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Artificial Intelligence, Automation and the Restructuring of the Global Labour Market: Occupational Displacement, Human-AI Complementarity and the Future of Work Beyond 2035

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Abstract

Artificial intelligence (AI), generative artificial intelligence (GenAI), and robotics are transforming employment at a speed that challenges conventional assumptions about occupational security, higher education, and workforce preparation. The current study comparatively examines occupational fields likely to experience significant automation, employment contraction, or task restructuring over the next decade, and identifies occupations expected to remain resilient or expand beyond 2035. This integrative comparative review draws on peer-reviewed labour-economics scholarship and evidence from the International Labour Organisation (ILO), International Monetary Fund (IMF), Organisation for Economic Co-operation and Development (OECD), World Bank, and World Economic Forum (WEF). This study develops an Occupational AI Vulnerability-Resilience Model based on task routineness, digitisation, predictability, interpersonal intensity, physical-world complexity, accountability, domain expertise, and complementarity with technology. Labour market areas such as clerical administration, data entry, routine bookkeeping, transcription, elementary editing, translation, basic content creation, telemarketing, routine customer service, cashiering, and selected elementary programming functions demonstrate comparatively high substitution in the future labour market. Conversely, nursing, medicine, counselling, skilled trades, infrastructure maintenance, cybersecurity, AI governance, scientific research, advanced education, entrepreneurship, and occupations involving complex physical environments, responsibility, trust, creativity, and contextual judgement demonstrate greater resilience in the future labour market. The present analysis finds substantial differences between advanced and developing economies in the future labour market discourse because capital costs, wages, digital infrastructure, informality, education, and technological readiness influence the feasibility of automation. For Jamaica and the Caribbean, the principal challenge is not merely preventing

technological unemployment but transitioning from routine service employment towards AI-augmented professional, technical, creative, healthcare, green-economy, and knowledge-intensive work. This study, therefore, concludes that future employability will increasingly depend on human-AI complementarity rather than occupational titles.

Keywords: artificial intelligence, automation, future of work, technological unemployment, generative AI, labour market, occupational displacement, human-AI complementarity, Caribbean, Jamaica, higher education.

Introduction

Technological change has repeatedly transformed human employment, but the contemporary AI revolution differs from many previous periods because intelligent technologies can increasingly perform cognitive functions historically associated with educated human workers. Earlier mechanisation predominantly substituted machinery for physical effort in agriculture and manufacturing, while computerisation automated repetitive information-processing activities and contributed to the decline of numerous clerical and production occupations (Autor et al., 2003; Autor, 2015; Fleming, 2020; Illéssy et al., 2021; Lábaj et al., 2025). Generative AI extends this technological frontier into writing, programming, visual design, translation, legal research, tutoring, data analysis, customer communication, document production, and other cognitive activities. Eloundou et al. (2024) indicated that large language models affect substantial proportions of the tasks undertaken in the contemporary labour market, especially when integrated with complementary software. Technological exposure increasingly affects not only factory workers but graduates, administrators, professionals, creators, programmers, teachers, and other knowledge workers. The traditional relationship between educational attainment and technological security requires considerable reconsideration for the future labour market structure and type.

The scale of anticipated labour-market transformation will be substantial, although contemporary forecasts do not support simplistic predictions of universal unemployment. The World Economic Forum (2025) estimates that structural economic and technological changes could produce approximately 170 million new positions globally while displacing approximately 92 million existing positions by 2030, resulting in substantial gross employment reallocation even if the net numerical effect remains positive. Its employer survey identifies clerical and secretarial occupations among the largest areas of expected contraction, while AI, big data, cybersecurity, renewable energy, healthcare, education, and several technical fields exhibit comparatively strong growth expectations. Furthermore, approximately 39% of workers' existing skills are expected to change or become less relevant during the 2025-2030 period (World Economic Forum, 2025). The reality is that even workers whose occupations may survive in the future may experience extensive changes in what employers expect them to know and perform for tasks. Labour-market transformation should be conceptualised as involving occupational creation, occupational contraction, task displacement, task augmentation, skill obsolescence, and emergence of entirely new forms of employment. Current World Economic Forum (WEF) evidence points towards major employment reallocation rather than a simple disappearance of work.

The International Labour Organization (2025) provides evidence against equating technological exposure with certain unemployment. Its refined 2025 occupational-exposure index estimates that approximately one in four workers worldwide is employed in an occupation demonstrating some exposure to GenAI, while only 3.3% of global employment falls within its highest exposure category (Gmyrek et al., 2025). Clerical occupations remain the most exposed occupational group, although advances in multimodal AI have increased exposure among specialised professional, media, technical, and web-related occupations. The International Labour Organization (ILO) concludes that transformation is more probable than complete occupational redundancy because most occupations contain combinations of automatable and non-automatable tasks. Exposure also differs substantially according to national income, with approximately 34% of employment in high-income economies indicating some GenAI exposure compared with around 11% in low-income countries (Gmyrek et al., 2025). These findings emphasise that automation is simultaneously an occupational, developmental, gender, educational, and distributional phenomenon.

The central research problem concerns the distinction between what technology can perform, what organisations will economically choose to automate, and which human capabilities will continue to create labour-market value. A language model may be capable of producing a grammatically acceptable article without eliminating investigative journalism, and an AI system may explain algebra without eliminating the social, developmental, motivational, and safeguarding responsibilities of teachers. Similarly, automated software may prepare routine accounts without eliminating professional responsibility for financial assurance, corporate governance, forensic investigation, or regulatory interpretation. Technological capability is a necessary but insufficient condition for occupational substitution. Labour costs, capital costs, legislation, social trust, institutional legitimacy, liability, customer preferences, organisational design, infrastructure, and the economic value of human interaction all influence whether automation occurs. Any credible future-of-work analysis must abandon deterministic statements such as “AI will replace teachers” in favour of task-level assessments of substitution, augmentation, and organisational restructuring.

This problem is consequential for educational institutions because millions of students continue to invest financial resources and several years of their lives preparing for professions undergoing rapid technological reconfiguration. Universities and vocational institutions traditionally develop qualifications around established occupational categories whose structures can remain embedded in curricula long after industry practice has changed. Students may consequently graduate highly competent in tasks whose market price is rapidly declining because AI can produce similar outputs at near-zero marginal cost. Conversely, alarmist reactions could cause universities to abandon disciplines that remain socially essential but require substantial curricular redesign. Editing, accounting, teaching, programming, journalism, law, marketing, graphic design, administration, and business remain necessary domains, although the routine components of these domains increasingly face technological competition. The relevant educational challenge is consequently determining which components of professional expertise should continue to be taught and which components should be reconceptualised around human-AI collaboration.

The issue possesses significance for developing economies. Advanced economies generally contain greater concentrations of cognitive-intensive employment, higher labour costs, larger technologically sophisticated firms, and stronger digital infrastructures, all of which can accelerate AI adoption (Cazzaniga et al., 2024). Developing economies may initially experience slower substitution because labour costs are lower and technological infrastructure is weaker, although this apparent protection can become a disadvantage if firms and workers cannot obtain AI-generated productivity improvements. Latin America and the Caribbean illustrate this dilemma well. Joint World Bank-ILO research estimates that approximately 26%-38% of regional employment may be exposed to GenAI, with 8%-14% potentially experiencing productivity-enhancing transformation and approximately 2%-5% having comparatively stronger full-automation potential under existing technological capabilities (Gmyrek et al., 2024). Digital inequalities could nevertheless prevent approximately 17 million potentially augmentable jobs from receiving those productivity benefits.

This paper contributes to the future-of-work literature through a comparative framework that distinguishes occupational disappearance from task automation and task augmentation. It develops an Occupational AI Vulnerability-Resilience Model, evaluates professions according to their underlying work characteristics, contrasts advanced and developing economies, and applies the analysis specifically to Jamaica and the wider Caribbean. Attention is also directed towards university programmes because occupational transformation raises fundamental questions about the future economic value of traditional qualifications. Rather than predicting precise employment levels in 2035, the paper identifies plausible directions based on contemporary technological capabilities, labour-market evidence, economic theory, and institutional forecasts. Its underlying proposition is that occupational resilience is increasingly determined by the interaction between technological substitutability and human complementarity. The study consequently reframes the central labour-market question from “Which jobs will AI eliminate?” to “Which combinations of human capabilities will remain economically scarce when advanced AI becomes widely available?”

Research Problem and Research Gap

A substantial literature has attempted to estimate the employment consequences of automation. Frey and Osborne (2017) generated influential estimates of occupations susceptible to computerisation, while subsequent researchers demonstrated that occupational-level estimates may overstate displacement because workers within the same occupation undertake heterogeneous combinations of tasks (Arntz et al., 2016). Autor et al. (2003) had previously established a task-based framework demonstrating that technologies substitute effectively for routine activities while complementing non-routine forms of human labour. More recent scholarship has extended exposure measurement from industrial robotics and conventional software towards machine learning and GenAI (Felten et al., 2021; Gmyrek et al., 2023, 2025; Webb, 2020). Nevertheless, rapidly evolving AI capabilities make historical occupational classifications increasingly unstable. An occupation considered relatively protected five years ago may contain tasks that multimodal generative systems can execute economically.

