Generative AI and Job Vulnerability: A Global Review

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Abstract

The rapid acceleration in the development of AI-in particular, generative AI-is changing the nature of work globally, with great significant for job creation, transformation, and displacement. Drawing on major studies, employer forecasts, and AI-driven evaluations, this review paper synthesizes evidence to investigate sectoral vulnerabilities to automation across different economic contexts. In doing so, it identifies professions and sectors that have emerged as particularly vulnerable to disruption by AI, with a specific focus on developments relating to generative AI since 2023. Clerical, administrative, financial, and customer service jobs are currently identified as those globally at the highest risk, while knowledge-based and creative jobs that have been considered hitherto safe are increasingly vulnerable. Conversely, occupations that are physically and emotionally demanding and unpredictable, such as health care, skilled trades, and hospitality, remain comparatively resilient. This review also explores regional variation in risks from automation, approaches to the methodological assessment of risk, and the strategic responses from employers across industries. Conclusively, this study emphasizes a set of policy recommendations targeting concerted upskilling, AI governance, and inclusive transition strategies in efforts to prevent labor markets from becoming more unequal. This systematic literature review used information obtained from peer-reviewed journals, policy reports, and organizational datasets published between 2013 and 2025. Altogether, 52 studies were thematically analyzed and comparatively mapped across sectors in line with predetermined inclusion criteria targeted at AI-driven automation and workforce vulnerability across sectors.

Keywords: AI Automation, Job Displacement, Sectoral Vulnerability, Generative AI, Future of Work, Workforce Adaptation.

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1. Introduction

Artificial Intelligence has undergone a radical transformation from a narrow set of computational tools to an entirely vast ecosystem of technologies that can execute complex tasks at high speed with uncanny precision. From its more mundane beginnings within repetitive industrial automation, AI has grown to include aspects such as machine learning, computer vision, natural language processing, and most recently generative capabilities, thereby emulating human creativity and cognitive reasoning itself [1]. In effect, this has brought about a fundamental shift in how global economies function, leading to grave discussions about the future of work, job displacement, and whether existing labor structures can be sustained [2], [3].

Earlier waves of automation largely disrupted low-skill, routine manual jobs, such as those in manufacturing, data entry, and clerical support [4]. These were structured and rule-based roles, which were the easiest to codify into automated systems. Pioneering studies, including the seminal work of [5], estimated that nearly 47% of U.S. occupations could be automated, with particular attention to roles entailing repetitive tasks: telemarketing, administrative assistants, and logistics coordination [6]. In contrast, occupations requiring creative, interpersonal, or analytical thinking were considered relatively impervious to automation. The rise of generative AI models post-2023, notably large language models (LLMs), including but not limited to OpenAI's GPT-4, Google's Gemini, and Meta's LLaMA, has fundamentally disrupted this assumption. These models perform tasks from ranging legal drafting to creative writing, data interpretation, coding, and sentiment analysis areas previously thought to be exclusive to human professionals [7-9]. Consequently, a wider range of occupations-from paralegals and journalists all the way to financial analysts, content creators, and even educators-across sectors now face varying levels of automation exposure [10-12].

The consequences of this shift are not equitably distributed across sectors or regions. Clerical and administrative jobs, long thought of as vulnerable, are now at the epicenter of automation risk, with studies indicating that nearly 25% of clerical tasks are highly automatable [13,14]. Customer service, finance, logistics, and sales are also seeing radical changes due to AI-powered chatbots, robotic process automation, and predictive analytics [14]. Even professions in healthcare and education, long regarded as safe, are experiencing task-level disruption. AI can now help diagnose medical imagery, transcribe patient notes, grade assignments, and generate teaching materials [15]. Contrary to the binary storyline of absolute job displacement, a truer portrait emerges along lines of partial automation and job reconfiguration. For most jobs, AI does not displace human labor but rather enhances it by undertaking monotonous subtasks and freeing human workers to focus on high-order responsibilities [16]. In this hybrid model, new competencies such as prompt engineering, data interpretation, ethics-based reasoning, and human-machine collaboration become necessary; hence, interdisciplinary and adaptive competence is in greater demand within the workforce [17]. At the same time, regional inequalities make the effects of automation more uneven: high-income countries, with higher digital infrastructure and service and knowledge work concentrated within their economies, are more prone to AI disruption, while the effect of automation on lower-income economies with employment centered around agriculture and informal labor is less direct in the short run. Unless active policy frameworks are put in place, these latter economies are likely to face significant obstacles in adopting AI in a way that is compatible with inclusive economic development, thereby widening inequalities globally. It is clear that in this context, knowing which occupations and sectors are most at risk from automation by AI is not just an abstract question but an issue of urgent practical concern for government, business, and workers. Indeed, for most such automation risks, traditional methods of assessment-such as expert scoring or binary classification-are increasingly supplemented with, or replaced by, more fine-grained, task-level analyses based on datasets such as O*NET, AI self-assessment capabilities, and global employer sentiment surveys. These multidimensional approaches help not only in identifying which jobs might be displaced, but also in understanding how they will evolve and what adaptive strategies might mitigate negative consequences. This review synthesizes existing research, empirical studies, and emerging methodologies that map the global landscape of AI-induced job vulnerability. It provides a sector-by-sector analysis of occupational risk, underlines demographic and regional differences, and assesses responses by employers from large multinationals to small businesses. Bearing in mind both the threats and opportunities that generative AI poses, this paper intends to contribute to policy, workforce planning, and academic discourse on how to manage such an epochal transformation in human labor. Though AI-induced job disruption has been widely discussed, little is known about the ways the post-2023 wave of generative AI differs from earlier automation waves in remaking white-collar and creative sectors. In the past, studies have too often treated automation risk as a static variable that neither evolves dynamically at the task level nor differentially responds between large firms and SMEs. The present paper contributes by providing an integrative framework linking AI exposure and workforce resilience with sectoral adaptation from a global comparative perspective that is rarely discussed in the literature.

