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How Has the Adoption of Machine Learning in Service Industries Influenced Labour Demand for Mid-Skill Workers?

Research Paper By
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Abstract

The fast-embracing of machine learning (ML) technologies in the service sectors has brought significant structural change in the labour markets, where mid-skill workers have carried the larger portion of displacement and reorganization of tasks. The present paper is a synthesis of secondary sources, such as international labour organization (ILO), organisation of Economic Co-Operation and Development (OECD), international monetary fund (IMF), world economic forum (WEF), McKinsey Global Institute and peer reviewed academic literature on the these topics to analyse the impact of ML deployment on the quantity and composition of employment as well as skill demand among mid-skill workers across various service industries, including finance, retail The data depicts a unique pattern of hollowing out: ML is automating routine cognition jobs concentrated in mid-skill jobs together with creating new high-skill jobs and retaining numerous low-skill face-to-face service jobs. IMF has estimated that about 40 percent of the jobs across the world are significantly exposed to AI and that this number reaches 60 percent in more advanced economies, and middle-skill workers in jobs with routine-intensive tasks are disproportionately impacted. According to Future of Jobs Report 2025 by the WEF, 92 million jobs will be lost worldwide by 2030 and 170 million new jobs will be created - a net gain concealing the harsh reality of structural inequity. Based on the Routine-Biased Technological Change (RBTC) theory and task-based approaches, the paper will argue that ML in service industries will augment high-skill labour, replace middle-skill routine cognitive labour, and leave much low-skill manual service employment comparatively intact. Policy reactions (upskilling, reskilling, and active labour market policy) are discussed in the context of evidence about employer and worker adaptation.

1. Introduction

Most of the advanced economies are dominated by the service industry where this industry takes in more than 70 percent of GDP as well as employment in OECD countries. It has a large proportion of workers in what labour economists describe as mid-skill jobs - jobs that demand greater than obligatory education but less than a four-year university diploma, and those in which there is a combination of routine cognitive tasks, interpersonal communication that is neither so low nor so high, and procedural-related understanding of the field. Bank teller, insurance claims processor, paralegal assistant, billing coordinator, data entry operator, customer service representative, and others have been the component of the middle-class labor in service economies of the past.

The last ten-year period has seen machine learning as a form of artificial intelligence arise as a revolution in service delivery as systems are equiproded with the ability to learn particular patterns using data and decide or make predictions without requiring explicit programming. In comparison with previous automation waves, where most automation gains were through manufacturing and other predictable, physical tasks, the ML systems are best at what hitherto were thought to be uniquely human cognitive tasks: reading unstructured documents, image classification, speech recognition, creditworthiness, customer behaviour prediction, and detection of anomalies in financial transactions. This is the ability that will address the fundamentals of many middle-skilled service jobs.

The question of this paper is: What is the impact of machine learning in services industries on the labour demand of middle-skill workers? It discusses three aspects of this impact: (1) the displacement effect, in which ML automates

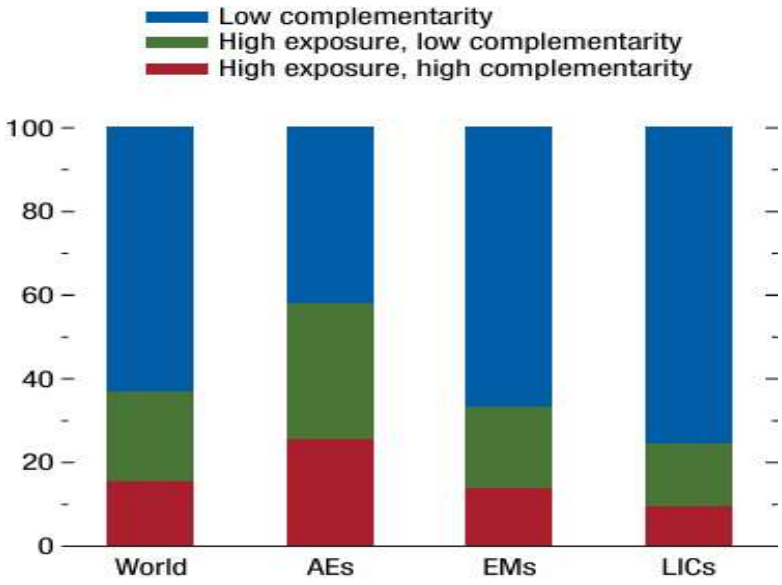
formerly occupied by mid-skill workers and must reduce staff or hours; (2) the augmentation effect, in which ML tools boost the productivity of mid-skill workers, or redeesign their work; and (3) the reinstatement effect, in which ML adoption introduces new types of mid-skill jobs previously not present. The article relies solely on secondary research based on peer-reviewed articles, reports of multilateral institutions and reliable think-tank analyses and is complemented by quantitative data during its evaluation.

