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Artificial Intelligence and Productivity: A Review of Labour Substitution, Augmentation and Task Reconfiguration

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Abstract- Artificial intelligence (AI) is reshaping how work is organised and performed across the global economy. This paper reviews the evidence on three core effects: labour substitution, where AI replaces tasks previously done by people; labour augmentation, where AI raises the output and quality of human workers; and task reconfiguration, where jobs are redesigned around the new division of work between humans and machines. Drawing on peer-reviewed studies, working papers and institutional reports published between 2013 and early 2026, the review finds that outright job destruction is less common than popular accounts suggest. Instead, AI tends to substitute for specific tasks within jobs, raises productivity most sharply among less experienced workers and triggers significant redesign of roles rather than wholesale elimination. Key themes include skill compression, the emergence of hybrid human-AI roles and the uneven distribution of both risks and gains across sectors, skill levels and regions. The paper identifies gaps in the literature and sets out directions for future research, with relevance to educational institutions and policymakers in the Global South.

Keywords- Artificial intelligence, productivity, labour substitution, labour augmentation, task reconfiguration, future of work.

I. Introduction

Artificial intelligence is already embedded in call centres, hospitals, law firms, factories and classrooms. Its effects on work, however, remain poorly understood. Public debate swings between warnings of mass unemployment and optimistic claims of a productivity revolution. The evidence sits somewhere between.

This paper examines three distinct effects of AI on labour. The first is substitution, where AI takes over tasks that workers previously performed. The second is augmentation, where AI raises the speed or quality of work humans still carry out. The third is task reconfiguration, where the bundle of tasks within a job changes as some activities are automated and new ones emerge.

Economists typically focus on substitution and displacement while management scholars focus on augmentation and workflow redesign. This review brings both strands together.

The findings matter to policymakers shaping retraining programmes, employers planning workforce transitions and educational institutions preparing graduates for a labour market where AI is a standard tool.

II. Theoretical Framework

Three bodies of theory frame this review.

The Task-Based Model

The most influential framework is the task-based model developed by Acemoglu and Restrepo (2018, 2020). The model focuses on tasks, the discrete activities that make up a job. Technology automates a subset of tasks, which lowers the labour share of those tasks but may raise productivity enough to create new tasks and increase overall employment. Automation displaces workers from specific tasks but need not destroy jobs, because firms expand output and create new roles.

The framework predicts that automation is concentrated in routine, codifiable tasks; workers shift towards tasks where human comparative advantage remains; and new tasks emerge as productivity rises. The evidence in Sections 4 to 6 broadly supports these predictions, though the pace and distribution of effects vary.

Routine-Biased Technological Change

The routine-biased technological change (RBTC) framework, developed by Autor, Levy and Murnane (2003) and extended by Goos, Manning and Salomons (2009), distinguishes between routine tasks that follow explicit rules and are susceptible to automation, and non-routine tasks that require judgment, creativity or interpersonal interaction.

RBTC predicts labour market polarisation: middle-skill routine jobs are most at risk while high-skill cognitive and low-skill manual jobs are more protected. This hollowing out of the middle has been borne out in many advanced economies. The rise of large language models has since extended automation pressures upward into cognitive and analytical tasks previously considered safe.

General Purpose Technology Theory

Brynjolfsson and McAfee (2014) situate AI within general purpose technology theory. Technologies such as the steam engine, electricity and the internet are pervasive, improve over time and spawn complementary innovations. AI fits this description. The theory predicts a productivity paradox: output gains may be delayed by years or decades while organisations restructure, workers retrain and complementary investments are made. This helps explain why aggregate productivity statistics have not yet fully reflected improvements in AI capability.

Together, the three frameworks guide this review. The task-based model explains the mechanism of substitution and task reconfiguration. The RBTC framework identifies which workers are most exposed. General purpose technology theory explains why productivity effects are uneven across time and sectors.

III. Research Methodology

Review Type

This paper follows a structured narrative review approach. The literature on AI and labour spans multiple disciplines with differing methodological conventions, which makes a strict systematic review impractical. The review aims to be transparent, replicable and comprehensive within defined scope.

Search Strategy

Literature was identified through Scopus, Web of Science, Google Scholar, NBER Working Papers, IZA Discussion Papers and SSRN. Institutional reports from the IMF, OECD, World Economic Forum, McKinsey Global Institute, Brookings Institution and WTO were also included, as they capture evidence not always found in peer-reviewed outlets.