2. Literature Review

The theoretical foundation for understanding automation's impact on labor markets was established by [18] through seminal work that introduced the concept of routine-biased technology and its framework. This theoretical insight provided the conceptual backbone for subsequent empirical investigations into job polarization and technological unemployment. Their framework posited that computers and early automation technologies excelled at performing routine tasks, whether manual or cognitive, but struggled with non-routine tasks that required flexibility, creativity, or complex decision-making. [19] further developed this framework by distinguishing between routine and non-routine tasks across the cognitive and manual dimensions; their analysis revealed that technological change had historically complemented non-routine cognitive tasks while substituting for routine tasks, leading to increased demand for high-skilled workers and contributing to rising wage inequality. The job polarization hypothesis, formulated in the mid-2000s based on an analysis of employment data from the 1980s to the 2000s, suggested that technological change was eliminating middle-skill routine jobs while preserving both high-skill analytical positions and low-skill manual jobs that remained difficult to automate [20].

The study [5] explained that the landscape of automation research was dramatically reshaped, providing the first systematic assessment of computerization risk across 702 occupations. Furthermore, their findings suggested that 47% of U.S. jobs were at high risk of computerization, including roles such as telemarketers, title examiners, and data entry clerks. Subsequent research has revealed significant limitations in this study. The paper [21] argued that occupation-level analysis overstated automation risk by failing to account for task heterogeneity within occupations; they suggested that only 9% of jobs in OECD countries were at high risk of automation, which is significantly lower. Building upon this framework, subsequent studies by [22] and [23] developed the concept of routine-biased technological change, demonstrating that computerization primarily affected middle-skill routine jobs while leaving high-skill analytical and low-skill manual jobs relatively protected.

The landscape of automation risk fundamentally shifted with the emergence of advanced AI systems, particularly large language models and generative AI technologies introduced after 2022 (such as OpenAI's GPT-3.5, GPT-4, and GPT-5; Google's PaLM; image generators like DALL-E and Stable Diffusion, etc.). Unlike previous automation technologies that targeted routine tasks, these new AI systems demonstrated capabilities in complex cognitive work, creative tasks, and sophisticated problem-solving that were previously considered uniquely human domains [8], [24], [25]. According to the research [7], a comparative analysis revealed minimal correlation between occupations rated as highly susceptible to computerization in 2013 and those vulnerable to AI language modeling in 2023.

A significant methodological advancement came with the analysis conducted by [11], [16] introduced the concept of "exposure" to generative AI, defining it as the potential for AI to reduce task completion time by at least 50% while maintaining quality. Their analysis revealed that approximately 80% of the U.S. workforce could have at least 10% of their work tasks affected by large language models, with 19% of workers potentially seeing 50% or more of their tasks impacted. The International Labour Organization conducted a comprehensive global analysis using GPT-4 to assess task exposure across occupational categories worldwide [13]. Their findings revealed that clerical support work was the only broad occupational category with substantial high-exposure tasks, with approximately 24% of clerical tasks rated as highly exposed to automation by generative AI and an additional 58% showing medium exposure. Research consistently identifies manufacturing, organization, and customer service as the sectors most vulnerable to AI-driven automation. These industries involve repetitive, structured tasks that AI and robotics can efficiently perform. For example, assembly line workers, warehouse staff, and customer service representatives are at substantial risk of displacement due to the adoption of AI-powered robots and algorithms [25], [26], [27]. Quantitative analyses estimate that 25% of occupations in major databases are at considerable risk of automation, with middle- and low-skilled workers particularly exposed [28], [29]. Moreover, different sectors such as health, education, and agriculture in the developing and underdeveloped countries focus on automation and reduced the direct involvement of human manpower. The authors of [30] developed an IoT based smart care infrastructure for elderly and noncritical patients to retrieve their vital signs to predict their health status so that in case of any emergency necessary precautions can easily be taken, which reduced the direct involvement of human resources.

Globally, the impact of AI automation is increasing day by day, High-income countries, with larger shares of clerical and knowledge work, are more exposed to generative AI, while lower-income countries, with more manual and agricultural labor, face less immediate risk. For example, clerical and administrative roles are highly exposed, with about 24% of tasks in these occupations rated as highly automatable by generative AI, compared to only 1–4% in other occupational groups [31], [29]. Regional differences in digital infrastructure and investment further mediate the pace and extent of AI adoption, potentially widening productivity gaps between. Despite widespread concern, empirical evidence of large-scale net job loss due to AI remains limited. Instead, the literature points to significant skills disruption and the transformation of work, with new job categories emerging alongside automation. The most likely scenario is partial automation, where humans and AI collaborate, and the demand for new skills especially in AI development, data analysis, and system maintenance rises. This underscores the importance of lifelong learning, reskilling, and adaptive policy frameworks to ensure an inclusive transition to the future of work.

Despite the risks, AI also creates new job categories, particularly in technology-driven fields such as AI development, data analysis, and cybersecurity. The development and maintenance of AI systems require skilled professionals, leading to opportunities in software engineering, AI ethics, and related domains. The net effect of AI on employment is thus nuanced, with job creation in emerging industries potentially offsetting some of the losses in routine-based sectors [7], [30]. To address the challenges posed by AI automation, comprehensive reskilling and upskilling initiatives are essential. Workers must acquire new technical and soft skills to remain competitive in the evolving job market. Successful reskilling programs, supported by governments, educational institutions, and private companies, are crucial for workforce adaptation [32] Additionally, robust policy frameworks are needed to ensure equitable distribution of AI's benefits, support displaced workers, and promote fair labor practices.

