement–Augmentation Continuum (DAC) Model

The Sectoral Impact and Resilience Model (SIRM) model posits how different sectors perceive and respond to AI/ML adoption on three axes: technological exposure, workforce and system flexibility, and policy or institutional readiness. By analyzing these variables, the SIRM model allows for cross-sectoral comparative analysis across healthcare, agriculture, finance, education, and manufacturing. It draws on empirical evidence in Section 4.1 and 4.4 of this paper that reveals sectoral dynamics and resilience patterns (World Bank, 2021; UNDP, 2023).

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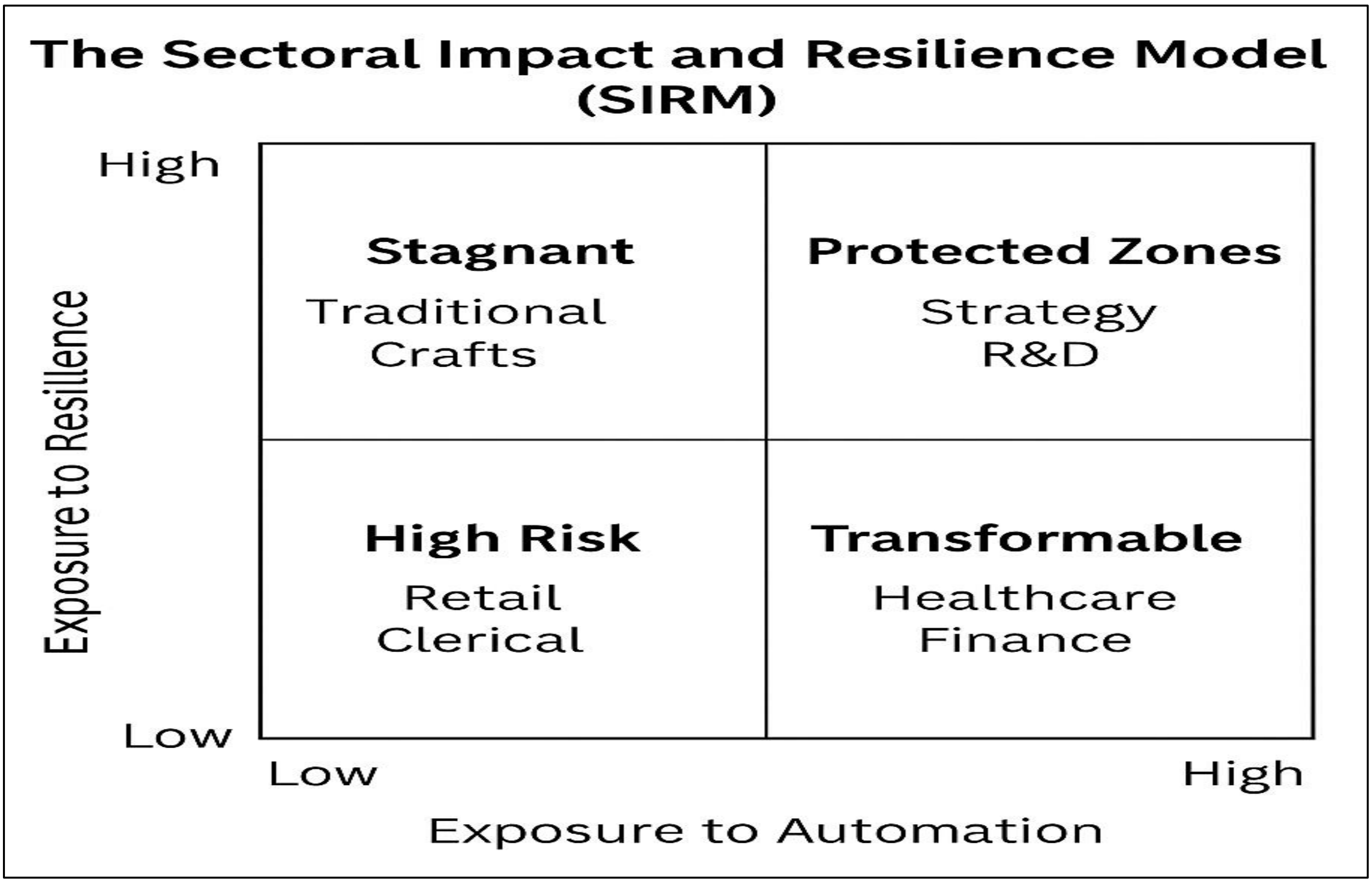

