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The Future of Careers in the Age of Disruptive AI: A Forecasting Study Based on Data and Systematic Literature Review

Amdan Mohamed[1]✉, Rusman Ghani[2], Mohd. Amir Mat Samsudin[3], Ismail Fahmi[4], Afit Istiandaru[5], Wuryanto[6]

[1-3]Tunku Puteri Intan Safinaz School of Accountancy, Universiti Utara Malaysia, Malaysia
[4]Faculty of Industrial Technology, Universitas Islam Indonesia, Indonesia
[5]Faculty of Teacher Training and Education, Universitas Ahmad Dahlan, Indonesia
[6]Faculty of Informatics and Applied Sciences, Universitas Bali International Muhammadiyah, Indonesia

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Abstract

This study examines how disruptive artificial intelligence (AI) may reshape occupational structures and career trajectories between 2025 and 2035. It employs a mixed-methods forecasting approach that integrates a systematic literature review guided by PRISMA principles, sectoral AI exposure analysis, and an Integrated Exposure–Adaptation Model incorporating scenario planning. The analysis investigates job displacement, job creation, occupational redesign, and the adaptive capacity required to navigate AI-driven labour-market transformations. The findings reveal substantial differences between theoretical AI exposure and observed workplace adoption, indicating that technological capabilities do not necessarily translate into immediate job elimination. Computer and mathematics occupations exhibit high theoretical AI exposure (94%), while office and administrative occupations demonstrate the highest observed exposure among the sectors examined (45%). Three plausible scenarios emerge: Rapid Displacement, Augmentation Equilibrium, and Innovation-Led Growth. Among these, Augmentation Equilibrium represents a balanced and potentially achievable pathway, provided that human–AI collaboration, continuous learning, and institutional adaptation are prioritised. The study also identifies emerging opportunities in AI governance, prompt engineering, data science, machine learning, and robotics, alongside increased automation risks for routine administrative and repetitive tasks. These findings highlight the importance of integrating AI literacy, analytical reasoning, creativity, and domain-specific expertise into education and workforce development. This study contributes an integrated forecasting framework that distinguishes theoretical from observed AI exposure and supports strategic planning for individuals, organisations, educational institutions, and policymakers. Nevertheless, the projections remain conditional and require further empirical validation across occupational sectors and geographical contexts.

Keywords: *akal imitasi*, artificial intelligence, career forecasting, scenario planning, adaptive capacity, prompt engineering, machine learning, data science, robotics.

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✉***Corresponding Author:***
Amdan Mohamed, Tunku Puteri Intan Safinaz School of Accountancy, Universiti Utara Malaysia, Malaysia
Email: amdan@uum.edu.my

1. Introduction

The advent of *Akal Imitasi* 'Artificial Intelligence' (AI) represents a pivotal technological shift, comparable in magnitude to the industrial revolutions that have historically reshaped human labour and societal structures. As AI technologies particularly generative AI and large language models (LLMs) become increasingly sophisticated and integrated into various facets of economic activity, profound questions arise regarding their impact on the future of work and careers (Manyika et al., 2017). The rapid pace of AI innovation, exemplified by the widespread adoption of tools such as ChatGPT since late 2022, has ignited both excitement about unprecedented productivity gains and apprehension about potential widespread job displacement (OpenAI, 2022).

This research addresses the critical need for a comprehensive and forward-looking understanding of how disruptive AI will transform career landscapes over the next decade (2025–2035). Whilst historical precedents suggest that technological advancements often lead to job creation alongside displacement, the unique characteristics of AI its ability to perform complex cognitive tasks and learn autonomously necessitate a re-evaluation of traditional forecasting models (Frey & Osborne, 2013). The uncertainty surrounding the scale and speed of AI's integration into the workforce poses significant challenges for individuals, educational institutions, businesses, and governments alike.

Our primary research question is: How will disruptive AI technologies reshape career landscapes across different sectors over the next decade (2025–2035)? To address this, we pursue several secondary questions, including identifying occupations and skills most vulnerable to AI, recognising emerging career opportunities, assessing the adaptability of educational systems, and exploring effective policy interventions. Furthermore, we critically examine the performance of forecasting methodologies in predicting career transformations within rapidly evolving technological contexts.

This paper aims to achieve several objectives: to systematically review and synthesise existing literature on AI's impact on careers; to identify current patterns and trends in occupational transformation; to develop a robust forecasting framework for career evolution; and to provide actionable, evidence-based recommendations for navigating the AI-driven future of work. The subsequent sections delve into a comprehensive literature review, detail our integrated methodological approach, present key findings from data analysis and forecasting, discuss their implications, and conclude with a summary of contributions, limitations, and avenues for future research.

a. Literature Review

1) Theoretical Frameworks for Understanding Technological Disruption and Careers

The discourse surrounding technological disruption and its impact on labour markets is rooted in several theoretical perspectives. Technological unemployment theories, dating back to Keynes (1930), posit that automation can lead to a permanent reduction in the demand for human labour. Conversely, compensation theories argue that technological advancements, whilst displacing some jobs, simultaneously create new ones through various mechanisms, such as increased productivity leading to new goods and services, or the demand for new skills to manage the technology itself (Autor,

2015). More recent frameworks, such as the task-based approach, offer a nuanced view, suggesting that AI primarily automates specific tasks within occupations rather than entire jobs, leading to job redesign and augmentation rather than outright replacement (Acemoglu & Restrepo, 2019). This perspective is crucial for understanding the heterogeneous impact of AI across different occupations, as highlighted by the U.S. Bureau of Labor Statistics (BLS), which emphasises that even significant task changes may not always result in employment impacts (Machovec et al., 2025).

2) Historical Perspectives on Technological Change and Employment

History offers valuable insights into the long-term effects of technological change on employment. Past industrial revolutions from mechanisation in agriculture to the rise of information technology have consistently demonstrated a pattern of initial disruption followed by adaptation and net job growth (Mokyr et al., 2015). For instance, the introduction of digital cameras led to a significant decline in photographic process workers, a trend accurately projected by the BLS (Machovec et al., 2025). However, the emergence of new roles in digital photography, software development, and e-commerce compensated for these losses. This historical context suggests that whilst AI may cause short-term dislocations, the economy possesses an inherent capacity for adaptation and the creation of new employment opportunities.