3. Methodology: Identifying At-Risk Occupations

3.1 Overview of Methodological Approaches

Assessment of the effect of AI automation on the global labor market is a modern intricate process that cannot be done merely through one research methodology. AI capabilities are not static, nor is the effect that AI has on jobs-declining and amplifying employment-and its very manifestation is under the influence of diverse economic, social, and regional factors. This study, therefore, proposes a triangulated methodological approach toward a robust, comprehensive understanding of sectoral vulnerabilities with regard to AI-induced automation.

Among these, this study places particular emphasis on task-level analysis using O*NET data, AI self-evaluation using LLMs, and survey-based employer sentiment forecasting, as these methods most directly align with the objective of quantifying job vulnerability and assessing adaptive capacity across sectors. Each of these methods has its own positives and negatives. For example, expert input yields imaginative, theoretic perspectives drawn from domain knowledge but tends to feature simple yes and no outcomes and overstated risk due to its lack of understanding and recognition of the nuances of partial automation. More quantitative measures at the task level provide depth and can be continuously updated to reflect changes in technology; still, they may fail to capture real-world implementation problems or behavioral responses. Evaluations driven by AI show the capability of technology readiness to be assessed on-demand for applicability but may lead to overshoot or lack domain-specific accuracy in convoluted scenarios. In combining heterogeneous and diversified approaches into a strategic, coherent body, this methodology aims to cross-validate findings, thereby reducing inherent individual biases and producing a more reliable, nuanced assessment of where AI will have its most profound effects.

3.2 Expert-based Occupational Risk Scoring

Historically, the assessment of automation risk often began with expert-based occupational risk scoring. A leading example is the study of [5], which classified U.S. occupations by their computerizability. That approach assigned human experts to appraise a set of bottlenecks for computerization in every occupation. Examples of such bottlenecks included tasks requiring perception and manipulation-such as dexterity or an unpredictable environment-creative intelligence, such as generating novel ideas or artistic expression, and social intelligence, including negotiation, persuasion, or caregiving. Occupations for which these bottlenecks were significant were considered less at risk of automation, while those engaged in either cognitive or manual routine tasks were assessed to have a high risk. This method yielded an extremely theory-grounded framework from which sharp and deeply intuitive insights into the very basic limitations of automation technology at any point in time could be gleaned. It helped highlight the vulnerability of routine and middle-skill jobs; therefore, this supports the idea of routine-biased technological change.

Early expert-based methods had a key limitation in that they were mostly binary: either a job is automatable or not. With such methods, one often finds an over-assessment of displacement risk. Automation is often very much partial; it affects only some tasks in an occupation and does not replace the entire job. Additionally, these assessments become outdated very quickly with the advancement of technology, especially considering how greatly advanced AI post-2023 has shifted its capability to challenge these so-called bottlenecks, whether they are creative or dependent on language. Another major shortcoming of these studies is the failure to make any distinction with respect to partial automation and augmentation.

3.3 Task-Level Analysis using O*NET

Task-level analysis is better used as a finely construed procedure and approach for breaking down occupations into tasks and assessing each of those tasks for susceptibility to automation by AI, thereby overcoming the limits of broad occupational classifications. The U.S. Department of Labor created the comprehensive database O*NET to provide necessary resource input to that method. This database contains detailed descriptions of many jobs in terms of their knowledge, skills, abilities, work activities, and tools of application.

Among these examples is the AI Occupational Exposure developed by [8]:

- **Key AI Capabilities Identification:** Research on which current theater capabilities the core form of AI has, such as natural language processing, image generation, and pattern recognition.
- **Map O*NET Tasks with AI Capability:** Given O*NET activities, the task-specific work noted for O*NET occupations is evaluated against AI capabilities already disclosed.
- **Quantify Exposure:** AI performs level calculation. The authors have gone a step further to detail the ratings between language-model AIs and image-generating AIs, since the two modalities would have distinguishing repercussions. They also divided exposure by complementarity-where AI adds to human effort versus where AI substitutes for human work-which enables a richer understanding of AI effects.

This approach ensures very high granularity and allows us to actually spot which specific tasks in that occupation are most vulnerable. It moves beyond simple either/or" job replacement" predictions for a much better understanding of partial automation and augmentation. The framework also allows incremental updates in line with the evolution of AI technology, ensuring assessments remain relevant. An excellent example is Pew Research Center's analysis from 2023 on "Which U.S. Workers Are More Exposed to AI on Their Jobs?" This study also drew on O*NET data, where analysts classified the 41 O*NET work activities into low, medium, or high exposure categories by exercising their judgment collectively. They then attached O*NET importance rating values to the activities' importance within occupations to build overall exposure scores for more than 800 occupations, thus allowing them to identify the most and least exposed jobs and relate exposure to other factors, including earnings and required skills.

3.4 AI-Self Evaluation Using LLMs

One such method is utilizing the capability of AI in rating its own ability related to the execution of tasks; this has earned recent attention because of the advent of state-of-the-art LLMs like GPT-4. Examples of such studies are those conducted under the aegis of OpenAI and University of Pennsylvania researchers, [11] and [16]. Here, their process included:

- **Task Identification:** They used O*NET to identify thousands of work activities that vary among occupations.

- **AI Task Assessment:** GPT-4 was prompted to assess each task in view of whether it could perform the task "significantly faster, such as at least 50% faster, while preserving quality" without, or with means that are readily available.
- **Estimation of Exposure Per Occupation:** Aggregating the proportion of tasks exposed per occupation to find respective overall exposure scores per occupation.

This method's key strength is that it gives a real-time, direct assessment of what AI is currently capable of doing. To the extent that this is a self-assessment by AI, it probably gives us truthful information about what is technically possible with the current models, free from human biases in thinking or prejudices toward antiquated views on what can or cannot be done by AI. While quite novel, this method has a host of weaknesses. The AI could be overly optimistic when it comes to its performance or may entirely misjudge the nuances and real-world complexity of certain tasks routinely performed by human beings and, therefore, may overestimate its abilities. Besides, the low domain accuracy for some highly specialized tasks can result in inaccurate self-assessments. Reproducibility and interpretability of self-assessments remain open questions for the nascent field at the present time.