A second limitation concerns the tendency of public discourse to conflate exposure, automation, displacement, and occupational disappearance. Exposure means a technology can materially affect activities within an occupation, whereas automation describes substitution of technology for tasks. Displacement describes reductions in labour demand arising from such substitution, while occupational disappearance requires technological replacement of enough economically important tasks to make the occupation itself substantially unnecessary. These concepts are related but not identical. For example, programmers exhibit high AI exposure because AI systems generate code, yet expanding software demand can simultaneously increase employment opportunities for specialised developers. Similarly, teachers are exposed to content-generation and tutoring systems while demographic expansion and educational demand may support employment growth. Failure to distinguish these concepts can generate exaggerated predictions and inappropriate education policy.

A third gap concerns geographical imbalance. Much empirical AI research has concentrated on North America, Western Europe, and other high-income economies because these locations possess richer occupational datasets, greater digital adoption, and more observable workplace AI deployment. Yet consequences of automation are mediated by wage structures, informality, broadband access, electricity reliability, firm size, educational attainment, and capital availability. Developing countries cannot be treated simply as delayed versions of advanced economies. Latin American and Caribbean workers may simultaneously confront displacement from internationally tradable AI services and exclusion from productivity-enhancing AI because of inadequate technological infrastructure (Gmyrek et al., 2024). Smaller Caribbean states additionally possess occupational structures shaped by tourism, business-process outsourcing, government administration, financial services, education, retail, and other service sectors with varying levels of GenAI exposure. This study addresses this geographical gap by explicitly integrating developing-country and Caribbean considerations throughout the analysis.

Aim and Research Questions

The primary aim is to examine comparatively how AI, GenAI, robotics, and associated automation technologies are likely to restructure employment during the next decade and beyond 2035. The study specifically investigates occupations vulnerable to displacement, occupations that are more likely to undergo augmentation, occupations demonstrating comparatively strong human resilience, and educational programmes requiring substantial redesign. It evaluates whether technological effects differ systematically according to countries' level of economic development and digital readiness. For this study, attention is given to Jamaica and the Caribbean because global AI adoption may affect service-based economies through both domestic automation and international competition. The study does not treat current technological capabilities as fixed because capability expansion is likely during the forecast period. Accordingly, the paper addresses five principal research questions:

1. Which occupational tasks and professions face the strongest potential for AI-driven substitution during the next decade?
2. Which occupations are more likely to experience human-AI augmentation than elimination?

3. Which fields are likely to demonstrate comparatively strong employment resilience beyond 2035?
4. How might AI-driven restructuring differ between advanced economies, developing economies, and Caribbean economies?
5. Which university and vocational programmes require the greatest curricular transformation to preserve graduate employability?

Theoretical Framework

Task-Based Technological Change

The first theoretical foundation is the task-based model of technological change. Autor et al. (2003) challenged simplistic occupational perspectives by demonstrating that technologies replace tasks rather than necessarily replacing entire workers. Occupations consist of portfolios of activities, some of which technology can substitute while others remain complementary to human labour. This distinction explains why automated teller machines did not immediately eliminate bank employees and why spreadsheets transformed accounting without eliminating accountants. Acemoglu and Restrepo (2019) subsequently formalised technological change through displacement and reinstatement effects, whereby automation can remove workers from existing tasks while technological development also creates new tasks in which human workers retain comparative advantage. The ultimate employment effect depends on the relative strength of labour-displacing and labour-creating mechanisms.

GenAI materially expands the number of cognitive tasks potentially subject to automation. Traditional computerisation was strongest where explicit rules could be programmed, whereas machine-learning systems can infer statistical patterns without complete rule specification. Large language models extend automation further because natural language itself becomes an interface through which workers delegate cognitive activities to machines. Drafting, summarisation, classification, coding, translation, and information extraction become increasingly automatable without specialised programming knowledge. Consequently, the boundary separating routine and non-routine cognition has become less stable. Nevertheless, contextual judgement, social relationships, physical manipulation, accountability, and complex problem definition remain important barriers to complete automation.

Routine-Biased and Skill-Biased Technological Change

Routine-biased technological change provides a second theoretical perspective. Earlier information technologies disproportionately affected middle-skill routine occupations, contributing to occupational polarisation in several advanced economies (Autor, 2015). High-skilled analytical professionals and low-wage interpersonal or physical-service workers were comparatively difficult to automate, while administrative, production, and clerical employment experienced considerable technological pressure. GenAI challenges this historical distribution because advanced language and multimodal models can perform portions of highly educated professional work. Lawyers, university lecturers, analysts, programmers, graphic designers, journalists, accountants, consultants, and researchers are technologically exposed despite

comparatively high educational attainment. Higher education alone can no longer be treated as sufficient technological protection.

This does not mean education has become economically irrelevant. Instead, the relationship between educational attainment and technological complementarity is changing. Highly educated workers may experience greater AI exposure precisely because they perform digitised cognitive work, but their expertise can simultaneously allow them to obtain greater productivity benefits from AI (Cazzaniga et al., 2024). The relevant distinction may consequently shift from high skill versus low skill towards complementary expertise versus substitutable production. A specialist capable of checking, contextualising, correcting, and applying AI output may command greater value than a worker whose primary value derives from producing the first version of that output. Educational systems must prioritise expertise that allows graduates to supervise technology rather than merely compete with it.

Displacement and Reinstatement

Acemoglu and Restrepo (2019, 2020) demonstrate that technological innovation can create opposing labour-market forces. Automation generates a displacement effect when machines assume tasks previously undertaken by workers, reducing labour's share of production within those activities. Productivity gains can counteract this decline by reducing costs, increasing output, generating complementary demand, and potentially expanding related employment. New technologies can additionally create entirely new tasks requiring human workers, generating what Acemoglu and Restrepo describe as reinstatement effects. Historical technologies produced occupations such as software engineering, digital marketing, web development, cybersecurity, and data science that would have been difficult to anticipate before widespread computing. AI will almost certainly generate occupational categories that are presently immature or nonexistent.

The policy problem arises when displacement occurs faster than reinstatement. Workers do not instantly transfer from an automated occupation into an emerging profession because skills, geography, credentials, age, income, and access to training constrain occupational mobility. A forty-five-year-old administrative assistant displaced by automation cannot reasonably become an AI engineer merely because AI engineering employment grows. Gross job creation provides an incomplete measure of labour-market welfare. The quality, location, qualification requirements, wages, and accessibility of newly created employment are equally important. Labour-market policy must consequently manage occupational transitions rather than assuming that aggregate job creation automatically compensates displaced individuals.

Human-AI Complementarity

A fourth theoretical pillar is complementarity. Autor (2024) argues that AI could potentially broaden access to advanced decision-making capabilities and rebuild portions of middle-skilled employment by allowing workers with complementary knowledge to perform tasks previously concentrated among elite professionals. Evidence from customer service supports this possibility. Brynjolfsson et al. (2025), analysing 5,172 customer-support agents, found that access to a generative AI assistant increased productivity by approximately 15% on average, with disproportionately large benefits among less experienced and lower-skilled workers. AI

functioned partly as a mechanism through which expertise embedded in organisational knowledge became available to workers who had not yet accumulated comparable experience. This evidence demonstrates why augmentation and displacement can coexist within the same occupation.

Occupational AI Vulnerability-Resilience Model

This study proposes an **Occupational AI Vulnerability-Resilience Model (OAVRM)** for conceptualising labour-market exposure. Occupational vulnerability is hypothesised to increase with routineness, digitisation, predictability, scalability, standardisation, and the ability to evaluate outputs automatically. Occupational resilience is hypothesised to increase with physical-world complexity, interpersonal intensity, trust, legal responsibility, ethical judgement, tacit knowledge, originality, contextual reasoning, and the capacity for AI to complement rather than substitute for human workers. Economic feasibility additionally moderates technological capability because automation will proceed faster when labour is expensive relative to technological capital. Institutional and regulatory environments similarly moderate substitution where society requires licensed individuals to remain accountable for consequential outcomes. Consequently, two occupations with similar technological exposure can experience considerably different employment consequences.

Conceptually:

$$\text{AI Occupational Vulnerability} = f(R, D, P, S, E) - f(H, C, A, T, J)$$

where:

R = task routineness

D = degree of digitisation

P = predictability

S = scalability of automated output

E = ease of automated evaluation

H = human-interaction requirement

C = physical/ contextual complexity

A = accountability requirement

T = tacit or domain-specific knowledge

J = human judgement requirement.

The model should not be interpreted as a directly estimated econometric equation in the present conceptual study. Instead, it provides a testable framework from which subsequent empirical research can construct occupation-level indices. A profession characterised by high R, D, P, S, and E but low H, C, A, T, and J should theoretically experience comparatively high automation pressure. Data entry represents a paradigmatic example because inputs and outputs are highly digitised, standardised, repeatable, and machine-evaluable. Nursing presents a contrasting example because although documentation and monitoring can be automated, substantial bedside activity involves physical interaction, contextual interpretation, accountability, communication, and human trust.