3) Current State of AI Technologies and Capabilities

Contemporary AI technologies, particularly generative AI and LLMs, possess capabilities that extend beyond traditional automation. These systems can generate creative content, perform complex reasoning, and engage in human-like conversation, leading to their rapid integration across various sectors (OpenAI, 2022). The McKinsey Global Survey on AI (McKinsey & Company, 2025) indicates that 88% of organisations are now using AI in at least one business function, with growing interest in AI agents capable of planning and executing multi-step workflows. This widespread adoption underscores the immediate relevance of understanding AI's impact on careers.

4) Existing Research on AI's Impact on Different Occupational Categories

Existing literature reveals a varied impact of AI across different occupational categories. Occupations involving routine, repetitive, and predictable tasks are generally considered most vulnerable to automation (Brynjolfsson & McAfee, 2014). Goldman Sachs Research (2025) estimates that 300 million jobs globally are exposed to automation, with computer programmers, accountants, and administrative assistants identified as high-risk occupations. Conversely, roles requiring complex problem-solving, creativity, emotional intelligence, and interpersonal skills are often deemed less susceptible to displacement and may even be augmented by AI (World Economic Forum, 2023). Research by Anthropic (2026) introduces the concept of "observed exposure," highlighting that whilst theoretical AI capabilities may be high, actual observed usage and displacement are often lower, suggesting a more nuanced impact on the workforce.

5) Gaps in Current Understanding and Research

Despite extensive research, several gaps remain in the understanding of AI's long-term

impact on careers. Many studies focus on the potential for job displacement, often overlooking the equally significant aspects of job creation, job redesign, and skill transformation (Autor & Salomons, 2018). There is also a need for more robust forecasting methodologies that can account for the dynamic and unpredictable nature of AI development and adoption. Furthermore, whilst qualitative assessments are abundant, quantitative models that integrate diverse data sources and provide granular, sector-specific predictions are still evolving. This research aims to address these gaps by developing an integrated forecasting framework and providing a data-driven analysis of career transformations from 2025 to 2035.

2. Method

This forecasting study employs a mixed-methods approach, integrating a systematic literature review with a data-driven analytical framework to project the future of careers in the age of disruptive AI. Our methodology is designed to provide a comprehensive and nuanced understanding of AI's impact, accounting for both theoretical capabilities and observed real-world applications.

a. Systematic Literature Review Protocol

Our systematic literature review adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, ensuring transparency and rigour in the selection and synthesis of evidence (Moher et al., 2009). The review encompassed peer-reviewed academic journals, high-impact industry reports from reputable consulting firms (e.g., McKinsey & Company; Goldman Sachs), and economic indices published between 2023 and 2026. The search strategy utilised keywords such as "AI impact on jobs," "AI workforce transformation," "career forecasting AI," "job displacement AI," and "AI skill demand."

Inclusion criteria were as follows: (a) studies that quantitatively or qualitatively discuss AI-driven job displacement, job creation, or skill transformation; (b) reports and academic papers providing forecasts or projections for the period 2025–2035; (c) research that proposes or utilises theoretical frameworks for understanding technological disruption in labour markets; and (d) English-language publications.

Data extracted from the selected literature included key findings, theoretical models, empirical evidence, and policy recommendations. A thematic synthesis approach was employed to identify recurring patterns, emerging trends, and areas of consensus or divergence within the literature. This process facilitated the identification of critical factors influencing AI's impact on careers and informed the development of a robust conceptual framework for the forecasting model.

b. Forecasting Methodology: The Integrated Exposure–Adaptation Model

To project career evolution, we developed an Integrated Exposure–Adaptation Model, which combines a task-based exposure analysis with a scenario planning approach. This hybrid model allows for both granular assessment of AI's direct impact on tasks and a broader consideration of macro-level economic and social responses.

1) Task-Based Exposure Analysis

Building upon the task-based framework, we quantify the potential for AI to affect specific occupations through an "observed exposure" (OE) metric, adapted from Anthropic (2026). This metric differentiates

between the theoretical capability of AI to perform tasks and its actual observed usage in professional settings. The formula for observed exposure is:

$$OE = \Sigma (T_i \times C_i \times W_i)$$

where T_i represents the proportion of time spent on task i within a given occupation; C_i denotes the AI capability or coverage for task i, reflecting the extent to which AI can perform or assist with that task; and W_i is a weighting factor set at 1.0 for tasks that are fully automated by AI and 0.5 for tasks where AI serves as an augmentation tool, assisting human workers (Anthropic, 2026).

This approach provides a more realistic assessment of AI's immediate impact by focusing on actual deployment rather than speculative potential. Figure 1 illustrates the divergence between theoretical and observed AI exposure across various occupational sectors based on our synthesised data.

2) Scenario Planning (2025–2035)

Recognising the inherent uncertainties in long-term forecasting, we developed three distinct scenarios for the period 2025–2035. These scenarios are constructed based on varying assumptions regarding the pace of AI adoption, the nature of technological development, and the responsiveness of institutional and societal adaptation mechanisms. This approach allows for the exploration of a range of plausible futures rather than relying on a single, deterministic prediction (Schoemaker, 1993).

The Rapid Displacement Scenario assumes a high rate of AI adoption coupled with slow or inadequate institutional adaptation. It projects significant frictional unemployment as AI rapidly automates tasks across numerous sectors, leading to a substantial mismatch between displaced workers and available new roles.

The Augmentation Equilibrium Scenario envisages AI adoption proceeding at a moderate pace, with a strong emphasis on human–AI collaboration. The focus is on job redesign and augmentation, where AI tools enhance human capabilities, leading to increased productivity and a gradual evolution of job roles rather than widespread displacement.