3.5 Survey-Based and Employer Sentiment Forecasting

Another key methodological approach is collecting data on the intentions and expectations of employers through structured surveys. Major publications in this domain are WEF reports on the Future of Jobs and the OECD employment outlooks. The surveys include very senior HR or strategy professionals in a large number of enterprises to share their opinions on what is expected regarding technological disruptions, automation plans, and employee strategies.

The report from WEF 2023 found that clerical and administrative jobs, data entry, bookkeeping, and customer service were most prone to phasing out. Jobs in artificial intelligence development, Internet security and data analysis were those expected to increase in number. Workers around the world were also projected to switch careers or jobs as a result of technological change by 2027 with the percentage standing at 23% [33]. Surveys provide an effective means of developing employer sentiment to incorporate technical feasibility into a business strategy perspective. They embody the behavior of the organization in terms of investment power, risk tolerance and market motivation which determine the speed of AI adoption. Such surveys are also used to facilitate public policy where governments match retraining schemes with the tendencies of employers. However, these are forward-looking in nature. The respondents may imply AI capabilities, delay or accelerate implementation, or make it contingent on an economic or political turn. Notwithstanding this, survey data remains a crucial source of information about sector workforce planning and anticipatory governance.

3.6 Macroeconomic Modelling and Scenario Forecasting

The research presented in this contribution uses macroeconomic modeling to determine overall economic outcome, including simulations of labor displacement, job creation, and productivity gains within the scenario of adopting AI. A good example is the latest report from Goldman Sachs, which estimates that generative AI is likely to automate the work of 18% of the global economy and impact 300 million full-time jobs [34]. The methodology combines exposure indices at the occupation level with macroeconomic data and labor share, GDP contribution, and technological investment rates. Such models apply sectoral input-output tables to model the mechanisms through which AI-induced productivity shocks spread to the rest of the economy. Macroeconomic models are useful in long-term policy planning. They predict possible changes in employment, income distribution, and value-added changes in sectors. These projections can be used by policymakers to allocate resources for reskilling or to structure tax codes to benefit displaced employees or to finance transition industries.

3.7 Regional Adjustments and Digital Infrastructure Considerations

Since the impact of AI cannot occur uniformly worldwide, the research methodology takes into account changes in regions along with differences in regional digital infrastructure. An excellent example can be seen in the study [35], which shows great disparities in exposure to AI depending on income level high-income countries show high rates, while low-income countries experience low rates of exposure to AI. Such discrepancies arise because of dissimilar occupational compositions, with a concentration of higher clerical jobs in advanced economies, and differences in technological readiness [13]. Key findings from the study developed by the ILO indicate that, according to its report, while there is significant exposure to generative AI at each income level for clerical and administrative activities, the size of workforces performing these jobs is extremely uneven. Countries with high incomes are said to have a larger portion of their labor force in service and knowledge-intensive areas; hence, they are at greater immediate risk from generative AI. Conversely, lower-income countries have higher levels of employment in farming and low-tech processes, making them less directly vulnerable to the existing capabilities of generative AI [13].

3.8 Methodological Triangulation and Justification

The mix of various methodological tools allows this study to capture the multi-dimensional nature of AI-driven labor disruption. Thus, the study can be both focused and wide-ranging, triangulating expert opinion, empirical task-level performance, real-time assessments of machine intelligence, employer projections, and macroeconomic modeling. Triangulation is also valid and will strengthen evidence-based assessments of occupations that are at high risk in several ways. For example, clerical support is present at every point of the Frey and Osborne risk of computerization list, in the quadrant of high exposure in the AIOE Index, in studies using GPT-4 self-evaluation, and in surveys conducted by the WEF among employers. This joining of dots adds evidence to the claim that clerical occupations should be considered the epicenter of the displacement caused by AI. Meanwhile, the methodological divergence is instructive: in LLM-based studies, creative jobs such as graphic designers have low risk, while in image-AI studies, there is a likelihood that creative jobs will be high risk. These inconsistencies confirm the need to draw a distinction between forms of AI and areas for future research. The integrative approach, therefore, offers a solid basis for measuring sector vulnerability while remaining flexible to changing AI capabilities and market conditions. High-risk sectors were quantified by exposure indices derived from O*NET-based task automation probabilities and corroborated by ILO and WEF datasets. “Resilience” is operationally defined as the capacity of a sector to maintain employment stability against automation pressures; it is measured through proxies such as task substitutability, upskilling capacity, and human–AI complementarity. Vulnerability frameworks follow the OECD’s automation exposure taxonomy and the ILO’s generative AI exposure matrix, allowing differentiation between automation potential and observed displacement. Analysis indicates that statistical validation of displacement forecasts follows sensitivity modeling of GDP contribution and labor share, as applied in [34].

4. Analysis: Sectors and Occupations at Greatest Risk

4.1 High Risk Occupations and Sectors (Global Overview)

Artificial intelligence technologies have been developing at a rapid pace, particularly in the areas of automation, language technology, robotics and in every industry, we can think of. On the positive side, smarter systems have the potential to increase productivity, reduce waste and generate new ideas, however, they also pose a danger to jobs because predictable tasks are the easiest to replace. According to [6], it was mentioned that about 47% of American labor could be heavily automated within twenty years. Similarly, a report by the McKinsey Global Institute (2017) followed by the update in 2024 estimates that up to 800 million jobs globally which is 30% could be displaced by 2030 under rapid automation scenarios. The Organisation for Economic Co-operation and Development [36], further emphasizes that 14% of jobs are highly automated, with another 32% facing significant task transformation. As student employment and entry-level jobs are more likely to be automated than jobs held by older workers, young people may find it challenging to enter the workforce. Routine jobs with low skill requirements will pose the greatest risk.