Table 1: Proposed Occupational AI Vulnerability-Resilience Matrix

Occupational characteristics	Higher displacement risk	Greater resilience
Task structure	Repetitive and standardised	Variable and ambiguous
Information form	Completely digital	Digital plus physical/ contextual
Output evaluation	Easily machine-checked	Requires professional judgement
Human interaction	Limited	Central to service
Physical environment	Controlled/ predictable	Unstructured/ unpredictable
Emotional component	Minimal	High empathy/ trust
Accountability	Limited individual responsibility	Licensed/ legal/ ethical responsibility
Knowledge	Easily codified	Tacit and contextual
Creativity	Formulaic production	Problem definition/ original synthesis
AI relationship	Substitution	Complementarity
Marginal cost advantage	Very high for automation	Smaller automation advantage
Likely outcome	Staff contraction	Augmentation/ transformation

Methodology

The study employs a comparative integrative review methodology. Integrative reviews are appropriate when a research problem requires synthesis across theoretical literature, empirical findings, institutional data, policy research, and differing methodological traditions. Evidence was prioritised from peer-reviewed research and internationally recognised organisations, including the ILO, OECD, IMF, World Bank, and WEF. Contemporary evidence received emphasis because GenAI capabilities have developed rapidly since 2022 and earlier automation studies may underestimate exposure to language, image, voice, video, and coding systems. Historical scholarship was nevertheless retained where necessary to establish the theoretical evolution from industrial automation towards task-based technological analysis. The resulting approach combines longitudinal conceptual interpretation with contemporary occupational forecasting.

Comparative analysis was undertaken across advanced economies, emerging markets, and developing economies. Attention was directed towards Latin America and the Caribbean because recent World Bank-ILO estimates permit clearer regional interpretation. Jamaica is examined as an illustrative small developing economy whose employment structure contains substantial service-sector, governmental, educational, retail, tourism, financial, and business-process employment. The analysis does not assume that international exposure estimates translate mechanically into identical Jamaican probabilities because national occupational distributions and technological adoption differ. Instead, global and regional findings are used to identify areas of strategic vulnerability and resilience requiring national empirical investigation. This limitation is explicitly recognised to avoid false precision.

Occupational classification employed three broad categories: high substitution potential, high transformation potential, and high resilience/ complementarity potential. Classification was

informed by task routineness, digitisation, physical complexity, human-interaction requirements, accountability, and evidence concerning expected occupational growth or decline. Complete replacement was treated as a considerably stronger condition than high exposure. An occupation was not classified as disappearing merely because GenAI could perform substantial portions of its activities. This methodology reflects the ILO's conclusion that occupational transformation is currently more probable than widespread complete redundancy (Gmyrek et al., 2025).

Occupations Facing the Strongest Automation Pressure

Data Entry and Routine Clerical Processing

Data-entry employment has among the weakest long-term positions because its core economic value derives from moving structured information between systems. Optical character recognition, robotic process automation, natural-language processing, application programming interfaces, and AI agents increasingly allow documents to be read, interpreted, classified, checked, and entered automatically. Human workers remain useful for exceptions and quality assurance, but dramatically fewer employees can supervise increasingly large data-processing volumes. WEF employer expectations consequently identify data-entry clerks among rapidly declining occupations (World Economic Forum, 2025). Clerical work more generally remains the occupational family exhibiting the greatest GenAI exposure in the ILO's refined assessment (Gmyrek et al., 2025).

Traditional clerical training faces considerable structural pressure. Typing proficiency, formatting, filing, scheduling, elementary spreadsheet use, and routine correspondence remain useful capabilities but are increasingly insufficient as standalone sources of labour-market value. Future administrative professionals will require project coordination, workflow management, stakeholder communication, data interpretation, procurement, compliance, AI supervision, and exception handling. The administrative profession is unlikely to disappear because organisations still require coordination, confidentiality, interpersonal communication, and executive support. Nevertheless, staffing ratios could change substantially as one AI-augmented employee performs work previously distributed among several assistants. Educational institutions should consequently distinguish administration as organisational coordination from clerical processing as repetitive production.

Transcription

General transcription possesses extremely high substitution potential. Speech-recognition technologies already convert audio into text quickly and inexpensively, while language models can identify speakers, improve punctuation, summarise conversations, extract decisions, and transform transcripts into reports. Human review remains important where audio quality is poor, accents are complex, terminology is specialised, or exact legal accuracy is essential. Nevertheless, the economic requirement for large numbers of workers manually typing clearly recorded speech is unlikely to remain strong. Legal and medical transcription may retain specialised niches because confidentiality, technical vocabulary, and evidentiary accuracy increase accountability. Even in these niches, however, the human role is likely to migrate towards verification rather than initial transcription.

Proofreading and Elementary Editing

Proofreading is another occupation in which the traditional unit of labour is directly targeted by GenAI. Automated systems can correct spelling, grammar, punctuation, syntax, tone, readability, and consistency nearly instantaneously. A worker whose primary economic function consists of detecting surface-level textual errors competes against software capable of processing enormous text volumes at very low cost. Elementary copy editing is also exposed because AI can rewrite sentences, simplify language, shorten manuscripts, adapt tone, and generate alternatives. These developments do not eliminate sophisticated editorial practice. They instead separate low-value mechanical correction from high-value substantive editing, argument development, factual verification, journal strategy, ethical oversight, cultural sensitivity, and maintenance of authorial meaning.

Publishing and academic communication illustrate occupational upgrading rather than inevitable disappearance. Editors able to interrogate evidence, identify conceptual contradictions, detect unsupported claims, evaluate sources, understand disciplinary conventions, and improve scholarly reasoning retain forms of expertise that are much harder to automate reliably. AI may even increase demand for trusted editorial verification because the quantity of machine-generated content can rise dramatically. The profession may consequently become numerically smaller at its routine end while becoming more intellectually demanding at its advanced end. Training programmes centred principally on grammar correction would become less competitive than programmes combining editorial judgement, research literacy, verification, publishing ethics, intellectual-property awareness, and AI-assisted production. The same technology that reduces demand for proofreading can increase the premium on substantive editorial expertise.

Routine Translation

Translation demonstrates similar differentiation. Contemporary machine-translation and GenAI systems perform routine translation rapidly and across many languages, substantially reducing the economic value of straightforward informational translation. Businesses needing a rough translation of correspondence, instructions, websites, or ordinary documents can increasingly obtain acceptable output without contracting a professional translator. Nevertheless, legal, diplomatic, literary, technical, medical, culturally sensitive, and high-consequence translation continues to require specialist oversight. Language frequently contains ambiguity whose significance depends on cultural, institutional, historical, or professional context. Human translators may shift towards transcreation, validation, specialised localisation, intercultural mediation, and high-risk verification.

Telemarketing

Telemarketing demonstrates strong substitution potential because its workflow is repetitive, scripted, measurable, digitally mediated, and scalable. Conversational AI systems can initiate or respond to large numbers of interactions without fatigue and can dynamically adjust scripts based on customer responses. Human workers remain superior in complex persuasion, relationship development, negotiation, and situations requiring nuanced trust. Nevertheless, routine outbound calling provides comparatively limited protection because much of the occupation's production

process can be codified. Regulatory restrictions concerning automated calling may slow adoption in some jurisdictions, illustrating the importance of institutional moderators. Where legally permissible and commercially accepted, however, routine telemarketing employment is likely to contract substantially.

Routine Customer Service

Customer service offers a more complex case because substitution and complementarity occur simultaneously. Chatbots and voice agents increasingly resolve straightforward questions concerning passwords, account balances, delivery status, reservations, refunds, product information, and standard company policies. Organisations consequently require fewer workers for Tier-1 enquiries. Yet difficult customers, ambiguous complaints, fraud allegations, emotionally charged disputes, complex troubleshooting, and commercially valuable accounts often still benefit from human intervention. The future customer-service structure is likely to resemble an automated front line combined with smaller numbers of more highly skilled human escalation specialists.

Brynjolfsson et al. (2025) demonstrate that GenAI can also make existing customer-service employees more productive. Their large-scale workplace study found an average productivity increase of approximately 15% among workers receiving AI assistance, with greater improvements among less experienced workers. This produces a critical labour-market paradox. If each worker becomes 15% more productive and customer demand remains unchanged, organisations may eventually require fewer workers even where no single employee is technically “replaced” by AI. Productivity-enhancing augmentation can become employment-reducing at the organisational level when output does not expand proportionately.

Cashiers, Ticket Clerks and Routine Retail Transactions

Cashiering is vulnerable to a combination of AI and earlier forms of automation. Self-service checkouts, electronic payments, e-commerce, automated ticketing, mobile ordering, computer vision, and increasingly autonomous retail environments transfer transaction-processing activities from employees towards customers and machines. The WEF identifies cashiers and ticket clerks among roles expected to experience substantial decline by 2030 (World Economic Forum, 2025). Human retail employment will nevertheless continue in relationship selling, luxury goods, specialist consultation, hospitality-intensive environments, store operations, security, fulfilment, and experiential retail. Consequently, the most vulnerable retail employees are those whose contribution is principally transactional. Retail workers who combine technological competence, product expertise, persuasion, relationship development, and problem-solving demonstrate greater resilience.

Bookkeeping, Payroll and Routine Accounting

Bookkeeping represents another high-pressure field because financial transactions are already predominantly digital. Software can classify expenses, reconcile accounts, generate invoices, calculate payroll, monitor budgets, identify anomalies, and produce standard reports. AI adds natural-language interfaces and advanced pattern recognition to this existing automation

infrastructure. Entry-level workers whose activities centre on transaction recording face considerable technological competition. Professional accounting, however, extends far beyond bookkeeping. Assurance, tax interpretation, forensic accounting, financial strategy, regulatory compliance, governance, valuation, risk management, and professional accountability continue to require substantial specialist judgement.

The WEF nevertheless identifies accountants and auditors among occupations employers expect to experience downward pressure, demonstrating that professional status does not guarantee protection (World Economic Forum, 2025). The likely outcome is a profession with fewer workers performing mechanical processing and stronger demand for professionals capable of interpreting automatically produced information. Accounting education must move upward along the value chain. Students need analytical reasoning, information systems, AI-assisted auditing, forensic techniques, regulation, taxation, financial modelling, cybersecurity awareness, and professional ethics alongside conventional accounting principles. The accountant whose principal comparative advantage is entering transactions is vulnerable; the accountant who determines what financial information means remains substantially more defensible.