The Innovation-Led Growth Scenario posits that AI acts as a powerful catalyst for the creation of entirely new industries, markets, and job categories. Whilst initial displacement may occur, the rate of job creation in novel AI-driven sectors is projected to quickly outpace job losses, leading to net employment growth after a transitional period estimated at approximately two years (Goldman Sachs Research, 2025).

c. Data Sources and Synthesis

Our analysis integrates data from multiple authoritative sources. Employment trend data and occupational classifications were primarily drawn from the U.S. Bureau of Labor Statistics (Machovec et al., 2025). Insights into AI adoption rates and their impact on various industries were derived from McKinsey & Company (2025) and Goldman Sachs Research (2025). The Anthropic Economic Index provided crucial data on observed AI usage patterns and task-level exposure (Anthropic, 2026).

d. Analytical Dimensions

The forecasting study evaluates career transformations across four key analytical dimensions. Technical vulnerability assesses the inherent susceptibility of an occupation's core tasks to automation or augmentation by current and emerging AI technologies. Economic viability considers the cost–benefit

analysis for organisations implementing AI solutions versus retaining human labour, including factors such as development costs, operational efficiency gains, and return on investment. Regulatory and social constraints account for legal, ethical, and societal barriers that may influence the pace and extent of AI adoption, particularly in sensitive sectors such as healthcare, legal services, and education. Finally, adaptive capacity evaluates the potential for workers within a given sector to acquire new skills, retrain, and transition into new or redesigned roles, influenced by factors such as educational infrastructure, training programmes, and individual willingness to adapt. By integrating these dimensions, our methodology aims to provide a holistic and robust framework for understanding and forecasting the complex interplay between AI and the future of careers.

3. Result and Discussion

The findings of this study reveal that the impact of disruptive artificial intelligence (AI) on the future of careers is multidimensional, encompassing changes in occupational structures, the emergence of new professional opportunities, and the evolving requirements for workforce competencies. Drawing on the systematic literature review, sectoral AI exposure analysis, and the Integrated Exposure–Adaptation Model, this section examines how AI is reshaping employment patterns and career trajectories between 2025 and 2035. To provide a comprehensive understanding of these transformations, the results and discussion are organised into three main themes: (1) AI exposure and occupational transformation, (2) future career forecasting and occupational shifts, and (3) workforce adaptation and strategic implications.

a. AI Exposure and Occupational Transformation

Artificial intelligence (AI) is transforming occupational structures through three interconnected mechanisms: job displacement, job creation, and job redesign. The findings of this study indicate that the impact of AI varies considerably across occupational sectors, depending on the nature of work tasks, the level of technological integration, and the extent to which human judgement remains necessary. Consistent with compensation theories, technological advancement can eliminate certain tasks while simultaneously generating demand for new occupations and complementary skills (Autor, 2015; Autor & Salomons, 2018). Consequently, AI exposure should not be interpreted as an immediate indicator of occupational disappearance, but rather as a measure of the extent to which existing tasks can be automated or augmented by AI technologies.

The distinction between theoretical AI exposure and observed exposure provides an important basis for understanding these occupational transformations. Theoretical exposure reflects the extent to which AI could perform or assist with particular tasks, whereas observed exposure represents the extent to which AI is actually integrated into professional activities. As presented in the original study, the Computer & Mathematics sector exhibits a theoretical exposure rate of 94%, compared with an observed exposure rate of 33%. Similarly, Office & Administration records theoretical exposure of 90% and observed exposure of 45%. These differences suggest that technological capability does not automatically translate into widespread implementation or immediate employment reductions. Organisational readiness, workflow integration, regulatory requirements, and the need for human

oversight may influence the pace of adoption (Anthropic, 2026; Machovec et al., 2025).

Table 1. AI Exposure and Job Creation Potential by Sector (2025–2026)

Sector	Theoretical Exposure (%)	Observed Exposure (%)	Job Creation Potential
Computer & Mathematics	94	33	High
Office & Administration	90	45	Low
Legal	85	25	Medium
Business & Finance	80	30	Medium
Arts & Media	75	35	High
Manufacturing	65	40	Low
Education	50	15	High
Healthcare	45	10	High
Construction	20	5	Medium

Note. Data synthesised from Anthropic (2026), Goldman Sachs Research (2025), and McKinsey & Company (2025).

Table 1 demonstrates substantial variation in AI exposure across occupational sectors. Computer & Mathematics records the highest theoretical exposure (94%), but its observed exposure is considerably lower (33%), while Office & Administration has an observed exposure of 45%, the highest among the listed sectors. This difference indicates that the actual implementation of AI does not necessarily follow its theoretical technical capabilities. Manufacturing also demonstrates a notable difference, with theoretical exposure of 65% and observed exposure of 40%. Conversely, Construction exhibits the lowest exposure rates, at 20% theoretically and 5% observationally, reflecting the challenges of automating tasks that require physical interaction with complex environments. Importantly, the job creation potential column indicates that exposure alone cannot determine whether a sector will experience employment growth or decline. For example, Education and Healthcare combine relatively lower observed exposure with high job creation potential, suggesting opportunities for AI-augmented professional services rather than the straightforward replacement of human workers (Anthropic, 2026; Goldman Sachs Research, 2025; McKinsey & Company, 2025).

These findings support the task-based perspective that AI is more likely to transform particular work activities than eliminate entire occupations uniformly (Acemoglu & Restrepo, 2019; Machovec et al., 2025). Within the same occupation, routine information processing may be automated while responsibilities involving interpretation, accountability, communication, and complex decision-making remain dependent on human expertise. This distinction is particularly important when evaluating the relationship between technological exposure and employment outcomes. A high exposure rate may indicate considerable potential for productivity improvements, but it does not establish that a corresponding proportion of jobs will disappear. The extent of displacement depends on whether AI substitutes for workers, complements their capabilities, or changes the organisation of work.

The relationship between AI adoption and occupational change can therefore be examined through three principal mechanisms: displacement of automatable tasks, augmentation of existing professional activities, and the creation of new employment opportunities. These mechanisms may occur simultaneously within the same sector, producing different outcomes according to organisational needs and the availability of complementary human skills.

Table 2. Principal Mechanisms of AI-Driven Occupational Transformation

Transformation mechanism	Main characteristics	Potential employment implications	Examples identified in the article
Job displacement	AI automates routine, repetitive, and predictable tasks.	Reduced demand for workers performing highly automatable activities.	Data entry and routine administrative support.
Job augmentation and redesign	AI assists workers with information processing, analysis, and task execution.	Existing roles evolve, with greater emphasis on human oversight and higher-value responsibilities.	AI-augmented professionals in healthcare, legal services, and financial analysis.
Job creation	AI generates demand for specialised technical, operational, and governance capabilities.	New occupations emerge alongside changing skill requirements.	AI ethicists, prompt engineers, data scientists, and machine learning engineers.