Search terms included: artificial intelligence, machine learning, large language model, automation, labour substitution, job displacement, augmentation, productivity, task reconfiguration, hybrid roles and future of work.

Searches were conducted in March 2026, covering studies from 2013 to early 2026. The lower bound corresponds to Frey and Osborne (2013), which marked the start of the modern academic debate on AI and employment.

Inclusion and Exclusion Criteria

Included: peer-reviewed journal articles; working papers from major economics research institutions; reports from major multilateral and policy institutions; studies with clear empirical methods or systematic evidence synthesis; studies available in English.

Excluded: opinion pieces and commentary without empirical grounding; studies focused solely on robotics without relevance to AI; studies predating 2013 except where foundational; duplicate reporting of the same underlying data.

IV. Labour Substitution

Labour substitution refers to the displacement of workers from tasks or roles by AI systems. It is the most discussed effect in the popular press, though the evidence is more nuanced than headlines suggest.

The Scale of Task Automation

Full automation of entire jobs is rare. What is far more common is the automation of specific tasks within jobs. The WTO (2025, p. 47) estimates that only around 3% of tasks done by low-skilled workers and 7-9% of those done by higher-skilled workers are fully automated with current technology, which directly challenges the narrative of mass job destruction.

Frey and Osborne (2013) estimated that 47% of US employment was at risk of computerisation, generating significant public concern. Subsequent research has substantially qualified this finding. Acemoglu et al. (2020) show that even in occupations with high automation potential, workers typically shift into new tasks rather than exit the labour force. The process is one of task displacement followed by task reallocation.

Modern AI has also shifted its automation targets. Earlier automation waves focused on middle-skill routine tasks. Webb (2020) used natural language processing to match AI patent descriptions to occupational task descriptions and found that AI innovations increasingly target high-skill tasks involving pattern recognition, advanced judgment and optimisation. This represents a qualitative shift in the nature of the automation threat.

Macroeconomic Exposure

Georgieva (2024) estimated that around 40% of global employment is exposed to AI disruption. In advanced economies, where cognitive and analytical work is prevalent, the figure rises to around 60% of occupations. Of the exposed jobs in advanced economies, roughly half face genuine displacement risk rather than augmentation, translating to around 30% of all employment. In emerging markets the figure is lower; a higher share of work involves physical tasks that current AI cannot perform.

Massenkoff and McCrory (2026) combined estimates of AI capability with data on actual corporate usage to construct an observed exposure metric. Their findings show that actual displacement has so far been limited. Through early 2026, there is no evidence of a systematic rise in unemployment among highly exposed workers. However, hiring rates for entry-level roles in exposed occupations have begun to slow, suggesting firms are reducing headcount through attrition rather than mass layoffs.

Sector-Level Evidence

The effects of substitution vary across sectors. Three patterns emerge from the evidence.

Manufacturing. Acemoglu et al. (2022) document that manufacturing automation increasingly targets codifiable and programmable tasks. Ryberg (2025) found that Swedish plants adopting automation grew and demanded new skills, while non-adopters shrank. Automation changes the mix of tasks rather than destroying jobs outright. The US manufacturing sector also faces a structural labour shortage of up to 2.1 million unfilled roles by 2030, meaning automation is partly filling vacancies rather than displacing workers (Deloitte and Manufacturing Institute, 2018).

Services and administration. Call centres, data entry and routine clerical work have been substantially automated. The IMF (2024) found that administrative and entry-level analytical roles face the highest near-term displacement risk. The pattern, however, again involves task reallocation: workers often shift to handling exceptions, managing customer relationships and overseeing AI output rather than losing jobs entirely.

Knowledge-intensive sectors. Legal drafting, financial analysis, coding and medical diagnosis are now within the capability range of AI systems. Webb (2020) found that AI patents increasingly target the tasks of database engineers, financial analysts and other professional workers. Acemoglu et al. (2022) confirm that AI adoption in professional services displaces mid-level analytical roles while creating new tasks in oversight and interpretation.