Unlike the previous waves of narrative AI and Large Language Models (LLMs) such as OpenAI’s GPT -4, Google’s Gemini, and Meta’s LLaMA, which significantly expanded the scope of job vulnerability into knowledge automation—primarily threatening manual, repetitive, and routine jobs, the rise of generative AI is affecting cognitive and even creative professions. These models are able to undertake tasks that were previously thought to be reserved for human beings, such as writing content, code, researching legislation, summarizing reports, conducting sentiment analysis, and even designing [9]. Consequently, white-collar occupations like paralegals, journalists, content writers, financial analysts, and software developers are also now at of being replaced or diminished in quantity. Moreover, task convergence is emerging, generative AI is not only replacing specific tasks but also enabling job merging across functions. For example, a customer support representative using a chatbot powered by LLMs might also handle basic legal compliance checks or conduct initial data analysis. This phenomenon, sometimes referred to as AI-enabled job blending, is redefining how organizational roles are designed and managed [24]. The [33] observes that secretarial and administrative roles are the most likely to be replaced due to generative technologies, while jobs requiring critical thinking, interpersonal interaction, and emotional intelligence remain more resilient.

4.1.1 Customer Service and Sales

Customer service and sales roles are among the most exposed to AI-driven automation, primarily due to their high volume of repetitive and structured tasks. Tasks such as order tracking, password resets, and account inquiries are increasingly handled by AI-powered chatbots and voice assistants, enabling faster, frictionless customer interactions. While the full replacement of human agents is not imminent due to ongoing talent shortages and high turnover, AI is rapidly augmenting these roles, reducing human involvement in routine cases and reshaping job functions. The pressure on contact centers to "do more with less" makes AI an attractive solution for improving efficiency, reducing costs, and addressing burnout in a profession already considered one of the world's most stressful.

4.1.2 Clerical and Administrative Support

Clerical and administrative support jobs are among the most vulnerable to automation by AI, especially with the rise of generative technologies. Jobs such as those performed by administrative assistants, data entry clerks, receptionists, and bank tellers have a strong component of routine, rule-based tasks that AI systems can now do well. According to the report [35], nearly a quarter of all clerical tasks are highly automatable, and most others are at least moderately exposed. This is echoed by the World Economic Forum [33], which forecasts heavy job losses among these occupations due to structural changes driven by the adoption of tools like chatbots, automated bookkeeping, and self-service technologies. Since women are overrepresented in clerical jobs globally, this displacement is likely to be disproportionately gendered.

4.1.3 Finance, Accounting, and Banking

Finance, accounting, and banking are most suitable for AI automation since they are data heavy. Account reconciliation, verification of compliance, and financial reporting are some of the tasks that can be more effectively managed by AI with minimal human involvement. Susceptible jobs to be displaced or supplemented by AI in this regard include accountants, tax preparers, loan officers, and junior financial analysts. While regular tasks are accomplished by AI, high-level strategic decision-making and jobs remain in the domain of humans. These sectors in broad terms will become streamlined, with a shift to analytical and advisory roles which as yet cannot be completely filled by AI.

4.1.4 Professional Services and Knowledge Work

The newest wave of AI, particularly since the publishing of large language models like GPT-4 in 2023, is changing knowledge-worker and professional work. Educators have been rated high-risk, especially language teachers, tutors, and corporate trainers, by the Dallas Federal Reserve, due to AI-powered learning software and adaptive learning platforms (Dallas Federal Reserve [37] Occupational Employment and Wage Statistics, n.d.). These platforms can perform tasks such as grading and rote instruction-even though human teachers may still be necessary when mentorship and more complex pedagogy are required.

Within the legal profession, AI has been utilized since the early 2020s to automate document review, prepare initial drafts of contracts, and conduct legal research. This puts paralegals and legal assistants in specific jeopardy with attorneys possibly seeing some of their work-like initial drafts of legal briefs-being automated. Journalism and writing are also being redefined. AI systems have written news summaries, sports reports, and financial reports for media companies since around 2022 [38]. Content creators/writers are featured in high-risk jobs in OpenAI's report for 2023, particularly when it comes to formulaic or data-driven content; creative and investigative work is still largely human-led.

In IT and software, GitHub Copilot and GPT-4-powered coding tools-which started coming out between 2021 and 2023—can now create code, test cases, and small applications from specifications [39]. This increases web designers' and programmers' exposure to AI, especially in repetitive coding and QA, even as the demand grows for AI-enabled developers. Since 2023, generative AI has been a "force multiplier" in white-collar occupations, mainly marketing, law, education, media, and technology, enabling solo professionals to do what used to take multiple support staff. This increases productivity but will likely cut entry-level jobs in these fields.

4.1.5 Manufacturing and Production

Traditional manufacturing automation via robotics is a well-established trend, but continued research in AI is now making robots even smarter and more flexible. Factory workers doing repetitive assembly or packaging continue to be at risk in developed economies; much of this work is already automated or outsourced. AI improves robotics with enhanced machine vision and decision-making, thus enabling automation of somewhat less structured tasks than before. For example, AI-enabled robots can sort heterogeneous objects or perform more delicate assembly by learning from examples. However, many manufacturing processes require human flexibility and problem-solving, particularly in small and medium-sized enterprises. Thus, manufacturing will see the progressive automation of standard production tasks; this is likely to affect fields such as electronics assembly, automotive manufacturing, and textile manufacturing. The impact on jobs here is mainly a skill shift, requiring more robotics technicians and machine learning specialists to install and maintain AI-powered machines. As early as 2025, as many as 2 million manufacturing jobs worldwide were estimated to be replaced by automation, particularly tasks like welding, basic machining, and packaging [40].

The impact varies by region: nations like China, reliant on factory labor, are adopting robotics rapidly to offset rising labor costs, while countries with low labor costs will adopt more slowly [41].