Routine Graphic Production

Generative image technologies have transformed the economics of elementary visual production. Businesses can now generate advertisements, mock-ups, illustrations, presentations, logos, backgrounds, and social-media images with dramatically less human production time. WEF reporting notably includes graphic designers among occupations increasingly affected by GenAI (World Economic Forum, 2025). This development places production-oriented graphic work under substantial pressure, where clients prioritise speed and low cost over distinctive authorship. High-level design remains more resilient because brands require strategy, coherent identity systems, cultural understanding, user research, art direction, originality, intellectual-property judgement, and communication across organisational stakeholders. Design faces the same transition as editing: production becomes cheaper while judgement becomes more valuable.

Elementary Programming

Programming once appeared to be among the clearest “future-proof” professions, but AI-generated code complicates that assumption. Modern systems can generate functions, explain code, detect bugs, write tests, translate between programming languages, create documentation, and produce simple applications from natural-language descriptions. Consequently, low-complexity coding faces increasing commodification. However, software engineering includes architecture, requirements analysis, security, database design, distributed systems, integration, product judgement, performance optimisation, reliability, and maintenance of complex organisational systems. The WEF simultaneously identifies software and application developers among major areas of employment growth, demonstrating that high AI exposure can coexist with expanding labour demand (World Economic Forum, 2025). The relevant educational conclusion is not that students should avoid computer science but that teaching syntax without advanced problem-solving is increasingly inadequate.

Occupations Likely to Be Transformed Rather Than Eliminated

Teaching

Teaching will experience extensive AI penetration but is unlikely to disappear as a profession. AI can produce lesson plans, explanations, examinations, worksheets, examples, translations, personalised feedback, and individualised tutoring. These capabilities reduce the amount of time teachers must spend on routine preparation and information transmission. Yet teachers simultaneously manage classrooms, identify social and emotional difficulties, motivate reluctant learners, communicate with families, resolve interpersonal conflicts, safeguard minors, adapt instruction dynamically, evaluate complex performance, and model human behaviour. Education is both a knowledge-transfer process and a social institution. Reducing teaching to content delivery produces an incomplete representation of the occupation.

The future teacher is likely to become more of a learning architect, mentor, evaluator, facilitator, and verifier of machine-assisted learning. AI tutors may provide students with twenty-four-hour explanations while teachers concentrate more heavily on misconceptions, collaborative activity, assessment, practical application, and social development. WEF forecasts identify secondary and tertiary educators among areas capable of experiencing employment growth, partly because demographic and developmental factors increase educational demand (World Economic Forum, 2025). The profession is likely to experience task subtraction without occupational extinction. Teachers who refuse technological integration may nevertheless face pressure from teachers capable of using AI to improve productivity and individualisation.

University Lecturing

University teaching presents an important variant because traditional lectures provide information in a format that AI systems can increasingly reproduce interactively. A student can request explanations, examples, practice questions, alternative explanations, summaries, translation, and immediate feedback without waiting for formal office hours. Consequently, the scarcity value of a lecturer cannot remain primarily “possessing information” because students have unprecedented access to information-generation systems. Academics retain value through research, disciplinary judgement, supervision, mentorship, assessment, methodological training, scholarly communities, professional networks, and institutional certification. Universities similarly provide laboratories, social development, peer communities, research infrastructure, professional legitimacy, and regulated qualifications. AI creates pressure to redefine the lecturer rather than necessarily eliminate higher education.

Journalism

AI can rapidly produce summaries, sports reports, financial updates, weather reports, headlines, transcripts, and routine news copy. This creates obvious pressure on journalists whose roles principally involve rewriting information supplied by others. However, investigative journalism requires source cultivation, field reporting, verification, confrontation of powerful institutions, contextual interpretation, legal judgement, and personal responsibility for publication. AI cannot independently witness events in the human sense or establish trust with confidential sources in

the manner required for investigative reporting. Machine-generated misinformation may additionally increase the social value of trusted verification. The profession may consequently become smaller in routine content production while investigative, analytical, specialist, and verification journalism remains comparatively important.

Law

Legal work contains many highly digitised activities, including document review, case summarisation, contract drafting, legal research, discovery, and standard correspondence. These tasks make parts of legal practice highly exposed to language models. However, lawyers also negotiate, advocate, interpret ambiguous facts, advise clients facing uncertain consequences, represent individuals before courts and regulators, and accept professional responsibility. Legal systems additionally operate through institutional authority, making complete machine substitution unlikely unless legislation and professional regulation fundamentally change. Entry-level legal work may nonetheless face considerable restructuring because junior lawyers traditionally develop expertise through research, drafting, and document review. The long-term challenge could concern professional pipelines more than complete elimination of senior lawyers.

Medicine

Medicine will become increasingly AI-intensive because diagnostic systems can analyse images, laboratory results, records, symptoms, and medical literature. Administrative documentation may become substantially automated, potentially freeing clinicians from some of the bureaucratic work currently associated with medical practice. Yet diagnosis is only one component of medicine. Physicians examine patients, integrate incomplete evidence, obtain consent, communicate difficult information, choose between competing treatment options, perform procedures, collaborate with multidisciplinary teams, and assume responsibility for consequences. Patients may also prefer identifiable human accountability when decisions concern life, disability, pain, and death. Medicine consequently demonstrates strong augmentation potential but comparatively low probability of complete occupational elimination.

Management

Managers perform numerous information-processing tasks AI can automate, including report preparation, scheduling, forecasting, performance analysis, scenario generation, meeting summarisation, and resource optimisation. Yet management is fundamentally connected with authority and responsibility. Managers recruit, negotiate, discipline, resolve conflict, persuade stakeholders, interpret organisational culture, determine priorities, represent institutions, and accept accountability for decisions. Organisations may become flatter if AI reduces information-coordination costs, potentially reducing some middle-management positions. Nevertheless, leadership and accountable decision-making remain institutionally important. The future manager is likely to supervise both human and artificial labour.

Fields Likely to Demonstrate Strong Resilience Beyond 2035

Nursing and Direct Healthcare

Nursing illustrates a profession whose administrative components can be heavily automated while its central human functions remain difficult to substitute. Nurses monitor patients, perform procedures, reposition bodies, administer treatment, detect subtle changes, reassure families, coordinate care, respond to emergencies, and interact with individuals experiencing fear, pain, disability, and uncertainty. Robotics may automate selected physical activities, while AI can improve monitoring and documentation. Nevertheless, real-world clinical environments remain highly variable. Population ageing additionally expands healthcare demand in numerous economies. Healthcare occupations should be interpreted as technologically transformed but structurally resilient.

Mental Health, Counselling and Social Work

AI conversational systems are already capable of providing general emotional support, psychoeducation, and structured information. These tools may expand access to low-intensity support and assist clinicians with documentation. Nevertheless, therapeutic relationships depend heavily on trust, confidentiality, human recognition, ethical responsibility, non-verbal information, and contextual interpretation. Severe mental-health conditions and safeguarding concerns additionally require professional accountability. Similar considerations apply to social work, where professionals interact with families, institutions, courts, healthcare providers, schools, and vulnerable populations. AI is likely to become a tool within these professions rather than a complete substitute for them.

Electricians, Plumbers and Skilled Trades

One of the most striking implications of contemporary automation is that certain skilled manual occupations may demonstrate greater technological resilience than routine graduate office employment. A language model can generate an acceptable business letter more easily than a robot can enter an unfamiliar building, diagnose hidden plumbing, manipulate irregular objects, work safely in confined spaces, and repair an unexpected physical fault. Skilled trades involve perception, mobility, dexterity, spatial reasoning, safety, adaptation, and interaction with highly variable physical environments. Robotics will progressively improve, but economically general-purpose physical automation remains considerably more difficult than digital information automation. Electricians, plumbers, maintenance specialists, HVAC technicians, specialised mechanics, and several construction occupations possess substantial medium-term resilience. This finding has important implications for societies that historically rank university office employment above technical and vocational work.

Cybersecurity

AI simultaneously automates portions of cybersecurity and increases the scale of cyber threats. Automated systems can detect anomalies, classify malware, analyse logs, identify vulnerabilities, and generate defensive recommendations. Attackers can similarly employ AI to automate

phishing, social engineering, vulnerability discovery, and malicious code development. This technological arms race increases the importance of professionals capable of system architecture, incident response, threat modelling, risk assessment, identity management, cloud security, and governance. WEF forecasts identify networks and cybersecurity among the fastest-growing skill areas (World Economic Forum, 2025). Cybersecurity demonstrates a favourable complementarity structure because more technology creates more assets requiring protection.

AI Engineering and AI Governance

The spread of AI creates demand for people who develop, integrate, test, monitor, audit, secure, regulate, and govern AI systems. Some of these functions will themselves become automated, but expanding implementation generates continuing technical and institutional requirements. Organisations need specialists capable of evaluating model bias, privacy, cybersecurity, explainability, reliability, intellectual property, procurement, compliance, and sector-specific risk. Governments similarly require policy expertise capable of balancing innovation with public protection. AI governance illustrates occupational reinstatement: technology creates tasks that barely existed in earlier labour markets. WEF forecasts likewise identify AI and machine-learning specialists among the fastest-growing technology occupations.