Summary Table: Key Substitution Studies

Table 4.1: Summary Table: Key Substitution Studies

Study	Method	Key Finding
Georgieva (2024) IMF Staff Discussion Note SDN/2024/001	Macroeconomic modelling of occupational exposure	40% of global employment exposed to AI. Advanced economies face 60% exposure due to cognitive task density.
Huang (2024) IMF Working Paper WP/2024/199	Shift-share analysis across US commuting zones, 2010–2021	Higher AI adoption linked to declines in employment-to-population ratios, heavily affecting middle-skill non-STEM roles.
WEF (2025) Future of Jobs Report	Survey of over 1,000 global employers representing 14 million workers	Forecasts severe declines in clerical positions. Structural tensions around displacement offset by growth in technology and green roles.
Webb (2020) Stanford Working Paper	NLP analysis matching AI patent texts to occupational task descriptions	AI targets high-skill tasks involving pattern detection and judgment. Will reduce wage inequality between middle and lower earners but leave top earners largely unaffected.
Massenkoff & McCrory (2026) Anthropic Research	Observed AI exposure metric combining LLM capability and corporate usage data	Disproportionate risk for older, female and educated workers. No systematic unemployment spike so far, but entry-level hiring is slowing.
Acemoglu et al. (2020) AEA Papers and Proceedings	Theoretical and empirical analysis of task structure	AI automates a subset of tasks but raises productivity, enabling new task creation. Net employment effect depends on the pace of task creation.
Ryberg (2025) Research Paper	Firm-level data from Swedish manufacturing plants	Automating plants grow and demand new skills. Non-adopters shrink. Automation changes task mix rather than destroying jobs outright.
Frey & Osborne (2013) Oxford Martin School Working Paper	Occupational susceptibility analysis of 702 US occupations	47% of US employment at risk of computerisation. Estimate has been substantially qualified by subsequent task-level research.

V. Labour Augmentation

Labour augmentation refers to AI raising the speed, quality or volume of work that humans perform without replacing them. The evidence here is largely positive, though it comes with important nuances.

Productivity Gains Across Sectors
Experimental and field studies consistently find large productivity gains when workers use AI tools. The gains range from around 15% to over 100% depending on the task and the worker.

Customer service. Brynjolfsson, Li and Raymond (2023) ran a randomised field trial with 5,179 customer support agents. Those using a generative AI assistant resolved around 15% more issues per hour on average, a substantial gain that required no structural change to the job.

Software development. Kalliamvakou (2022) found that developers using GitHub Copilot completed tasks approximately 55% faster. Paradis et al. (2024) found a 21%

speed gain in an enterprise randomised controlled trial. Both are substantial gains in a sector where developer time is expensive.

Healthcare. A cluster-randomised trial of an autonomous AI system for diabetic retinopathy screening found that clinic productivity rose by around 40% (Abramoff et al., 2023). In radiology, AI assistance reduced image reading time by 21-23% and raised less experienced radiologists to a performance level comparable with specialists (Rajpurkar et al., 2022).

Writing and research. Noy and Zhang (2023) found that access to ChatGPT reduced writing time by around 40% while improving quality by 18%. A Cornell University study (2025) found that researchers using large language models produced 33-50% more papers, though average quality declined. The gains were largest for non-native English speakers.

Law. AI tools are increasingly used for contract review, case research and document drafting. Sector-specific productivity metrics are still being established, but the pattern mirrors other knowledge-intensive sectors: AI reduces time on routine analytical tasks and frees human effort for judgment and strategy (Dell'Acqua et al., 2023; Noy and Zhang, 2023).

Education. An RCT in Scientific Reports (Kestin et al., 2025) showed that an AI-powered tutor helped students learn more per minute than traditional classroom instruction.

Skill Compression: AI Helps Novices Most

One of the most consistent findings is that AI helps less experienced workers far more than experienced ones. This is sometimes called skill compression, as AI narrows the performance gap between junior and senior workers.

In the Brynjolfsson et al. (2023) trial, junior agents saw large improvements in speed and quality while highly experienced agents saw only modest gains. The AI appears to give novice workers access to the knowledge and guidance that experienced colleagues would normally provide.The same pattern appeared in both coding studies. AI tools significantly aided recent hires and junior engineers, while senior developers gained little.

In medicine, AI assistance raised less experienced radiologists to the performance level of unaided specialists, effectively transferring knowledge from the evidence base to the practitioner. If AI compresses skills and raises junior worker productivity, it could accelerate workforce development and reduce the cost of bringing new entrants up to a useful level of performance.

Limits of Augmentation

Dell'Acqua et al. (2023) identified what they called the Jagged Technological Frontier. AI performs well on tasks within its capability boundary and poorly on tasks outside it. The problem is that the boundary is not visible to users. BCG consultants in the study who used AI on tasks outside the frontier produced worse results than those who worked without it, because they over-relied on AI output without applying sufficient critical judgment.

Augmentation therefore requires active human oversight. Without an understanding of a tool's limits, AI can reduce quality rather than raise it.