4.1.6 Transportation and Logistics

AI is trending toward the automation of transport by autonomous cars and drones, but it is unclear when this will occur. Truck drivers, taxi and ride-hailing drivers, and delivery couriers have been highlighted as particularly vulnerable due to advances in autonomous driving [42]. AI optimizes logistics and route planning, with opportunities to decrease the number of drivers required. For example, better algorithms increase truck utilization and reduce superfluous trips. Another good example is warehouse logistics: warehouse pickers and packers interact with AI-powered robots (such as Amazon's warehouse robots) that move goods around and can eventually using through improved machine vision [43]. The overall impact will likely continue the shrinkage of low-skilled logistics jobs, partly offset by job gains in managing, supervising, or maintaining computerized equipment. Tesla's fleet of autonomous trials and early evidence from Amazon's logistics automation in the UK are case studies illustrating early workforce restructuring, whereby human drivers are transitioned to supervisory or maintenance roles. SME case studies in logistics, such as Parcelly in the UK, exhibit partial automation success, where hybrid delivery models allow for human oversight and AI route optimization.

4.1.7 Healthcare

Health care has been assumed to be highly resistant to automation because it is based on human empathy, high-stakes decision-making, and complex manual skills. Nevertheless, AI is beginning to make an impact on some tasks. Speech recognition is already replacing medical transcriptionists and medical record coders by documenting doctor-patient interactions and assigning billing codes. Radiologists and pathologist physicians who diagnose medical images and laboratory samples have witnessed AI software that is able to read images (X-rays, MRIs, biopsies) with almost expert-level proficiency for some conditions [44]. This is not a prediction of doctors being replaced by AI, but AI may assist with preliminary screening or highlight results, allowing one radiologist to do much more. Pharmacists could be complemented or even partly substituted by dispensing robots and computerized drug management systems. Nevertheless, occupations involving physical contact surgeons, nurses, home health aides are low-risk for substitution; rather, AI software may support them, e.g., AI diagnostic assistants, human-controlled surgical robots, etc. The weakness of the healthcare sector, therefore, lies primarily in administrative and diagnostic subdomains compared to direct patient care. The high exposure of health and education sectors in Canadian research implies that a large part of the work in these sectors can be performed by AI, but it is mostly complementary in character, i.e., the job of a physician consists of 30% data analysis that AI can perform and 70% interaction with patients, which cannot be effectively performed by AI. Such professionals are hence rendered efficient, not obsolete [45]. For instance, Babylon Health and Ada Health illustrate successful AI integration in clinical decision support, whereas smaller healthcare SMEs face challenges around affordability and regulatory compliance. These examples illustrate that scalability and ethical deployment of AI are at the core of resilience in healthcare automation.

4.1.8 Creative Industries

It is only in recent times that AI has entered creative work. Generative AI can generate art, designs, and multimedia content. Graphic designers and commercial artists are competed with by AI image generators that can instantly create logos, illustrations, or advertisements [46]. Video game artists or animators can utilize AI to create assets, too. Professions such as photographers and videographers may find some of their editing and post-production work taken over by AI (auto-enhancement, filtering, and even deepfake technology to remove backgrounds or add effects) [47]. Yet creative occupations generally involve some degree of originality, client communication, and awareness of trends that AI is missing. AI can help with brainstorming or drafting, but human beings still choose and polish the final output. We might witness a decline in routine creative work (such as easy logo design work falling off since anyone can have an AI tool do that), but a rise in demand for high-end creative talent and for jobs that work with AI (such as an artist who understands how to prompt-engineer an AI to achieve a desired style) [49]. Studies of Canva's AI design tools and Runway ML show SME-level adaptation where creative professionals leverage generative AI to enhance productivity without replacing human creativity. Conversely, smaller studios lacking technical capacity have reported project losses, reflecting uneven adaptation outcomes.

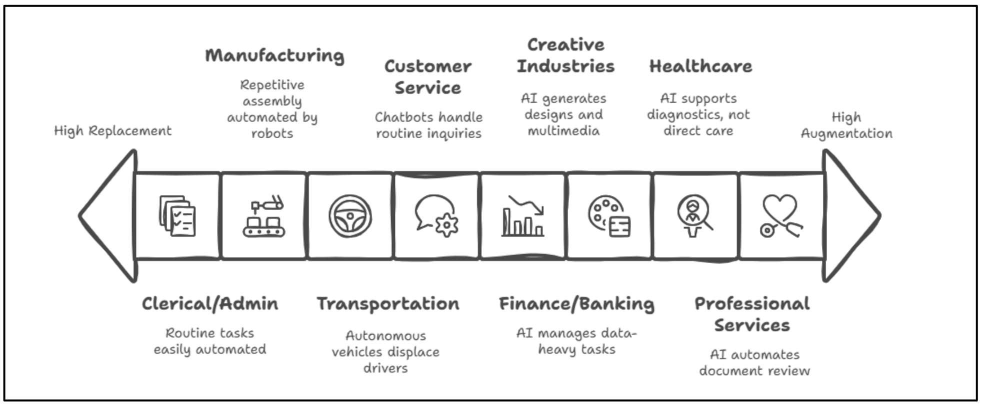

Figure 1. AI Impact on Jobs Ranges from Replacement to Augmentation

Figure 1 presents a spectrum of AI impact across job sectors, ranging from high replacement on the left to high augmentation on the right. Sectors like clerical/administrative, manufacturing, and transportation are positioned on the high-replacement end due to their repetitive, rule-based, or automatable tasks such as data entry, assembly line work, and driving. In contrast, sectors like healthcare and professional services fall toward high augmentation, where AI supports rather than replaces human roles for example, assisting in diagnostics or automating document review while humans maintain oversight. In the middle, sectors like customer service, creative industries, and finance experience partial automation, with AI handling routine inquiries, generating content, or managing data-heavy tasks. This continuum underscores how AI affects different occupations to varying degrees, from full task substitution to supportive collaboration. Table 1 below synthesizes findings from several key studies and reports, listing examples of occupations identified as highly susceptible to AI-driven automation and the sources that support these assessments. Each study has its own lens, whether focusing on generative AI exposure, expert opinion on computerization, or employer surveys, but there is clear convergence on certain roles.