Source: Synthesised from the findings and discussion in the original article, drawing on Autor (2015), Autor and Salomons (2018), Acemoglu and Restrepo (2019), and World Economic Forum (2023).

Table 2 clarifies why AI-driven occupational transformation should not be assessed exclusively through the number of jobs that might be automated. Job displacement occurs when automation reduces the need for particular human activities, whereas augmentation changes how workers perform their responsibilities without necessarily eliminating their positions. Job creation, meanwhile, reflects the emergence of new roles associated with developing, implementing, maintaining, and governing AI systems. These processes are interconnected rather than mutually exclusive. An organisation may reduce its need for routine administrative processing while increasing demand for employees who can supervise AI outputs, interpret analytical results, and ensure responsible technology use. Nevertheless, the creation of new occupations does not automatically compensate for displaced workers, particularly when new positions require different qualifications. This temporal and competency mismatch reinforces the importance of reskilling and cross-sectoral workforce mobility (Autor & Salomons, 2018; Goldman Sachs Research, 2025).

A further distinction emerges when sectoral exposure is considered alongside the potential for job creation. The original study identifies Computer & Mathematics, Healthcare, Education, and Arts & Media as sectors with high job creation potential. However, their pathways to employment growth differ. Computer & Mathematics is positioned to generate specialised technical occupations, while Healthcare and Education may benefit from AI-supported services that complement professional expertise. Arts & Media may experience growing opportunities in AI-assisted content production, although human creativity and oversight remain important. In contrast, Office & Administration and Manufacturing are identified as having low job creation potential

within their respective sectors, indicating a greater risk that automation and job redesign will not be accompanied by sufficient new positions in the same occupational categories.

Table 3. Comparative Interpretation of AI Exposure and Occupational Transformation

Sector	Theoretical Exposure (%)	Observed Exposure (%)	Job Creation Potential	Implications for Occupational Transformation
Computer & Mathematics	94	33	High	Expansion of AI-related technical roles and human–AI collaboration.
Office & Administration	90	45	Low	Greater pressure to automate routine tasks and transition workers to other roles.
Business & Finance	80	30	Medium	Transformation of analytical tasks and increasing demand for AI-assisted decision-making.
Arts & Media	75	35	High	Expansion of AI-assisted creative production alongside human creative oversight.
Manufacturing	65	40	Low	Automation of selected production activities and potential workforce restructuring.
Education	50	15	High	Opportunities for AI-supported learning and the redesign of educational roles.
Healthcare	45	10	High	Opportunities for AI-assisted professional services and decision support.
Construction	20	5	Medium	More limited exposure to current AI capabilities, with potential for selective task augmentation.

Source: Analytical synthesis of the sectoral data reported in the original article, based on Anthropic (2026), Goldman Sachs Research (2025), and McKinsey & Company (2025). Occupational implications are interpretations of the reported exposure rates and job creation categories.

Table 3 provides a comparative interpretation of how AI exposure and job creation potential may interact across sectors. The findings suggest that high exposure combined with low job creation potential, as observed in Office & Administration and Manufacturing, warrants particular attention because displaced workers may need to transition into other occupational categories.

A closer examination of the sectoral exposure data reveals that the gap between theoretical and observed AI exposure represents an important dimension of occupational transformation. Computer and Mathematics occupations exhibit a difference of 61 percentage points between theoretical exposure (94%) and observed exposure (33%), whereas Office and Administration occupations demonstrate a smaller gap of 45 percentage points. Although these differences should be interpreted cautiously because the underlying exposure measures may capture different dimensions of AI capability and usage, they suggest that technological feasibility alone is insufficient to explain occupational transformation. The relatively higher observed exposure in administrative occupations may reflect the greater standardisation of information-processing activities, while the integration of AI into computing-related occupations may involve more complex workflows and requirements for human verification. This comparison highlights the importance of distinguishing the technical potential of AI from the organisational conditions under which its

capabilities are translated into actual professional practice.

Conversely, sectors with high job creation potential may offer opportunities for professional development and new employment, although such growth is not guaranteed by exposure rates alone. Education and Healthcare illustrate how AI can support professional activities without necessarily replacing the human expertise required in these fields. These differences indicate that workforce strategies should be tailored to sectoral conditions rather than based on a uniform assumption that AI will produce identical employment outcomes across the economy.

Taken together, the findings establish that AI exposure is a multidimensional indicator of occupational transformation rather than a direct measure of job loss. The gap between theoretical and observed exposure demonstrates that technical feasibility must be distinguished from actual adoption, while the coexistence of displacement, augmentation, and job creation highlights the complexity of labour-market adjustment. This interpretation is consistent with research arguing that technological change can both substitute for existing tasks and generate new activities that complement human labour (Acemoglu & Restrepo, 2019; Autor, 2015). Nevertheless, the benefits of AI-driven productivity gains may not be distributed evenly, particularly when the creation of new roles occurs more slowly than the displacement of existing tasks. Therefore, the central challenge is not simply to predict which occupations will disappear, but to understand how workers can move into redesigned or emerging roles. This requires coordinated efforts in skills development, organisational workforce planning, and educational adaptation to ensure that AI adoption supports sustainable employment and productive human–AI collaboration (World Economic Forum, 2023; McKinsey & Company, 2025).

b. Future Career Forecasting and Occupational Shifts (2025–2035)

Forecasting the future of careers in the age of disruptive artificial intelligence (AI) requires consideration of technological development, adoption rates, economic incentives, and the capacity of institutions and workers to adapt. The findings of this study indicate that occupational transformation between 2025 and 2035 is unlikely to follow a single, uniform trajectory. Instead, the future labour market may develop through different pathways depending on how rapidly AI is adopted, whether organisations prioritise human–AI collaboration, and how effectively education and public policies respond to changing skill requirements. To address this uncertainty, the study applies the Integrated Exposure–Adaptation Model, which combines task-based exposure analysis with scenario planning to distinguish between the potential effects of AI on individual tasks and the broader consequences for employment (Acemoglu & Restrepo, 2019; Schoemaker, 1993).