Summary Table: Key Augmentation Studies

Table 5.1: Summary Table: Key Augmentation Studies

Study	Method	Key Finding
Brynjolfsson, Li & Raymond (2023) NBER Working Paper No. 31161	RCT with 5,179 customer support agents	+15% overall productivity. Novice workers improved by 34%, showing large skill compression.
Noy & Zhang (2023) Science, 381(6654), 187–192	RCT with 444 college-educated professionals on writing tasks	40% reduction in time taken. 18% increase in quality. Disproportionate benefit for lower-ability workers.
Dell'Acqua et al. (2023) Organization Science (Online First)	Field experiment with BCG management consultants	Identified the Jagged Technological Frontier. High productivity inside the frontier; over-reliance causes errors outside it.
Kalliamvakou (2022) GitHub Research	Controlled coding task study with GitHub Copilot	Developers completed tasks approximately 55% faster. Gains concentrated among junior engineers.
Paradis et al. (2024) arXiv:2410.12944	Enterprise-based RCT of AI coding tools at Google	Developers approximately 21% faster on real coding problems when using AI assistance.
Abramoff et al. (2023) npj Digital Medicine, 6, 1–10	Cluster-randomised trial of autonomous AI for diabetic retinopathy screening	Clinic productivity rose by approximately 40%. Autonomous AI system achieved real-world specialist clinic deployment.
Rajpurkar et al. (2022) Nature Medicine, 28(1), 31–38	Systematic review of AI in health and medicine	AI systems match or exceed human performance in radiology. Junior clinicians benefit most from AI assistance. Evidence base spans multiple imaging modalities.
Cornell University (2025)	Analysis of preprint output by researchers using AI tools	33–50% increase in papers produced. Largest gains for non-native English speakers; average quality declined.
Kestin et al. (2025) Scientific Reports, s41598-025-97652-6	RCT of AI tutoring versus classroom learning	Students learning more per minute with AI tutor than with traditional classroom instruction.

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VI. Task Reconfiguration

Task reconfiguration refers to the redesign of jobs as AI absorbs some activities and creates new ones. It determines what humans will do alongside AI systems.

Job Reorganisation Over Job Displacement

The weight of evidence suggests that AI reorganises jobs more often than it destroys them. OECD surveys across advanced economies confirm that job reorganisation is significantly more common than outright displacement (Lane, Williams and Broecke, 2023). Employers and workers in manufacturing and finance generally report positive views, with the strongest endorsements coming from AI's ability to eliminate the most tedious and repetitive elements of work.

Acemoglu et al. (2020) show that AI alters the task structure of jobs by replacing some human-performed tasks while generating new ones with different skill demands. The productivity gains from automation are often large enough to create new responsibilities, offsetting some of the displacement (Acemoglu and Restrepo, 2018).

Hering et al. (2025) find, based on job posting data, that around 46% of job skills now fall into a hybrid transformation category, where AI handles routine parts of the task but human oversight remains essential. This is reconfiguration, not substitution.

The Orchestration Thesis

The orchestration thesis holds that as AI takes over specific tasks, human agency moves upward along the value chain. Workers shift from being primary creators or executors to becoming orchestrators, editors and contextual interpreters of AI-generated outputs.

In professional writing, for example, workers now prompt the AI, evaluate its output, refine it against strategic goals and integrate it into a broader context. The skills required involve judgment about AI output quality, not only subject matter expertise.

Some researchers describe a supervisory economy (Hering et al., 2025; Acemoglu and Restrepo, 2018) in which an increasing share of human work involves overseeing and interpreting AI outputs. This is a significant structural shift.

Case Studies of Role Redesign

Healthcare administration. Medical secretaries are moving from transcribing clinical notes to overseeing and validating AI-generated documentation. The transcription task is automated; quality control has expanded. The role has changed but not disappeared (Jurowetzki et al., 2025).

Manufacturing. Assembly-line and quality-control workers are becoming system supervisors who manage AI-driven inspection systems and handle exceptions. The manual task is automated; the oversight task has grown (Jurowetzki et al., 2025).

Finance. Brookings Institution (2025) documents one of the clearest examples of task reconfiguration. One financial technology firm automated around 700 roles and then rehired many workers into redesigned hybrid positions requiring AI oversight, interpretation and judgment. New titles have emerged, including AI auditor, model-risk officer, AI prompt engineer and LLM trainer.

Education. Educators are offloading routine grading and content generation to AI tools, freeing time for mentoring, facilitation and personalised feedback.