Table 1. Summary of Key Studies on AI Automation Risk by Occupation

Study and Scope	Occupations Most Susceptible to AI Automation (Examples)	Source/Notes
Frey & Osborne (2013)– Computerization risk (US) [6]	Telemarketers; Title examiners; Sewers; Data entry keyers; Insurance underwriters, Cargo/freight agents.	High probability of automation; focus on routine, repetitive tasks
Felten et al. (2023) – LLM Exposure [8]	Language teachers; Tutors; Lawyers; Journalists; Writers; Sociologists	High exposure from LLMs; tasks involving writing, reviewing, interpreting.
Felten et al. (2023) – Visual Generative AI Exposure [8]	Interior designers; Architects; Mechanical drafters; Art directors; Astronomers	High image/visual AI exposure; tasks relying on design and visualization
Eloundou et al. (OpenAI, 2023) – GPT-4 Exposure [11]	Mathematicians; Tax preparers; Writers; Accountants; PR specialists; Legal secretaries	High share of tasks sped up or performed by GPT-4 and GPT-5
World Economic Forum (2023) – Global Employer Survey (2027 Forecast) [33]	Data entry clerks; Admin/executive secretaries; Cashiers; Bank tellers; Ticketing clerks	Clerical roles face steepest declines from automation and digitization
ILO (2023) – Global Generative AI Exposure [13]	Clerical support workers; Office assistants; Typists; Record-keepers	Clerical tasks highly exposed; 1 in 4 workers are in an occupation with some Gen AI exposure
Brookings Institution (2019) –Task Automation Risk [50]	Admin assistants; Sales clerks; Transport workers; Production operators	Routine manual and service roles seen as high risk
McKinsey Global Institute (2024) [51]	Accountants; Claims processors; Warehouse	30% of work hours automated by 2030, 12 million job transitions in Europe and US

	pickers; QA testers; Retail workers	
Goldman Sachs (2023) – Generative AI Impact [34]	Paralegals; Legal researchers; Financial analysts; Media professionals	Predicts 300M full time jobs affected globally; high risk in legal, finance, media
OECD (2024) – AI Exposure by Skill Intensity [36]	Programmers; Designers. Financial analysts; Customer service reps	Both routine and cognitive tasks exposed; mid-skill roles vulnerable
Institute for Public Policy Research (2024) [52]	Scheduling clerks; Admin assistants; HR clerks. Receptionists	60% of administrative tasks automatable now due to AI in UK
Forbes / Analyst Roundups (2025) [48]	Bookkeepers; Copywriters; Customer support agents; Entry-level data analysts	Routine cognitive work in early stages of AI replacement
Stanford Study (2024) – Legal AI Tools [53]	Paralegals; Contract drafters; Legal researchers	AI tools achieve good accuracy in document review, fast automation path
WEF (2025) – Programmers and Engineering [54]	Junior developers; QA engineers; Standard data analysts	63% of employers see skill gaps as the top barrier to transformation (2025-2023), 85% will prioritize upskilling, 70% plan to hire new skilled staff, 40% will reduce outdated roles
Forbes (2025) – Healthcare Admin [12]	Medical transcriptionists; Medical secretaries; Billing clerks	25% of healthcare admin roles automatable by 2035
Forbes (2025) – Media Jobs [12]	Journalists; Ad copywriters; Editors	30% of media jobs automatable by 2035

5. The Recruiter's Perspective: Strategic Shifts Across the Business Spectrum

To recruiters, though, AI's rise is the trigger not for mass displacement of jobs but for strategic workforce transformation. At Amazon, IBM, and Meta-all large corporations-recruiters and HR leaders carry a double mandate: to downsize automatable roles while vigorously pursuing. AI-related talent. Amazon cut over 27,000 jobs between 2022 and 2023 as it moved to eliminate positions amid pandemic-era overhiring. IBM announced a hiring pause for back-office functions considered automatable by AI. Its CEO, Arvind Krishna, estimated that about 30% of such jobs-7,800 positions-can be replaced within five years on the way to boosting productivity and shaving costs. Meanwhile, the recruiters for such organizations say their focus has been on filling high-demand jobs like AI and machine learning engineers, data scientists, and prompt engineers as internal transitions and reskilling occur in more routine areas including customer service, data entry, and HR administration.

5.1 The SME Lens: Pragmatism Integration and Resource Constraints

In contrast, small and medium-sized enterprises (SMEs) view AI integration through a more pragmatic and resource-conscious lens. Without the large R&D budgets or dedicated HR analytics teams of tech giants, recruiters in SMEs, often the business owners themselves adopt AI selectively to support day-to-day operations. The focus is not on replacing employees, but on augmenting existing teams with AI tools that improve efficiency. Common applications include AI-powered chatbots to manage routine customer inquiries, bookkeeping automation, predictive inventory systems, and targeted marketing through AI-driven platforms. These allow SMEs to "do more with less," enhancing productivity without expanding payroll. A comparative analysis reveals that large firms typically adopt AI to restructure roles and optimize efficiency through internal reskilling programs, whereas SMEs employ incremental integration focused on cost reduction and operational support. This contrast highlights differing workforce adaptation mechanisms, strategic transformation in large firms versus pragmatic augmentation in SMEs.

5.2 Adaptation of Work Skills in the Age of Artificial Intelligence

The rapid integration of AI into industries worldwide translates into a paradigm shift in the competency requirements of the workforce. As AI increasingly assumes routine cognitive and procedural tasks, such as data processing, transactional services, and standardized analyses, economic value is being placed on hybrid skill profiles comprising technical proficiency in conjunction with advanced cognitive and socio-emotional competencies.