Green-Economy Occupations

Climate transition creates another area of employment demand that interacts with technological rather than solely AI forces. Renewable-energy engineers, environmental engineers, energy-system technicians, battery specialists, grid engineers, and electric-vehicle specialists benefit from investment in decarbonisation and infrastructure transformation. AI can enhance system design, forecasting, optimisation, and maintenance without eliminating substantial physical infrastructure requirements. WEF evidence identifies environmental and renewable-energy engineering among rapidly growing occupational categories (World Economic Forum, 2025). Developing economies with abundant renewable resources could combine digital transformation with energy transition. The strongest long-term employment strategies need not concern AI jobs alone but rather AI-enabled occupations addressing persistent material problems.

Comparative Occupational Outlook

Table 2: Likely Labour-Market Position of Selected Fields, 2026-2035 and Beyond

Field	AI task exposure	Complete replacement risk	Likely labour-demand direction	Expected human role
Data entry	Very high	Very high	Strong decline	Exception checking
Transcription	Very high	Very high	Strong decline	Specialist verification
Proofreading	Very high	High	Strong decline	Final quality assurance
Basic translation	Very high	High	Decline	Specialist

				localisation
Telemarketing	Very high	High	Strong decline	Complex sales
Routine customer support	Very high	High	Decline	Escalation/relationships
Clerical administration	Very high	High	Decline	Coordination
Cashiering	High	High	Decline	Customer assistance
Bookkeeping	Very high	High	Decline	Oversight/interpretation
Basic graphic production	Very high	High	Decline	Art direction
Routine content writing	Very high	High	Decline	Strategy/verification
Junior coding	Very high	Medium-high	Restructuring	Verification/integration
Accounting	High	Medium	Transformation	Advisory/assurance
Journalism	High	Medium	Transformation	Investigation/verification
Law	High	Medium	Transformation	Advocacy/accountability
Teaching	High	Low-medium	Transformation/growth	Mentorship/evaluation
University lecturing	High	Low-medium	Transformation	Research/supervision
Medicine	High	Low	Growth/transformation	Clinical judgement
Nursing	Medium	Very low	Growth	Direct care
Counselling	Medium	Low	Growth	Therapeutic relationship
Management	High	Low-medium	Transformation	Leadership/accountability
Software engineering	Very high	Medium	Growth/transformation	Architecture/integration
Cybersecurity	High	Very low	Strong growth	Defence/ risk governance
Electrician	Low	Very low	Stable/ growth	Physical skilled work
Plumbing	Low	Very low	Stable/ growth	Physical skilled work
Construction trades	Low-medium	Low	Stable/ growth	Physical execution

Renewable energy	Medium	Very low	Strong growth	Engineering/ installation
AI engineering	High	Very low	Strong growth	Development/ integration
AI governance	High	Very low	Strong growth	Oversight/ compliance
Advanced research	High	Low	Transformation/ growth	Discovery/ judgement
Entrepreneurship	High	Very low	Potential growth	Opportunity creation

The Entry-Level Employment Problem

One of AI's most consequential labour-market effects may concern the destruction of traditional pathways into professional expertise. Junior employees historically develop occupational knowledge by completing relatively routine activities. Trainee lawyers conduct basic research and document review, junior accountants reconcile accounts, graduate analysts build elementary reports, trainee editors proofread manuscripts, junior programmers write straightforward code, and early-career consultants prepare presentations and background analyses. These activities provide organisations with useful labour while simultaneously giving beginners opportunities to acquire tacit professional knowledge. AI can perform many of these beginner tasks effectively. Organisations may consequently discover that fewer entry-level employees are necessary even while experienced professionals remain valuable.

This creates what may be termed the AI apprenticeship paradox. Firms can reduce current costs by automating junior work, but the experienced specialists required in the future traditionally emerge from populations of juniors who learned through that work. If junior recruitment contracts severely, organisations may eventually encounter shortages of experienced personnel capable of evaluating AI-generated output. Professional education must consequently develop alternative mechanisms for acquiring experience. Simulation, supervised AI collaboration, apprenticeships, clinical practice, laboratories, project-based education, and structured professional mentoring may become increasingly important. Merely awarding academic credentials without authentic practice becomes less defensible in an environment where employers no longer need large graduate cohorts for routine production.

The consequences could be especially serious for young graduates. Entry-level employment already functions as a bridge between theoretical education and economically productive expertise. If AI removes portions of that bridge, labour markets could display a paradoxical combination of graduate unemployment and shortages of experienced professionals. Employers may increasingly advertise vacancies requiring several years of experience while simultaneously providing fewer opportunities through which young workers can acquire those years of experience. Governments and universities should consequently treat entry-level employment infrastructure as an important component of AI transition policy. Apprenticeship incentives may become as important for professional occupations as they historically were for skilled trades.

University Degrees and Programmes Requiring Major Redesign

The rise of AI does not imply that degrees become universally “useless”. Such terminology ignores the heterogeneous tasks within professional fields and the broader intellectual purposes of education. Nevertheless, programmes whose curricula are dominated by routine activities vulnerable to AI face greater labour-market risk if they remain unchanged. The critical question is not which degrees should automatically disappear, but which programmes must undergo the most substantial redesign. This distinction protects against technological determinism while recognising genuine structural change. Universities that fail to adapt may continue producing graduates whose qualifications retain formal status but weaken market scarcity.

Table 3: Higher-Education Fields Requiring Different Levels of AI-Era Redesign

Programme/ discipline	Risk if traditionally taught	Required curricular direction
Office administration	Very high	AI workflow, project coordination, analytics
Secretarial studies	Very high	Executive operations, digital systems
Transcription	Very high	Specialist documentation, compliance
Editing/ publishing	High	Substantive editing, verification, publishing strategy
Translation	High	Specialised translation, localisation, intercultural expertise
Graphic design	High	Brand strategy, UX, art direction, AI production
Journalism	High	Investigation, verification, data journalism
Marketing	High	Analytics, behavioural science, strategy, AI systems
Accounting	High	Assurance, analytics, forensic accounting, AI audit
Finance	Medium-high	Modelling, regulation, quantitative analytics
Computer programming	High	Architecture, security, AI integration
Computer science	Medium	AI systems, algorithms, cybersecurity, architecture
Law	Medium-high	Advocacy, negotiation, AI law, complex reasoning
Education	Medium	AI pedagogy, assessment, learning science
Business administration	Medium-high	Strategy, entrepreneurship, analytics, leadership
Human resources	Medium-high	Organisational behaviour, employment law, workforce analytics
Medicine	Medium	AI-enabled clinical judgement
Nursing	Low	Digital health and clinical technology

Engineering	Low-medium	AI-enabled design, systems engineering
Skilled technical education	Low	Robotics diagnostics, advanced systems
Cybersecurity	Low	AI threat intelligence
AI/ data science	Low	Advanced mathematical and domain integration
Environmental/ energy studies	Low	Technology, data and infrastructure

Office-administration programmes face perhaps the most urgent transformation because their historical curricula frequently concentrate on document preparation, office software, filing, scheduling, correspondence, and routine organisational procedures. These skills will not entirely disappear, but AI systems can perform them with increasing efficiency. Institutions should reposition programmes towards executive operations, procurement, project management, stakeholder relations, business analytics, compliance, workflow automation, digital records, cybersecurity awareness, and AI-agent supervision. Graduates should be capable of redesigning administrative systems rather than merely operating conventional ones. Without such curricular expansion, administrative qualifications risk preparing students for the most automatable component of organisational employment. This is especially important for institutions serving students who expect qualifications to produce immediate occupational mobility.

Accounting programmes similarly require repositioning rather than abandonment. Fundamental principles of double-entry accounting, taxation, financial reporting, audit, and corporate finance remain indispensable because AI systems cannot be responsibly supervised by individuals who do not understand the underlying domain. What becomes less defensible is allocating substantial programme time to manually reproducing processes that commercial software performs automatically. Students should learn how automated financial systems work, how to test their outputs, how to identify fraud and anomalies, how to interpret standards, and how to provide strategic advice. AI literacy should complement rather than replace professional accounting knowledge. This principle—domain expertise plus AI rather than AI instead of expertise—should guide curricular reform across professions.

Computer science provides another instructive example. The capacity of AI to generate code does not imply that computer-science degrees become obsolete, especially when technological employment itself is expected to expand. It does imply that curricula centred disproportionately on elementary syntax may lose value. Students require algorithmic reasoning, architecture, cybersecurity, distributed computing, databases, AI systems, mathematics, system reliability, human-computer interaction, and sophisticated problem-solving. Code generation shifts programming from producing every line manually towards specifying, testing, integrating, securing, and maintaining systems. The strongest graduates will consequently understand what software should do, why it works, when generated code is unsafe, and how complex systems interact.

Developed Economies Versus Developing Economies

Advanced economies are likely to experience earlier and more extensive cognitive automation because they possess larger proportions of professional, administrative, technical, and knowledge-intensive employment. Their higher wages increase the financial incentive to substitute capital for labour, while better digital infrastructure reduces adoption barriers. IMF analysis consequently estimates substantially higher AI exposure within advanced economies and emphasises their greater immediate need for regulation, worker transition, and social protection (Cazzaniga et al., 2024). High educational attainment creates an unusual paradox: advanced countries contain more workers capable of benefiting from AI while simultaneously containing more occupations technologically exposed to it. Their challenge concerns managing fast adoption without allowing productivity improvements to generate severe inequality. Strong institutional capacity may nevertheless provide greater opportunities for reskilling and redistribution.