Hybrid Roles and New Occupations

The most visible outcome of task reconfiguration is the emergence of new occupational categories that combine human and AI capabilities. The World Economic Forum (2025) forecasts that while AI will displace millions of traditional roles, it will simultaneously create millions of new ones, potentially offsetting job losses.

Four categories of hybrid roles have emerged.

- Analytical and decision-intelligence roles. Positions such as AI-augmented analyst and decision-intelligence manager use predictive models and large language models to generate forecasts, while applying human judgment to contextualise findings for strategic use.
- Workflow and interaction design roles. Human-AI interaction specialists and AI workflow engineers design the prompts, interfaces and feedback loops that allow human teams to collaborate with AI systems effectively.
- Governance and ethical oversight roles. AI bias auditors, algorithm risk managers and AI ethics officers ensure that AI deployments are transparent, legally compliant and free from discriminatory effects.
- Strategic alignment roles. Architects of AI solutions and data ecosystem managers identify which processes can be improved through AI and oversee the integration of AI into organisational workflows.

Demand for these hybrid skill sets is already visible in job advertising. In the legal sector, leading firms in the United States and Singapore explicitly seek lawyers with combined legal and AI competencies.

Summary Table: Key Task Reconfiguration Studies

Table 6.1: Summary Table: Key Task Reconfiguration Studies

Study	Method	Key Finding
Lane, Williams & Broecke (2023) OECD Report	Surveys of employers and workers across OECD member countries	Job reorganisation is far more prevalent than displacement. Workers report that AI improves job quality by removing tedious tasks.
Acemoglu & Restrepo (2018)	Theoretical and empirical analysis of automation and task creation	Automation displaces tasks but raises productivity sufficiently to generate new tasks. Net employment effect is positive when task creation is robust.

Acemoglu et al. (2020) AEA Papers and Proceedings, 110, 383–388	Analysis of task structure across occupations	AI alters task structure of jobs rather than destroying them. New skill demands accompany task displacement.
Hering et al. (2025) Indeed AI at Work Report	Analysis of job posting data across major economies	46% of skills now in a hybrid transformation category, requiring human oversight of AI-performed components.
Brookings Institution (2025) Hybrid Jobs Report	Case study analysis of AI adoption in finance	New hybrid job titles documented. Workers who were displaced were rehired into redesigned roles requiring AI oversight and judgment.
Jurowetzki et al. (2025) Repository Working Paper	Qualitative analysis of AI adoption in healthcare and manufacturing	Medical secretaries and quality-control workers have shifted from execution to oversight and validation roles.
WEF (2025) Future of Jobs Report	Survey of over 1,000 global employers	AI will displace millions of traditional roles but create millions of new positions, particularly in technology and green sectors.
Fouarge et al., (2025) IZA Discussion Paper No. 18224	Survey data on AI-augmented training programmes	AI-augmented training raises worker productivity and reduces the time required to reach competency thresholds.

VII. Cross-Cutting Issues

Several themes cut across all three phenomena. They affect the magnitude, distribution and interpretation of the evidence.

Inequality and Wage Polarisation

The benefits and costs of AI are distributed unevenly. Within firms, augmentation gains are concentrated among less experienced workers, narrowing internal skill differentials. Across the labour market, the picture is more troubling. Displacement of routine cognitive tasks threatens middle-skill workers most, while high-skill workers who can collaborate with AI and low-skill workers in physical roles are more protected. This is consistent with the wage polarisation predicted by the RBTC framework.

There is also a geographic dimension. Advanced economies face greater exposure due to their higher share of cognitive occupations. Emerging market economies face lower immediate exposure because their labour forces contain more physical and manual work, but lower exposure also means fewer productivity gains.

Vivarelli and Piva (2022) find that AI innovation is associated with modest positive employment effects in services but more mixed effects in manufacturing, depending on the level of economic development. This underscores the importance of context-specific analysis.

Sector and Firm-Size Heterogeneity

The effects of AI vary enormously across sectors and between large and small firms. Large intensive technology firms have the resources to adopt AI at scale, retrain workers and redesign roles. Smaller firms, particularly in lower-income countries, often lack these resources, raising the risk that AI adoption accelerates a divergence between high-productivity firms and the rest.

Manufacturing, finance and professional services are being transformed in different ways and at different speeds. Healthcare faces specific regulatory constraints. Education is still at an early stage. Generalisations across sectors should be treated with caution.

Acemoglu et al. (2022) finds that high-productivity firms are best positioned to redesign roles after automation, while lower-productivity firms in the same sector face net employment losses. This divergence is likely to intensify as AI adoption spreads.