The model identifies three plausible scenarios: Rapid Displacement, Augmentation Equilibrium, and Innovation-Led Growth. These scenarios should be interpreted as conditional projections rather than definitive predictions. Each represents a different combination of AI adoption, technological development, and institutional adaptation. The Rapid Displacement Scenario assumes that AI adoption accelerates while education systems, organisations, and labour-market institutions respond inadequately. Under these conditions, workers in highly exposed occupations may face displacement before suitable alternative employment

becomes available. By contrast, the Augmentation Equilibrium Scenario emphasises the integration of AI into existing occupations, enabling workers to improve productivity while assuming greater responsibility for complex decision-making, evaluation, and oversight. The Innovation-Led Growth Scenario anticipates that AI will stimulate new industries and professional categories, potentially generating additional employment opportunities after an initial period of adjustment (Goldman Sachs Research, 2025).

Table 4. Comparative Characteristics of AI Career Forecasting Scenarios (2025–2035)

Analytical dimension	Rapid Displacement	Augmentation Equilibrium	Innovation-Led Growth
AI adoption	Rapid adoption with limited institutional adaptation	Moderate adoption supported by proactive adaptation	Extensive adoption accompanied by technological innovation
Employment effects	Increased displacement and frictional unemployment	Job redesign and gradual occupational transformation	New industries and occupations emerge
Human–AI relationship	Greater substitution of human tasks	Collaboration and complementary capabilities	New forms of human–AI collaboration
Skill requirements	Urgent reskilling for displaced workers	Hybrid technical and domain-specific skills	Advanced AI, data, governance, and innovation skills
Institutional response	Insufficient or delayed	Proactive education and policy interventions	Strong investment in research, education, and entrepreneurship
Expected trajectory	Elevated risk of structural unemployment	More balanced employment adjustment	Potential net employment growth after transition

Source: Synthesised from the three scenarios presented in the original article, drawing on Goldman Sachs Research (2025) and Schoemaker (1993).

Table 4 illustrates that the future of employment depends not only on the technical capabilities of AI but also on the interaction between technology and institutional responses. The Rapid Displacement Scenario highlights the risk of employment losses when automation advances faster than workforce adaptation. The Augmentation Equilibrium Scenario offers a more balanced pathway because AI is used to complement human capabilities and support the redesign of existing roles. Meanwhile, Innovation-Led Growth emphasises the potential for technological innovation to generate new occupations and economic activities. However, the latter two scenarios are not guaranteed outcomes; their feasibility depends on sustained investment, effective reskilling, and organisational readiness. Accordingly, the scenarios provide a framework for evaluating possible labour-market trajectories rather than establishing precise probabilities for their occurrence.

The temporal dimension further differentiates the projected career transformations. During 2025–2030, the article anticipates an adjustment period in which organisations integrate AI into existing workflows and workers experience changing task requirements. Under the Rapid Displacement Scenario, frictional unemployment could reach 0.5 percentage points above baseline as AI adoption accelerates while institutional responses lag (Goldman Sachs Research, 2025). The study identifies administrative support, data entry, and basic coding among the activities potentially vulnerable to immediate displacement, particularly where workers have limited opportunities to acquire new

skills. Nevertheless, even within this scenario, job redesign may remain a more immediate outcome than the disappearance of entire occupations.

By 2030–2035, the projected outcomes diverge more substantially according to the prevailing scenario. Under Augmentation Equilibrium, continuous learning and the integration of AI into professional workflows are expected to support the development of hybrid roles. Under Rapid Displacement, however, job creation may fail to compensate for employment losses in vulnerable segments, increasing the risk of structural unemployment. Innovation-Led Growth anticipates the emergence of new economic sectors and specialised occupations, supported by investment in research and development, education, and entrepreneurial ecosystems. These differences demonstrate why forecasting should account for both short-term adjustment costs and longer-term opportunities.

Table 5. Projected Career Transformations Across Time Horizons (2025–2035)

Time Horizon	Forecasting Scenario	Expected Labour-Market Development	Main Workforce Challenge
2025–2030	Rapid Displacement	Accelerated automation of exposed tasks and increased frictional unemployment risk	Transitioning displaced workers into alternative employment
2025–2030	Augmentation Equilibrium	Gradual AI integration and redesign of existing occupations	Developing hybrid technical and professional competencies
2025–2030	Innovation-Led Growth	Initial disruption accompanied by the emergence of AI-related roles	Preparing workers for new occupational requirements
2030–2035	Rapid Displacement	Continued employment pressure where job creation lags behind displacement	Preventing persistent structural unemployment
2030–2035	Augmentation Equilibrium	Greater human–AI collaboration and continuous occupational adaptation	Sustaining lifelong learning and human oversight
2030–2035	Innovation-Led Growth	Potential expansion of new industries and specialised career categories	Supporting innovation, investment, and entrepreneurial capacity

Source: Synthesised from the short-term and medium-term projections in the original article.

Table 5 highlights the importance of distinguishing between short-term disruption and medium-term structural change. During the initial period, the central challenge is managing the transition as AI is incorporated into established work processes. The risks are particularly pronounced when displaced workers cannot readily access retraining or alternative employment. In the subsequent period, the direction of change depends on whether organisations and institutions have developed the capabilities needed to support occupational transitions. Although the Innovation-Led Growth Scenario anticipates potential employment expansion, this outcome depends on investment and the emergence of viable new economic activities. The table therefore underscores that the period 2025–2035 should be understood as a sequence of adjustments rather than a uniform shift from human labour to automation.

An important consideration in interpreting the 2025-2035 forecasts is that the three scenarios are not necessarily mutually exclusive across occupations, industries, or geographical contexts. Rapid displacement may occur in highly standardised administrative functions while augmentation simultaneously characterises professional services that depend on human judgement and accountability. Innovation-led growth may also emerge in specialised

technological sectors without immediately compensating for employment losses elsewhere. Consequently, the development of future labour markets may be characterised by the coexistence of different transformation pathways rather than the dominance of a single scenario. This interpretation also underscores the importance of monitoring intermediate indicators, including the pace of workplace AI adoption, changes in occupational skill requirements, access to reskilling, and the emergence of new employment opportunities. Such indicators could provide an empirical basis for periodically reassessing the plausibility of each scenario as technological and institutional conditions evolve.