Developing countries confront a different configuration. Lower wages can temporarily weaken the economic incentive for automation because a machine that costs less than an American employee may not cost less than a worker in a lower-income country. Large informal sectors also contain physical, interpersonal, and small-scale economic activity that is difficult to automate rapidly. However, these apparent buffers should not be confused with technological advantage. Countries adopting AI slowly may experience weakening international competitiveness if firms elsewhere use technology to reduce costs and improve quality. Developing economies can lose employment indirectly even without domestic automation because foreign clients may automate previously outsourced services.

The international tradability of digital work intensifies this concern. A manufacturing robot must physically operate in a factory, but a language model can replace or augment a digital task regardless of whether the human worker previously performing it lived in Kingston, Manila, London, or New York. Developing countries specialising in exported business services may consequently encounter AI competition unusually quickly. Call centres, transcription services, routine back-office processing, elementary software development, accounting support, content moderation, and digital marketing services all contain internationally tradable cognitive tasks. Low wages provide decreasing protection where automated marginal costs approach extremely low levels. Developing economies should avoid pursuing service-export strategies based solely on providing routine labour more cheaply than workers in advanced economies.

Latin America and the Caribbean

Latin America and the Caribbean provide an important setting because digital inequality simultaneously moderates technological displacement and technological opportunity. Gmyrek et al. (2024) estimate that approximately 26%-38% of employment in the region possesses some exposure to GenAI. Approximately 8%-14% could experience productivity-enhancing transformation, while approximately 2%-5% display stronger full-automation potential under current technological capabilities. Higher exposure tends to occur among urban, formally employed, better educated, and higher-income workers. The traditional assumption that low-

skilled workers are necessarily the primary technological losers is incomplete. Cognitive digitisation exposes substantial numbers of educated service workers.

The regional digital divide generates another paradox. Up to approximately half of jobs capable of obtaining productivity benefits from GenAI may be prevented from doing so because workers lack sufficient digital infrastructure and technology use, representing around 17 million regional jobs (Gmyrek et al., 2024). Digital exclusion does not provide a desirable shield against AI. Workers may avoid immediate automation while simultaneously failing to acquire productivity benefits that could improve wages and competitiveness. Poorer individuals and workers outside formal employment are especially vulnerable to this form of exclusion. Regional AI policy must consequently address both technological displacement and technological deprivation.

This distinction has profound developmental implications. High-income countries can invest in AI, increase worker productivity, and potentially reduce the price of internationally traded professional services. Caribbean firms competing without equivalent capabilities could lose market share despite continuing to employ humans. Productivity inequality between countries may widen even where developing countries experience fewer direct redundancies initially. Broadband, cloud computing, digital identification, computing equipment, reliable electricity, cybersecurity, and digital skills consequently function as productive infrastructure rather than optional technological luxuries. Regional development policy should treat access to AI-enhancing infrastructure similarly to earlier investments in electricity, roads, and telecommunications. The objective is not maximum automation but maximum socially productive technological complementarity.

Jamaica: Vulnerability and Strategic Opportunity

Jamaica presents a relevant case because substantial employment occurs in service industries that can be affected by language-processing and automation technologies. Business-process outsourcing and global services have provided important employment opportunities, especially for younger workers possessing communication and customer-service skills. Yet routine customer support represents one of the earliest environments in which conversational AI has demonstrated meaningful productivity gains (Brynjolfsson et al., 2025). International firms deciding where to locate customer-service activities will increasingly compare not only Jamaican labour costs with other countries' wages but human labour with automated and AI-assisted service models. The traditional competitive proposition of providing English-language labour at lower cost may consequently weaken. Jamaica should aim to move the industry upward from routine voice processing towards higher-value knowledge-process outsourcing, analytics, specialised technical support, healthcare administration, finance, cybersecurity, legal-process support, and AI-supervised services.

Public administration represents another area requiring strategic attention. Governments contain numerous forms of routine documentation, records processing, application handling, correspondence, scheduling, data entry, licensing, benefit administration, and public enquiries. AI and workflow automation can potentially improve public-sector efficiency substantially, where citizens experience long processing times. However, efficiency gains raise workforce questions

because governments are also major employers. Reform should emphasise reassignment and reskilling rather than relying solely on redundancies. Public servants could shift from routine document processing towards case management, citizen support, compliance, inspection, analysis, and complex decision-making.

Education is simultaneously a vulnerable and strategically essential sector for Jamaica. AI will reduce the scarcity of generic instructional explanations but increase the importance of high-quality teachers capable of developing critical reasoning, mathematics, scientific understanding, technological competence, character, and social skills. Educational institutions must themselves become engines of AI adaptation. Teachers require training not merely in prompting but in assessment integrity, model limitations, misinformation, personalised learning, data privacy, and AI-supported pedagogy. Universities must similarly ensure that students continue acquiring genuine intellectual competence when machines can generate assignments. An education system that permits AI to substitute for learning would produce graduates less rather than more capable of competing in an AI economy.

The skilled trades provide Jamaica with another potentially underappreciated opportunity. Construction, renewable energy, electrical installation, plumbing, refrigeration, air-conditioning, advanced automotive maintenance, telecommunications infrastructure, industrial maintenance, mechatronics, and related fields combine physical dexterity with increasing technological sophistication. Such occupations may exhibit greater automation resilience than several conventional office professions. Expanding high-quality technical and vocational education should consequently be viewed as a technological-development strategy rather than merely an alternative pathway for students considered unsuitable for universities. Stronger articulation between vocational qualifications and tertiary education could further prevent technical careers from being perceived as educationally inferior. AI may unintentionally increase the relative economic value of skilled technical expertise.

Healthcare also constitutes a strategic field. Jamaica, like many countries, requires physicians, nurses, allied-health practitioners, therapists, public-health specialists, technicians, and health administrators. AI can improve diagnosis, documentation, epidemiological analysis, scheduling, and patient communication, but substantial healthcare activity remains human-intensive. Training healthcare professionals to use intelligent systems safely could improve productivity without abandoning human care. The combination of healthcare demand, demographic change, international labour mobility, and limited automobility makes health professions important for long-term workforce planning. Jamaica should consequently avoid interpreting “technology careers” narrowly as computer programming; many of the strongest future occupations will combine technology with health, energy, engineering, agriculture, logistics, education, or public services.

A Comparative Jamaica-Advanced Economy Framework

Table 4: Expected Differences in AI Labour-Market Transition

Dimension	Advanced economies	Jamaica/ Caribbean developing economies
Labour cost	High	Lower
Incentive for direct automation	Very high	Moderate but increasing
Digital infrastructure	Generally stronger	Uneven
Cognitive occupation exposure	High	Moderate/ high in formal services
Informality	Lower	Higher in region
BPO vulnerability	Limited domestic dependence	Strategically important
Capital availability	Greater	More constrained
Ability to develop frontier AI	High in leading economies	Limited
Opportunity to apply existing AI	Very high	High if infrastructure improves
Skilled-trade resilience	High	High
Healthcare demand	Strong	Strong
AI skills availability	Relatively greater	Emerging
Risk from digital divide	Lower	Substantial
Reskilling capacity	Generally greater	More constrained
Key policy priority	Managed transition	Adoption plus inclusion plus transition

The comparison indicates that Jamaica does not need to become a frontier-model developer to benefit from AI. Few countries possess the capital, semiconductor infrastructure, computing capacity, data resources, and research ecosystems required to compete directly with the world's leading AI laboratories. Jamaica's more realistic opportunity lies in application specialisation. Professionals can apply AI to tourism, agriculture, education, healthcare, finance, logistics, public administration, creative industries, disaster management, cybersecurity, and business services. Small-country size may even facilitate targeted national experimentation where public institutions, universities, and firms cooperate effectively. The central constraint is less the absence of a Jamaican frontier language model than the absence of sufficient institutional capability to apply global technologies productively and responsibly.

Gender and Inequality

AI exposure also contains an important gender dimension. The ILO's 2025 analysis estimates that 4.7% of female employment globally falls within its highest GenAI-exposure category compared with 2.4% of male employment, with the difference becoming larger in high-income countries (Gmyrek et al., 2025). This partly reflects women's stronger representation in clerical and administrative occupations. Automation could consequently reverse some employment gains

made through women's increased participation in white-collar services. Governments should avoid gender-neutral transition policies that fail to consider occupational segregation. Reskilling opportunities must be designed so workers in exposed administrative occupations can transition into growing areas rather than simply absorb employment losses.

Income inequality can additionally increase even where AI raises aggregate productivity. Owners of technology and firms capable of deploying AI effectively may capture substantial returns, while workers whose tasks are easily automated experience downward wage pressure. Highly educated professionals who use AI complementarily may also experience productivity and earnings gains, potentially widening differences from workers possessing weaker digital and foundational skills (Cazzaniga et al., 2024). Conversely, technologies that distribute expert knowledge more widely could reduce some skill inequalities, as Autor (2024) hypothesises. Distributional outcomes are not technologically predetermined. Institutions, bargaining power, education, taxation, competition, and ownership influence how productivity gains are distributed.

Why Human Skills Become More Valuable, Not Less

AI's extraordinary capacity to generate information paradoxically reduces the scarcity of information production while increasing the scarcity of reliable judgement. When anyone can generate a polished report, the ability to determine whether the report is correct becomes more valuable. When images can be produced instantly, distinctive creative direction becomes more important. When code can be generated rapidly, architecture, cybersecurity, and verification become more important. When students can obtain unlimited explanations, the ability to assess whether they genuinely understand becomes more important. AI alters the location of economic value within professions rather than simply eliminating intellectual work.