Fig 6 Sectoral Impact and Resilience Model (SIRM) Figure

➢ *Contextualizing Africa's AI Trajectory*

The African labor market is defined by a strange paradox: even as infrastructure, education gaps, and digital divides constrain AI adoption, leapfrogging is feasible with AI too. Bottom-up innovations—such as Kenyan mobile diagnostics and Nigerian AI-based agriculture—show the promise of contextual innovations on the continent. But without scalable programs for building skills and inclusive innovation policies, long-term marginalization looms over the demographic bulge in youth. DAC and SIRM frameworks offer new ways to think about this trajectory. Inclusive work can be at the displacement pole of the DAC spectrum unless it is supplemented by targeted interventions. Similarly, several African industries can be in the low resilience/high susceptibility quadrant of SIRM that may signal a call for upfront investments in digital skills, infrastructure, and public-private innovation networks.

➢ *Towards a Human-Centric AI Work Future*

The convergence of empirical findings, theoretical insights, and original models points toward a central conclusion: AI's labor impact is not fixed — it is mediated by how societies choose to adapt. A human-centered approach to AI and labor transformation should prioritize:

- Lifelong learning and AI-complementary skills development,
- Inclusive technology policies that reduce inequality,
- Organizational cultures that integrate human-AI collaboration,
- Safeguards for mental health and dignity in AI-enhanced workplaces.

Through cooperation among technology, human capacity, and institutional strength, the future of work can be smart and inclusive. The DAC and SIRM frameworks are the new phase in the investigation of these questions — setting up additional conceptual and empirical research into a second study focused on these models.

➢ *Summary and Policy Implications*

This study offers three main contributions. First, it synthesizes prior evidence on the transformative and disruptive role of AI/ML across global and African labor markets. Second, it builds theory by combining Technological Determinism, SBTC, and Socio-Technical Systems Theory into an applied theoretical framework. Third, it offers two conceptual models — DAC and SIRM — that provide systematic, pragmatic frameworks for making sense of and brokering the labor transformation with AI.

➢ *Policy Recommendations Include:*

- Developing human-centered national AI plans that prioritize human development,
- Investing in upskilling programs tailored to sector requirements,

- Enhancing digital infrastructure and connectivity in underprivileged areas,
- Supporting human-centered organizational transformation,
- Establishing legal frameworks to protect workers' rights in algorithmic environments.

The future of work in the AI/ML era is not predetermined. It depends on collective choice, inclusive innovation, and a willingness to place human agency at the center of technological progress.

➢ *Study Limitations and Future Research Directions*

Although this study offers thorough coverage, several limitations need to be noted. First, the review is limited to studies published largely in English, which may exclude significant findings from non-English publications. Second, while the study has a global scope, there is an unequal focus on data from high-income countries, limiting the generalizability to low-income or informally organized labor markets. Third, the hypothesized conceptual models derived theoretically — DAC and SIRM — are hypotheses that require empirical testing to challenge their cross-sectional robustness across different sectors and regional settings. Subsequent research should address these gaps with comparative empirical case studies, particularly in the Global South. Longitudinal research should measure unfolding effects over time, especially as AI technologies mature. Participatory and interdisciplinary approaches involving workers, technologists, and policymakers can provide richer, context-dependent analyses. A rigorous follow-up study will delve deeper into the DAC and SIRM models, extending them to real-world labor industry practices. This will further inform academics and policymakers about the socio-economic changes resulting from AI/ML.

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