Beyond scenario-based forecasting, the study identifies specific occupational categories that may expand or decline as AI adoption progresses. Emerging opportunities include AI ethics and governance, prompt engineering, data science, machine learning engineering, robotics maintenance, and green AI specialisation. These roles reflect the growing need to develop, supervise, maintain, and evaluate AI systems. At the same time, routine administrative support, data entry, repetitive manufacturing activities, and selected entry-level analytical tasks may experience substantial automation or redesign. These projections are consistent with the broader task-based perspective, which suggests that technological change alters the composition of work and the demand for particular skills rather than affecting every occupation equally (Acemoglu & Restrepo, 2019; World Economic Forum, 2023).

Table 6 demonstrates that occupational change involves both the emergence of specialised careers and the transformation of established roles. AI ethics, governance, and green AI illustrate opportunities arising from the need to manage the technical, social, and environmental implications of AI deployment. Meanwhile, administrative and repetitive activities face greater exposure because their tasks can often be standardised or automated. However, the projected direction of an occupation should not be interpreted as a guaranteed employment outcome. In particular, the article describes the potential transformation of transport and logistics over a longer horizon while acknowledging regulatory constraints. These distinctions suggest that workforce planning should prioritise transferable skills, technical proficiency, and the capacity to adapt to evolving job requirements.

Table 6. Emerging and Vulnerable Occupations in the AI-Driven Labour Market

Occupational category	Representative roles or activities	Projected direction	Main implication
AI ethics and governance	AI ethicists and governance specialists	Emerging or expanding	Increased demand for responsible AI oversight
AI interaction and design	Prompt engineers and AI interaction designers	Emerging or expanding	Greater need for effective human–AI communication
Data and AI engineering	Data scientists and machine learning engineers	Sustained or increasing demand	Need for advanced technical and analytical skills
Robotics and automation	Robotics and automation technicians	Emerging or expanding	Increased demand for installation, maintenance, and repair capabilities
Green AI	Specialists in AI energy efficiency and sustainability	Emerging or expanding	Integration of AI expertise with environmental objectives

Occupational category	Representative roles or activities	Projected direction	Main implication
Administrative support	Data entry clerks and administrative assistants	Vulnerable to automation or redesign	Reduced demand for routine information-processing tasks
Manufacturing	Repetitive production workers	Vulnerable to automation	Workforce restructuring and technical reskilling
Financial analysis and market research	Entry-level analytical and research roles	Vulnerable to automation or augmentation	Greater emphasis on interpretation and strategic judgement
Customer service and telemarketing	Customer service representatives and telemarketers	Vulnerable to automation or redesign	Greater use of chatbots and virtual assistants
Transport and logistics	Truck drivers and logistics operators	Potential longer-term transformation	Adoption constrained by technological and regulatory factors

Source: Synthesised from the emerging and declining occupational categories identified in the original article, including its discussion of Machovec et al. (2025) and World Economic Forum (2023).

Table 6 demonstrates that occupational change involves both the emergence of specialised careers and the transformation of established roles. AI ethics, governance, and green AI illustrate opportunities arising from the need to manage the technical, social, and environmental implications of AI deployment. Meanwhile, administrative and repetitive activities face greater exposure because their tasks can often be standardised or automated. However, the projected direction of an occupation should not be interpreted as a guaranteed employment outcome. In particular, the article describes the potential transformation of transport and logistics over a longer horizon while acknowledging regulatory constraints. These distinctions suggest that workforce planning should prioritise transferable skills, technical proficiency, and the capacity to adapt to evolving job requirements rather than treating occupational classifications as fixed indicators of future employment.

Taken together, the forecasting results indicate that the future of careers between 2025 and 2035 will be shaped by the interaction between AI adoption, occupational exposure, and adaptive capacity. The three scenarios demonstrate that technological progress can produce substantially different employment outcomes depending on the effectiveness of institutional responses and the development of complementary human capabilities. The Augmentation Equilibrium Scenario emerges in the original study as a balanced and potentially achievable pathway, provided that education, workforce development, and policy interventions support meaningful human–AI collaboration. Nevertheless, this scenario remains conditional rather than certain. The findings therefore reinforce the importance of continuous monitoring, targeted reskilling, and strategic investment in emerging occupations to reduce the risks of displacement while enabling workers to benefit from new opportunities. This approach is consistent with the argument that technological innovation must be accompanied by adaptive labour-market institutions and skills development to support more sustainable employment transitions (Autor, 2015; Goldman Sachs Research, 2025; World Economic Forum, 2023).

c. Workforce Adaptation and Strategic Implications: Skills Development, Education, and Policy

The findings of this study indicate that workforce adaptation is a critical determinant

of how societies respond to AI-driven occupational transformation. As artificial intelligence (AI) increasingly automates routine tasks, augments professional activities, and creates new occupational opportunities, individuals and institutions must develop the capabilities required to navigate changing employment conditions. The results suggest that the consequences of AI adoption depend not only on technological exposure but also on the adaptive capacity of workers, organisations, educational institutions, and policymakers. This interpretation is consistent with the task-based perspective, which emphasises that technological change can simultaneously substitute for certain activities and generate new tasks that complement human labour (Acemoglu & Restrepo, 2019; Autor, 2015).

At the individual level, lifelong learning, upskilling, and reskilling are essential for maintaining career resilience. The article identifies critical thinking, creativity, complex problem-solving, digital literacy, data analysis, and emotional intelligence as important competencies in the AI era (World Economic Forum, 2023). These capabilities complement technical AI proficiency by enabling workers to interpret AI-generated outputs, evaluate their limitations, and apply contextual judgement. Rather than focusing exclusively on learning how to operate AI tools, workers need to understand when and how those tools can support professional decisions. The increasing importance of hybrid competencies also suggests that domain-specific expertise must be combined with technological understanding to support effective human–AI collaboration.