Trust similarly becomes economically significant. Humans do not interact with institutions purely to obtain information; they seek responsibility, reassurance, legitimacy, advocacy, negotiation, and recognition. Patients may want a physician to remain responsible for treatment even where AI provided substantial diagnostic assistance. Parents may expect identifiable teachers to safeguard children despite widespread use of AI tutors. Corporate boards require accountable executives rather than algorithms to answer for organisational decisions. Courts require authorised participants operating within established legal institutions. Human accountability should be conceptualised as a productive economic function rather than an inefficient barrier to technological substitution.

Skills Most Likely to Retain or Increase Value

The strongest long-term workforce strategies will combine technological competence with capabilities that remain difficult to commoditise. Analytical thinking enables workers to interrogate outputs rather than accepting AI recommendations passively. Domain expertise enables them to distinguish plausible language from professionally correct conclusions. Communication enables workers to persuade, negotiate, teach, lead, care, and coordinate. Creativity allows people to identify important problems rather than merely produce requested

outputs. Ethical reasoning and accountability become more important as AI influences consequential decisions.

The WEF similarly identifies AI, big data, cybersecurity, and technological literacy among rapidly growing skill domains while continuing to emphasise analytical thinking, resilience, leadership, and collaboration (World Economic Forum, 2025). Approximately 59 of every 100 workers in its survey-based projections may require training by 2030, illustrating the scale of anticipated reskilling. Employers themselves appear to recognise the dual nature of AI: 77% report plans to upskill workers in response to AI, while 41% anticipate reducing portions of their workforce where AI automates tasks (World Economic Forum, 2025). These apparently contradictory strategies are entirely compatible. Organisations can simultaneously reduce routine staffing while investing more heavily in employees occupying complementary roles.

Proposed Research Propositions

The conceptual framework generates several propositions suitable for subsequent empirical testing. First, occupational displacement should be positively associated with the proportion of work comprising routine, digitised, predictable, and machine-evaluable tasks. Second, human-interaction intensity should moderate the relationship between technological exposure and employment contraction. Third, professional accountability should reduce complete occupational substitution even where technical exposure is high. Fourth, AI complementarity should predict stronger wage and employment outcomes than AI exposure considered independently. Fifth, digital infrastructure should positively moderate productivity benefits from AI within developing economies.

A sixth proposition concerns education: graduates from programmes emphasising reproducible production tasks should experience weaker labour-market outcomes than graduates combining domain expertise with AI-complementary capabilities. Seventh, entry-level occupations should experience greater staffing compression than senior professional positions where junior work is disproportionately routine. Eighth, lower national labour costs should delay domestic automation but should not necessarily protect internationally tradable service employment. Ninth, highly digitised Caribbean service sectors should experience stronger international automation pressure than non-tradable physical services. Finally, national AI readiness should moderate whether technological exposure produces productivity enhancement or labour displacement. These propositions could be examined using labour-force surveys, employer studies, occupational vacancy data, wage records, and longitudinal graduate-tracer studies.

Discussion

The primary finding of this comparative review is that describing occupations as either “safe” or “replaced” is theoretically inadequate. Occupations consist of bundles of tasks whose technological substitutability differs substantially. AI may eliminate some tasks, accelerate others, create additional responsibilities, reduce staffing requirements, and increase the productivity of remaining workers simultaneously. This framework explains why exposure indices should not be converted mechanically into unemployment projections. A highly exposed

profession may expand if demand grows strongly enough, while a less exposed occupation may decline for unrelated demographic or economic reasons. Future-of-work analysis must combine technology with economics, institutions, demographics, and human preferences.

The findings further challenge the historical hierarchy between intellectual and manual employment. Digitised cognitive tasks are accessible to GenAI because the technology operates directly within information environments. Many skilled trades take place in complex physical environments requiring manipulation, movement, perception, safety, and continual adaptation. Consequently, proofreading can be technologically easier to automate than plumbing, while basic coding can be easier to automate than electrical fault diagnosis in an unfamiliar building. This inversion carries important educational implications. Societies that have systematically encouraged young people to pursue generic office qualifications while treating vocational education as a secondary pathway may need to reconsider their assumptions about technological security.

The analysis additionally indicates that education remains crucial but must change its relationship with occupational preparation. Teaching students tasks machines perform better does not constitute sustainable human-capital development. Yet removing fundamental knowledge because machines can provide answers would be equally damaging. Accountants must understand accounting to identify AI errors, doctors must understand medicine to evaluate automated diagnoses, and programmers must understand computing to determine whether generated systems are secure. The appropriate educational strategy is neither resistance nor intellectual outsourcing. It is the development of **AI-enhanced expertise grounded in independent human competence**.

For developing countries, the results reveal what may be termed the **automation-exclusion dilemma**. Weak digital infrastructure can temporarily reduce domestic automation while simultaneously preventing productivity-enhancing AI adoption. Such countries can then suffer the disadvantages of both systems: workers remain less productive while internationally exposed sectors face competition from AI-enabled foreign firms. Latin American and Caribbean evidence showing that millions of potentially augmentable jobs are constrained by digital access illustrates this problem directly (Gmyrek et al., 2024). Digital inclusion must become part of employment strategy. Protecting workers by keeping them technologically disconnected is neither feasible nor economically desirable.

Jamaica's strategic problem should consequently not be framed as whether the country should accept or reject AI. Global adoption will proceed irrespective of the decisions of any small economy. The meaningful choice concerns whether Jamaican organisations and workers become low-value consumers of imported AI, displaced providers of routine labour, or skilled users capable of applying AI to higher-value problems. Business-process outsourcing provides an urgent example because routine voice and text operations sit near the technological frontier of conversational automation. Moving towards knowledge-process outsourcing, cybersecurity, technical support, healthcare services, analytics, finance, specialised compliance, and other high-complexity activities would provide greater resilience. National workforce strategy must anticipate occupational restructuring before employment losses become severe.

Policy Recommendations

Educational institutions should establish systematic AI occupational-risk reviews for their programmes. Programmes should be evaluated not simply by historical enrolment and graduate numbers but by the technological substitutability of the tasks for which students are being prepared. High-risk programmes need not automatically close, but their curricula should migrate towards higher-value, human-complementary functions. Universities should establish employer advisory systems capable of identifying changing skill requirements rapidly. Curriculum revision cycles of five or ten years are increasingly incompatible with technologies whose capabilities can change materially within months. Second, AI literacy should become a cross-disciplinary graduate attribute. This does not mean every student should become a computer scientist. Nurses should learn clinical AI, accountants should learn AI-supported assurance, educators should learn AI pedagogy, journalists should learn AI-assisted verification, managers should learn algorithmic governance, and engineers should learn intelligent-system integration. Students also require knowledge of hallucination, model bias, cybersecurity, privacy, copyright, misinformation, and responsible use. Technological literacy must include critical scepticism rather than mere proficiency in prompting.

Third, governments should substantially strengthen lifelong learning. The conventional education model assumes individuals obtain most formal training before entering employment and then apply that knowledge for several decades. AI weakens this assumption because technological transformation can alter professions repeatedly during one person's career. Short-cycle qualifications, micro-credentials, professional conversion programmes, subsidised retraining, employer-based learning, and recognition of prior learning become increasingly important. Workers should be able to update capabilities without abandoning employment for several years. Social-protection systems should similarly facilitate rather than punish occupational mobility.

Fourth, Jamaica and other Caribbean countries should give technical and vocational education greater strategic status. Skills in electricity, industrial automation, renewable energy, refrigeration, construction technology, telecommunications, mechatronics, advanced automotive systems, healthcare technology, and maintenance combine technological sophistication with physical-world requirements. Such careers should not be marketed principally as alternatives for students unsuccessful in academic education. They represent potentially resilient components of twenty-first-century human capital. Stronger pathways between technical colleges and universities could improve prestige, mobility, and lifelong professional development.

Fifth, national AI strategies should emphasise productive adoption within existing sectors rather than AI rhetoric alone. Governments should identify specific use cases in agriculture, healthcare, tourism, education, public administration, finance, logistics, disaster management, environmental monitoring, and creative industries. Small firms require support because large corporations possess greater resources for experimentation. Universities can serve as technological extension institutions supporting local organisations in adopting AI responsibly. Public-sector procurement can similarly encourage local capability development. AI strategy should ultimately be assessed through improvements in productivity, employment quality, public services, innovation, and national competitiveness.

Limitations

Forecasting employment beyond a decade contains unavoidable uncertainty. AI capabilities may advance more rapidly or more slowly than currently expected, and breakthroughs in robotics could alter the resilience of physical occupations. Regulatory responses can similarly accelerate or restrict deployment. Consumer preferences may preserve human services even when automation is technically feasible. New occupations may emerge that cannot presently be described with sufficient precision.

The analysis is additionally based principally on secondary research rather than original employer or worker survey data. International occupational classifications do not perfectly represent Jamaica's labour-market structure, and regional Latin American and Caribbean estimates should not be interpreted as Jamaica-specific automation probabilities. Future research should calculate occupational exposure using Jamaican Labour Force Survey microdata and detailed occupational classifications. Employer surveys could determine current AI adoption, planned workforce reductions, emerging vacancies, and reskilling activity. Longitudinal graduate research would additionally determine whether AI exposure is already influencing early-career employment, wages, underemployment, and occupational transitions.