5.2.1 Emergence of Hybrid Competency Frameworks

Contemporary labor markets now demand an interdisciplinary blend of capabilities:

- **Applied AI Literacy:** Employees across sectors must develop proficiency in using AI tools, including prompt engineering, output validation, and workflow integration.
- **Augmented Human Skills:** With AI handling routine analysis, human strengths such as critical thinking, contextual decision-making, creativity, and emotional intelligence become essential.
- **Adaptive Meta-Skills:** The future of work requires cognitive flexibility, ethical reasoning, and cross-functional collaboration.

5.2.2 Systemic Barriers and Enablers

Despite promising corporate initiatives, several structural challenges hinder widespread adaptation:

- **SME Constraints:** According to the OECD, fewer than 35% of small and medium-sized enterprises (SMEs) offer formal AI-related reskilling, largely due to budget limitations.
- **Demographic Gaps:** Older workers face disproportionate challenges, with employees aged 45 and above adopting AI tools at rates 2.3 times slower than their younger counterparts.
- **Education-Industry Misalignment:** Many academic programs have yet to integrate critical AI-related competencies.

6. Security Requirements for Modern Grid Networks

Generative AI expanded the working capacity of narrow AI, focused on a single task, into a general-purpose system able to create new content, text, images, code, and more in a wide array of domains. By contrast with previous incarnations, these generative models-which include LLMs and diffusion models-are able to execute a host of creative and analytical tasks using little or no instruction, while earlier versions of AI could perform jobs like defect detection or logistical system optimizations with unprecedented efficiency. In explanation, the reasons lie with deep learning, neural networks, and enormous datasets, enabling them to learn complex patterns and give rise to outputs much like human creativity and reasoning.

6.1 Sectoral Impact and Vulnerability

Generative AI has started to change both knowledge and service-based economies by automating tasks that were previously considered resistant to machine intervention. Already today, LLMs in law, marketing, architecture, and health draft legal briefs, create ad copy, develop design blueprints, and summarize clinical notes. When firms use the AI initially as an assistive tool to free employees for higher-value tasks, there is consideration regarding gradual job displacement as capabilities advance and organizations adapt. Early evidence for disruption in job displacement has been witnessed in content creation and customer service, even though the wide job losses have remained limited due to re-skilling and workforce repositioning.

The creative industries are equally in flux. Diffusion models, alongside LLMs, have churned out images, music, and prose at a never-before-seen rate. While this can rapidly accelerate ideation, several problems emerge. These same shifts occur around authenticity, intellectual property, and the blurring of human-machine creativity. These same shifts are happening in more technical areas: software engineering includes automated coding, debugging, and architectural suggestions done by tools such as GitHub Copilot, which raise the bar for productivity but shift much of junior-level work to oversight while retaining high value for senior architects. Healthcare is adopting AI in decision support, patient interaction, and administrative automation, while education benefits from personalized learning, content creation, and research assistance. Recent analysis by the International Labour Organization ILO [56, 57] shows that clerical support work is uniquely vulnerable to automation. About 24 % of all employment is in occupations with some generative AI exposure, yet only 3.3 % in the highest exposure category. Clerical roles account for most of that: roughly 24 % of clerical tasks are highly automatable and 58 % moderately so, while for other occupational groups, these figures are just 1-4 %. The ILO also comments that in high-income countries, women are especially affected: 9.6 % of women's jobs fall into the highest exposure group versus 3.5 % for men. It is this concentration of automatable tasks in clerical functions that explains why they are thought to be most vulnerable.

6.2 Policy Interventions and Evaluation

The study further evaluates policy interventions that seek to mitigate job displacement. Evidence from the German AI Skills Initiative in 2024 and the Skills Future program in Singapore showed improvement in the reemployment rate and adaptability of the workforce. Cross-national scenario analyses underpin the finding that proactive government-industry partnerships correlate with lower automation-induced unemployment rates, emphasizing a policy focus on continuous learning ecosystems. Against displacement, targeted programs have been launched by governments. In Singapore, the Skills Future Digital Workplace 2.0 takes workers through AI literacy and other digital skills using a SG$500 training credit [58]; more than 26 000 participants completed the various train-and-place schemes, and 64% of under-40s and 56% of those over 40 found work within six months [59]. Germany's AI Studios programs holds workshops and demonstrations for SMEs and employees. However, the OECD points out that across countries such as Australia, Germany, Singapore, and the US, AI-focused content is visible in only 0.3-5.5% of training courses, indicating a lack of scale. Broader labor-market policies also contribute to resilience. Germany offers five days of paid training leave and a short-time work scheme, which subsidizes wages during reduced hours, and Denmark's flexicurity model provides unemployment benefits covering approximately 60 % of prior wages alongside compulsory training or job-search activities. The level of participation in government-supported training in Germany is nevertheless around 8 % compared with a 12 % EU average, leaving scope for growth. Such measures underpin macroeconomic scenario analyses whereby generative AI might make 300 million full-time jobs equivalent worldwide obsolete, but only one-quarter to one-half of the tasks per occupation are automatable. Such projections therefore tend to offer the view that changes in jobs - rather than outright eliminations - are on the way, and thus make programs that help workers adapt.

7. Conclusion and Future Recommendations

Large-scale changes are hitting the global job market because of AI-driven automation; clerical and customer service jobs are among the worst hit. While jobs that require a lot of physical labor and emotional intelligence remain somewhat safe, evidence shows there is unlikely to be mass unemployment but rather task-level transformations and the need for collaboration between humans and AI. Key strategic recommendations include investing in reskilling, carrying out sector-specific policies, enabling SMEs, ensuring inclusive AI governance, and enhancing collaboration in education between the public and private sectors. Generative AI differs from previous waves of automation in that it impacts intellectual and creative roles: this requires a different approach to workforce resilience and continuous risk assessments in order to support effective targeting of interventions.

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