Table 7. Key Workforce Competencies for AI-Driven Career Adaptation

Competency category	Representative competencies	Role in AI-driven work	Expected adaptation benefit
AI and digital literacy	Understanding AI capabilities, limitations, and applications	Supports informed and responsible use of AI tools	Improves technological readiness
Data and analytical skills	Data analysis, interpretation, and evidence-based reasoning	Helps workers evaluate AI-supported insights	Strengthens analytical decision-making
Cognitive skills	Critical thinking, creativity, and complex problem-solving	Supports tasks requiring judgement beyond routine automation	Enhances adaptability to changing tasks
Interpersonal skills	Emotional intelligence and human communication	Supports collaboration, relationship management, and contextual understanding	Preserves human-centred professional value
Hybrid professional skills	Integration of AI proficiency and domain-specific expertise	Enables AI-assisted performance in specialised occupations	Supports occupational mobility and role redesign
Lifelong learning	Continuous learning, upskilling, and reskilling	Enables workers to respond to evolving technologies and job requirements	Improves long-term career resilience

Source: Synthesised from the original article, drawing on World Economic Forum (2023), Autor (2015), and Acemoglu and Restrepo (2019).

Table 7 demonstrates that workforce adaptation requires a combination of technical, cognitive, interpersonal, and professional competencies. AI literacy enables workers to understand the capabilities and limitations of emerging technologies, while analytical skills support the evaluation of AI-generated information. Critical thinking

and creativity remain important because many professional responsibilities require contextual interpretation and the consideration of competing alternatives. Interpersonal competencies also retain value in occupations involving communication and human relationships. These competencies should therefore be developed together rather than treated as separate training objectives. However, the table represents a synthesis of competencies identified in the article and does not establish a measured ranking of their effectiveness.

The capacity to adapt to AI-driven occupational change is unlikely to be distributed equally across the workforce. Workers with access to quality education, digital infrastructure, employer-supported training, and opportunities for occupational mobility may be better positioned to benefit from AI-enabled productivity gains. In contrast, workers performing routine tasks may face greater transition difficulties when access to professional development and alternative employment is limited. This suggests that technological exposure alone provides an incomplete basis for assessing workforce vulnerability, as the consequences of automation also depend on the availability and accessibility of adaptation mechanisms. Therefore, reskilling policies should not be evaluated exclusively by the number of training programmes delivered, but also by their accessibility, relevance to emerging occupational requirements, and capacity to support meaningful employment transitions. Such an approach would strengthen the equity dimension of workforce adaptation strategies.

At the organisational level, workforce adaptation requires a shift from viewing AI primarily as a mechanism for reducing labour costs toward treating it as a means of improving productivity, innovation, and the quality of professional work.

The original article emphasises that organisations should invest in upskilling and reskilling programmes, redesign job responsibilities, and establish clear AI adoption strategies that prioritise human–AI collaboration and ethical deployment (McKinsey & Company, 2025). This approach is particularly important in sectors where AI can automate selected tasks without eliminating the need for human accountability. For example, AI-supported financial analysis may reduce the time required for routine data processing, while employees continue to interpret results, evaluate risks, and make strategic recommendations.

Organisational readiness also depends on the capacity to integrate AI into existing workflows. The difference between theoretical and observed AI exposure indicates that technical feasibility alone does not ensure successful implementation. Organisations must consider operational requirements, employee competencies, workflow compatibility, and the need for human oversight (Anthropic, 2026; Machovec et al., 2025). Accordingly, effective workforce planning should identify which tasks can be automated, which activities can be augmented, and which responsibilities require continued human involvement.

Table 8 translates the article's findings into organisational priorities. Workforce assessment provides a foundation for identifying tasks that can be automated and responsibilities that should be redesigned, while upskilling and reskilling prepare employees for evolving professional requirements.

Table 8. Organisational Strategies for Workforce Adaptation to AI

Strategic Area	Recommended Organisational Action	Primary Objective	Expected Outcome
Workforce assessment	Identify tasks suitable for automation, augmentation, or human-led execution	Understand the implications of AI for existing roles	More informed workforce planning
Upskilling and reskilling	Provide continuous training in AI, data analysis, and domain-specific competencies	Prepare employees for changing job requirements	Improved workforce adaptability
Job redesign	Reallocate routine tasks and strengthen higher-value human responsibilities	Align job structures with AI capabilities	Greater productivity and role flexibility
Human–AI collaboration	Establish workflows combining AI assistance with human review and decision-making	Balance technological efficiency with professional judgement	More effective and accountable work processes
Ethical AI governance	Establish guidelines for responsible AI use and human oversight	Address ethical and operational risks	More responsible technology deployment
Career transition support	Facilitate internal mobility and preparation for emerging roles	Reduce barriers to occupational transition	Better opportunities for workforce continuity

Source: Synthesised from the organisational implications discussed in the original article, particularly McKinsey & Company (2025) and Machovec et al. (2025).

Job redesign is particularly important because AI adoption may change the composition of work without eliminating entire occupations. Human–AI collaboration and ethical governance further ensure that productivity improvements are accompanied by appropriate oversight. Finally, career transition support can help employees move into redesigned or emerging positions when their previous responsibilities are reduced. These strategies are complementary: technology adoption without workforce preparation may intensify disruption, whereas coordinated investment in people and processes can create better conditions for sustainable organisational adaptation.

Educational institutions constitute another essential component of the adaptation process. The original article argues that curricula should integrate AI literacy, data science, and computational thinking across disciplines while strengthening critical thinking, creativity, and adaptability. Vocational education and professional training also need to respond to the practical requirements of emerging occupations, including the development, operation, and maintenance of AI systems (World Economic Forum, 2023; McKinsey & Company, 2025). These recommendations imply that AI-related competencies should not be restricted to computing programmes. Students in business, healthcare, education, law, and other fields also need to understand how AI affects their professional tasks and decision-making processes.

Nevertheless, curriculum reform must be accompanied by accessible training opportunities and institutional support. Workers already in employment may require flexible programmes that enable them to develop new competencies without abandoning their existing responsibilities. Similarly, educational institutions must continually review whether learning outcomes align with changing occupational requirements. Although the article identifies these priorities, it does not provide a direct empirical comparison of specific training

interventions; therefore, their relative effectiveness requires further investigation.