Future Research Agenda

Future Jamaican research should construct an occupation-specific AI Exposure Index matched to national employment data. Such research could estimate the number and proportion of Jamaican workers employed in occupations demonstrating high substitution, high augmentation, and low exposure. Analysis should be disaggregated by sex, age, educational level, parish, industry, occupation, income, and employment status. Special attention should be directed towards business-process outsourcing, public administration, financial services, tourism, education, retail, and professional services. This would transform the present conceptual assessment into a nationally quantified labour-market model. Scenario analysis could additionally compare conservative, moderate, and accelerated AI-adoption pathways to 2030, 2035, and 2040.

Higher-education research should similarly examine whether degree supply corresponds with future occupational demand. University enrolment and graduation data could be mapped against occupational exposure measures to create a Graduate Automation Risk Index. Programmes producing large graduate cohorts for contracting occupational functions could then be identified before severe graduate underemployment develops. Importantly, the purpose should not be to discourage education but to improve the alignment between curricula and technological change. Such research could provide an evidence base for national tertiary-education planning in Jamaica and the wider Caribbean.

Conclusion

Artificial intelligence will substantially restructure the global labour market over the next decade, but the available evidence does not justify predictions that human employment will simply disappear. The more plausible outcome is a complex redistribution of tasks between people and machines accompanied by occupational contraction, occupational expansion, productivity

growth, new professions, changed skill requirements, and substantial worker transition. Clerical processing, data entry, transcription, basic proofreading, elementary translation, telemarketing, routine customer service, cashiering, bookkeeping, standardised content creation, basic graphic production, and portions of elementary coding face strong technological pressure. Teaching, accounting, law, journalism, management, medicine, and software engineering are more accurately described as transformable professions because AI can automate substantial tasks without eliminating their complete human function. Nursing, counselling, skilled trades, cybersecurity, AI governance, advanced technical work, renewable energy, and occupations involving complex physical environments, trust, accountability, and interpersonal relationships demonstrate comparatively stronger resilience.

The distinction between job exposure and job replacement is fundamental. ILO evidence indicates that approximately one-quarter of global employment possesses some GenAI exposure, but only a small fraction lies within the highest exposure category, while transformation remains the more likely outcome for most affected occupations (Gmyrek et al., 2025). WEF projections similarly anticipate simultaneous creation and displacement, demonstrating that technological change can produce considerable turbulence without generating a permanently shrinking global quantity of employment (World Economic Forum, 2025). The critical problem concerns who obtains the new employment, whether displaced workers possess the required skills, and how quickly transitions occur. Aggregate job growth provides little comfort to an administrative worker whose experience does not qualify her or him for an emerging cybersecurity position. Employment policy must consequently focus on occupational mobility rather than headline job totals.

For advanced economies, the primary challenge involves managing rapid cognitive automation, inequality, professional restructuring, and workforce transition. Developing economies confront an additional challenge because slower technological adoption can become a competitive disadvantage. Latin America and the Caribbean demonstrate that inadequate digital infrastructure can prevent millions of workers from accessing potential AI-driven productivity gains while digitally exposed workers remain susceptible to automation (Gmyrek et al., 2024). Jamaica must avoid treating weak AI adoption as protection. A small service-based economy can lose internationally tradable employment when foreign organisations automate even if Jamaican firms themselves adopt technology slowly. Digital inclusion, technological capability, educational transformation, and economic upgrading are consequently integral components of labour-market protection.

The most consequential educational lesson is that qualifications themselves will provide decreasing protection when their underlying competencies can be automated. A university degree remains valuable when it develops domain expertise, analytical reasoning, professional judgement, communication, creativity, research capability, ethical responsibility, and the capacity to use sophisticated technologies effectively. Programmes become vulnerable when they prepare students primarily to reproduce standardised outputs that intelligent systems can generate more quickly and cheaply. Universities should move from educating students for established job descriptions towards educating them for adaptable professional capability. Technical and

vocational institutions should likewise be elevated because technologically sophisticated physical occupations can provide strong resilience in an AI-intensive economy.

Ultimately, the AI revolution should not be conceptualised solely as a contest between humans and machines. The more consequential competition will increasingly occur between individuals, firms, institutions, and countries differing in their ability to combine human capability with intelligent systems. A professional using AI effectively can outperform both an unaided professional and an unreliable autonomous system in many environments. Nations that develop infrastructure, education, regulation, entrepreneurship, and complementary human capital may obtain significant productivity gains, while nations that preserve outdated occupational structures risk declining competitiveness. The central economic asset of the post-2035 labour market will consequently not be the ability to reproduce information that machines make abundant. It will be the ability to exercise judgement, responsibility, creativity, expertise, trust, physical adaptability, and strategic control over increasingly capable machines.

References

- Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, 108(6), 1488-1542. <https://doi.org/10.1257/aer.20160696>
- Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2), 3-30. <https://doi.org/10.1257/jep.33.2.3>
- Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128(6), 2188-2244. <https://doi.org/10.1086/705716>
- Arntz, M., Gregory, T., & Zierahn, U. (2016). *The risk of automation for jobs in OECD countries: A comparative analysis* (OECD Social, Employment and Migration Working Papers No. 189). OECD Publishing. <https://doi.org/10.1787/5jlz9h56dvq7-en>
- Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, 29(3), 3-30. <https://doi.org/10.1257/jep.29.3.3>
- Autor, D. H. (2024). *Applying AI to rebuild middle class jobs* (NBER Working Paper No. 32140). National Bureau of Economic Research. <https://doi.org/10.3386/w32140>
- Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4), 1279-1333. <https://doi.org/10.1162/003355303322552801>
- Bessen, J. E. (2019). AI and jobs: The role of demand. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda*. University of Chicago Press.
- Brynjolfsson, E., Li, D., & Raymond, L. R. (2025). Generative AI at work. *The Quarterly Journal of Economics*, 140(2), 889-942. <https://doi.org/10.1093/qje/qjae044>
- Cazzaniga, M., Jaumotte, F., Li, L., Melina, G., Panton, A. J., Pizzinelli, C., Rockall, E. J., & Tavares, M. M. (2024). *Gen-AI: Artificial intelligence and the future of work* (Staff

- Discussion Note 2024/ 001). International Monetary Fund. <https://doi.org/10.5089/9798400262548.006>
- Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2024). GPTs are GPTs: Labor market impact potential of LLMs. *Science*, 384(6702), 1306-1308. <https://doi.org/10.1126/science.adj0998>
- Felten, E., Raj, M., & Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, 42(12), 2195-2217. <https://doi.org/10.1002/smj.3286>
- Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254-280. <https://doi.org/10.1016/j.techfore.2016.08.019>
- Gmyrek, P., Berg, J., & Bescond, D. (2023). *Generative AI and jobs: A global analysis of potential effects on job quantity and quality* (ILO Working Paper 96). International Labour Organization.
- Gmyrek, P., Berg, J., Kamiński, K., Konopczyński, F., Ładna, A., Nafradi, B., Rosłaniec, K., & Troszyński, M. (2025). *Generative AI and jobs: A refined global index of occupational exposure* (ILO Working Paper 140). International Labour Organization. <https://doi.org/10.54394/HETP0387>
- Gmyrek, P., Winkler, H., & Garganta, S. (2024). *Buffer or bottleneck? Employment exposure to generative AI and the digital divide in Latin America* (ILO Working Paper 121). International Labour Organization & World Bank. <https://doi.org/10.54394/TFZY7681>
- International Labour Organization. (2025). *Generative AI and jobs: A 2025 update*. International Labour Organization.
- International Monetary Fund. (2024). *Gen-AI: Artificial intelligence and the future of work*. International Monetary Fund.
- Nedelkoska, L., & Quintini, G. (2018). *Automation, skills use and training* (OECD Social, Employment and Migration Working Papers No. 202). OECD Publishing. <https://doi.org/10.1787/2e2f4eea-en>
- Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science*, 381(6654), 187-192. <https://doi.org/10.1126/science.adh2586>
- Organisation for Economic Co-operation and Development. (2023). *OECD employment outlook 2023: Artificial intelligence and the labour market*. OECD Publishing. <https://doi.org/10.1787/08785bba-en>
- Organisation for Economic Co-operation and Development. (2024). *How is AI changing the way workers perform their jobs and the skills they require?* OECD Publishing.
- Organisation for Economic Co-operation and Development. (2025). *OECD skills outlook 2025*. OECD Publishing.
- Webb, M. (2020). The impact of artificial intelligence on the labor market. *Labour Economics*, 67, 101916.

- World Bank. (2024). *Generative AI and jobs in Latin America and the Caribbean: Is the digital divide a buffer or bottleneck?* World Bank.
- World Bank. (2025). *Artificial intelligence revolution in higher education: What you need to know.* World Bank.
- World Economic Forum. (2023). *The future of jobs report 2023.* World Economic Forum.
- World Economic Forum. (2025). *The future of jobs report 2025.* World Economic Forum.
- Lábaj, M., Oleš, T. & Procházka, G. (2025). Impact of robots and artificial intelligence on labor and skill demand: evidence from the UK. *Eurasian Bus Rev* 15, 953-1001. <https://doi.org/10.1007/s40821-025-00314-w>
- Fleming, S. (2020, September 3). *A short history of jobs and automation.* World Economic Forum. <https://www.weforum.org/stories/2020/09/short-history-jobs-automation/>
- Illéssy, M., Huszár, Á., & Makó, C. (2021). Technological Development and the Labour Market: How Susceptible Are Jobs to Automation in Hungary in the International Comparison? *Societies*, 11(3), 93. <https://doi.org/10.3390/soc11030093>