The Productivity Paradox

Aggregate productivity statistics have so far failed to reflect the gains documented in individual studies. This is consistent with the general purpose technology productivity paradox (Brynjolfsson and McAfee, 2014): organisational restructuring, worker retraining and complementary investment take time. The full productivity dividend from AI may still be years away.

Standard productivity statistics were designed for an economy dominated by goods production and struggle to capture quality improvements, time savings and gains in non-market activity. The productivity of AI-augmented knowledge work may be growing faster than official statistics record.

Developing Economies and the Global South

Most of the evidence in this review comes from advanced economies, particularly the United States, Western Europe and East Asia. Labour markets in lower-income countries include a higher share of informal work, agriculture and physical services that are less exposed to AI. Access to AI tools is also lower, skilled workers who could benefit from augmentation are scarcer and the infrastructure needed to support AI adoption is often inadequate.

Khan (2024) analyses Singapore as a useful intermediate case, finding that AI exposure is concentrated in finance and professional services and that labour market adjustment has been managed through upskilling. For lower-income countries, the challenge is to build the infrastructure, skills and regulatory environment needed to capture AI's productivity gains.

VIII. Research Gaps and Future Directions

Literature has grown rapidly but important gaps remain.

Longitudinal Evidence

Most studies in this review are cross-sectional or cover short time periods. Longitudinal studies tracking the same workers, firms or occupations over several years are needed to understand how effects evolve as technology matures, workers adapt and firms reorganise. Without long-run evidence, it is hard to assess whether task creation keeps pace with task displacement.

Evidence from Low- and Middle-Income Countries

The evidence base is heavily skewed toward advanced economies. Research is needed on how AI adoption affects labour markets in India, Sub-Saharan Africa, Latin America and South-East Asia, where baseline conditions, regulatory environments and digital infrastructure differ considerably from those in the United States or Germany.

Measuring Augmentation

Substitution is easier to measure than augmentation. Displacement shows up in lost jobs and reduced wages, while augmentation appears in quality improvements, time savings and output expansions that are harder to quantify. Studies also use different outcome metrics, making direct comparison difficult. Better measures and greater methodological standardisation are needed.

Generative AI and the New Frontier

Most empirical studies in this review predate or cover only the early adoption of generative AI tools such as ChatGPT, GPT-4 and Claude. These tools have extended AI's reach into creative writing, complex reasoning and multi-step analysis. The evidence base is only beginning to catch up, and studies published after 2023 need to be synthesised in future reviews.

Organisational and Managerial Factors

The evidence suggests that the same AI tool can produce very different outcomes depending on how it is deployed and how workers are trained. The organisational conditions that enable successful augmentation, and those that lead to over-reliance and performance degradation, are not yet well understood.

Educational Implications

The key unanswered question for educational institutions is which skills will retain value as AI capabilities expand. There is broad agreement that judgment, creativity, interpersonal communication and critical evaluation of AI outputs will matter. The specific curriculum changes required, and the best pedagogical approaches, are not yet established.

IX. Conclusion

This review has brought together evidence on three distinct effects of AI on labour: substitution, augmentation and task reconfiguration. The picture is more complex than either the dystopian or the utopian accounts that dominate public debate.

On substitution, AI is automating specific tasks within jobs rather than destroying jobs wholesale. The scale of full automation is more modest than early estimates suggested. Displacement tends to affect middle-skill routine work first, though modern AI is increasingly capable of targeting high-skill cognitive tasks. The aggregate employment effects so far are contained, primarily through reductions in hiring rather than mass layoffs.

On augmentation, the evidence is broadly positive. AI tools raise productivity substantially across sectors, with the largest gains going to less experienced workers. This skill compression effect could accelerate workforce development if managed well. But over-reliance on AI without adequate human judgment can reduce quality, as the Jagged Technological Frontier finding shows.

On task reconfiguration, job reorganisation is the dominant outcome of AI adoption rather than job destruction. Workers are shifting from execution to oversight, from creation to curation and from routine tasks to judgment-intensive ones. New hybrid roles are emerging that blend domain expertise with algorithmic literacy, requiring a different kind of preparation than traditional occupational training.

Three policy implications follow. Retraining programmes should focus on oversight, interpretation and critical evaluation skills that AI cannot replicate. Access to AI tools should be widened, as augmentation gains are largest for less experienced workers, a group that includes many in developing economies. Educational institutions should redesign curricula to develop AI literacy alongside domain expertise, preparing graduates for a labour market where working with AI is a standard requirement.

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