For higher education institutions, the projected transformation of occupations implies that curriculum responsiveness should extend beyond the introduction of standalone AI-related courses. The distinction between task automation and augmentation suggests the need to identify which professional competencies remain essential, which tasks can be supported by AI, and which new competencies emerge through human–AI collaboration. Curriculum development should therefore integrate discipline-specific knowledge with AI literacy, analytical reasoning, critical evaluation, and responsible technological decision-making. In practice, this may involve redesigning learning activities and assessments to require students not only to use AI tools but also to evaluate their outputs, justify professional decisions, and demonstrate independent disciplinary understanding. Such an approach may better prepare graduates for occupational roles characterised by changing task compositions rather than fixed technological requirements. However, its effectiveness requires empirical evaluation across different academic disciplines and employment contexts.

Table 9. Strategic Roles of Educational Institutions and Policymakers in AI Workforce Adaptation

Stakeholder	Strategic priority	Proposed intervention	Intended outcome
Higher education institutions	Curriculum transformation	Integrate AI literacy, data science, and computational thinking across disciplines	Graduates better prepared for AI-transformed occupations
Vocational education providers	Practical skills development	Update technical training to reflect emerging AI-related occupational requirements	Improved readiness for workplace transitions
Professional training providers	Lifelong learning	Deliver continuous upskilling and reskilling programmes	Greater capacity to adapt to changing skill demands
Policymakers	Workforce transition support	Invest in public education, retraining initiatives, and social safety nets	Reduced social and economic disruption
Regulatory bodies	Responsible AI governance	Establish ethical guidelines and regulatory frameworks for AI development and deployment	Better protection of workers and responsible AI adoption
Public and private stakeholders	Equitable access	Coordinate investment in training and AI-driven opportunities	Broader access to the benefits of technological change

Source: Synthesised from the original article's discussion of educational institutions, policymakers, and regulatory bodies, drawing on McKinsey & Company (2025), Goldman Sachs Research (2025), and World Economic Forum (2023).

Table 9 highlights the complementary responsibilities of educational institutions, training providers, and policymakers in preparing the workforce for AI-driven transformation. Higher education and vocational institutions are responsible for developing relevant competencies, while professional training providers support workers who need to adapt during their careers. Policymakers and regulatory bodies, meanwhile, can facilitate transitions through retraining initiatives, social safety nets, and appropriate governance frameworks. The emphasis on coordination is important because curriculum reform alone cannot resolve employment disruption if workers lack access to training or alternative opportunities. Similarly, technological

innovation may produce uneven benefits without policies that protect workers and support equitable access to emerging occupations. These proposed interventions reflect the article's recommendations rather than measured effects of particular policy programmes.

Beyond these stakeholder-specific responsibilities, the findings suggest that workforce adaptation should be understood as a coordinated process involving individuals, organisations, educational institutions, and governments. Individuals need to develop transferable competencies and remain prepared for changing occupational requirements. Organisations must redesign work and invest in employee development, while educational institutions should align learning outcomes with evolving professional demands. Policymakers must complement these efforts with accessible retraining, social protection, and regulatory mechanisms that encourage responsible innovation. Such coordination is particularly important under the Rapid Displacement Scenario, where delayed institutional responses may intensify the gap between job losses and the availability of alternative employment. Conversely, proactive adaptation may improve the conditions for human–AI collaboration envisaged in the Augmentation Equilibrium Scenario.

The findings also reveal that workforce adaptation involves challenges beyond technical proficiency. Access to education, the availability of retraining opportunities, and the capacity to move between occupational sectors influence whether workers can benefit from emerging career opportunities. Consequently, the transition to AI-enabled employment should not be evaluated solely through productivity gains or the number of new occupations created. It should also be assessed in terms of workers' capacity to access those opportunities and the distribution of the costs and benefits of technological change. The original article accordingly emphasises social safety nets, worker protection, ethical AI governance, and equitable access to AI-driven opportunities as important policy considerations (Goldman Sachs Research, 2025).

In conclusion, workforce adaptation represents a central condition for managing the occupational transformations projected for 2025–2035. The results indicate that effective responses require the integration of individual skill development, organisational workforce planning, educational reform, and proactive public policy. AI literacy and technical proficiency must be complemented by critical thinking, creativity, complex problem-solving, and interpersonal capabilities to support professional judgement and human–AI collaboration (Autor, 2015; World Economic Forum, 2023). At the same time, organisations and institutions must ensure that reskilling opportunities, career transitions, and responsible AI governance accompany technological adoption. Although the article identifies the Augmentation Equilibrium Scenario as a balanced and potentially achievable pathway, its realisation depends on sustained investment and effective coordination among stakeholders. Future empirical research should therefore evaluate the effectiveness of specific training programmes and workforce policies, including their contribution to employment transitions, skill development, and equitable access to emerging career opportunities.

4. Conclusion

This study examines how disruptive artificial intelligence (AI) may reshape career trajectories and occupational structures between 2025 and 2035 through a systematic literature review, sectoral exposure analysis,

and the Integrated Exposure–Adaptation Model. The findings demonstrate that AI influences employment through three interconnected mechanisms: job displacement, job augmentation and redesign, and job creation. A key finding is the divergence between theoretical AI capabilities and observed workplace adoption, indicating that technological exposure does not necessarily translate into the immediate elimination of entire occupations. The forecasting analysis identifies three plausible pathways: Rapid Displacement, Augmentation Equilibrium, and Innovation-Led Growth, with the Augmentation Equilibrium Scenario representing a balanced and potentially achievable outcome if human–AI collaboration, continuous learning, and institutional adaptation are prioritised. The study further highlights the importance of developing hybrid competencies, reforming educational curricula, strengthening organisational workforce planning, and implementing policies that support reskilling, social protection, and responsible AI deployment. Nevertheless, the projected outcomes remain subject to uncertainty regarding technological development, adoption rates, and institutional responsiveness. Future research should validate occupational exposure estimates across different geographical contexts and evaluate the effectiveness of specific educational and workforce interventions. Ultimately, ensuring that AI contributes to sustainable and equitable employment requires coordinated efforts to align technological innovation with human capabilities, workforce adaptability, and inclusive policy frameworks.

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