2. Theoretical and Conceptual Framework

2.1 Defining Mid-Skill Workers

In labour economics, the notion of skill level is generally operationalised in two ways: using education level and occupation complexity. In this article, middle-skilled workers are workers who hold the middle-level occupational groups as designed by the International Standard Classification of Occupations (ISCO) at the 2-digit level (ISCO groups 4, 5 and parts of 3). Mid-skill occupations are at the centre of labour market polarisation analyses in terms of wage distribution, with most falling around the median.

The OECD (2023) observes that the exposure to AI does not spread the same at all skill levels: high-skill cognitive jobs may open up an opportunity to make use of AI as an augmenting resource, low-skill manual service jobs are often resistant to the impact of algorithms (they are physical, variable, and interpersonal), and middle-skill jobs with codifiable, repeatable cognitive tasks are the most vulnerable to automation using AI It is the characteristic of the contemporary technological transition significance.



Sources: Cazzaniga and others 2024; International Labour Organization; and IMF staff calculations.
Note: Share of employment within each country group is calculated as the working-age-population-weighted average. AEs = advanced economies; AI = artificial intelligence; EMs = emerging markets; LICs = low-income countries; World = all countries in the sample.

This three-level-tiered AI exposure in terms of skill and income level is mapped in Figure 1 below (founded on the IMF, 2024). The chart indicates that high-income economies are being exposed disproportionately (a ratio of about 60% of jobs) and that, in each economy, the risk is skill-graded in an acute form, the most extreme risk concentration being in the middle band of skill (administrative and clerical). To have the complete visualisation, the original IMF working paper is

recommended to the readers.

2.2 Routine-Biased Technological Change (RBTC)

The prevailing theoretical paradigm of explaining automation influence on labour is the Routine-Biased Technological Change (RBTC), modelled by Autor,

Source: Employment shares by AI exposure and complementarity

Source: IMF (2024), World Economic Outlook

Levy and Murnane (2003) and furthered by Acemoglu and Autor (2011). The RBTC hypothesis separates routine (cognitive) tasks (place invoices, run standard bookkeeping software or algorithms, solution to decision-trees used in customer service) and non-routine tasks, both cognitive-abstract (encompassing creative problem solving, managerial decisions and strategic planning) and also manual-physical (e.g., caring for an elderly person, cooking, craft trades).

The fundamental observation that RBTC makes is that technological change has been overeasy to replace routine, and all of it is found in middle-wage jobs. A one-standard deviation occupation that has more content of routine tasks also increases in speed, as Goos, Manning, and Salomons (2014) present, by 0.90 percentage-points less than corresponding non-routine occupations, over the course of one year, meaning that an occupation characterized by a one standard deviation greater content of routine tasks is, over time, increasing in pace by a factor of 0.9 Figure 2, based on the historic Goos, Manning, and Salomons (2009, 2014) European polarisation studies, is the typical change in employment shares - an increase in the top (abstract, high-skill) and the bottom (manual service, low-skill) and a decline in the middle (routine, mid-skill) of the wage distribution.

ML goes further than RBTC, which automates tasks on simple rule-based actions. In contrast to older forms of automation (where each rule had to be explicitly coded), ML can work with unstructured data and deal with ambiguous inputs and can learn on the job. This extends the frontier of automatable tasks to hitherto-safe non-routine cognitive tasks - casting serious doubts on whether the pattern of polarisation between high and low skills established in the U-shape will be replicated in the ML era, or whether mid- and high-skill and even high-skill cognitive tasks will experience more consistent pressure to the downward.

2.3 Displacement, Augmentation, and Reinstatement

Acemoglu and Restrepo (2018) present a task-based model that breaks down the effects of technologies into three channels: a displacement effect (machines crowd out labour in current tasks), a productivity effect (technology increases the output, possibly increasing the demand for labour), and a reinstatement effect (new tasks are created that require human labour). The net effect of these forces on the employment rate is theoretically ambiguous depending on the balance of these forces. The OECD Employment Outlook (2023) bases its empirical overview on these three channels, noting that the available evidence indicates that these have cannibalised each other in aggregate employment respects - although distributional impacts by skill group have proven to be vivid and uneven.

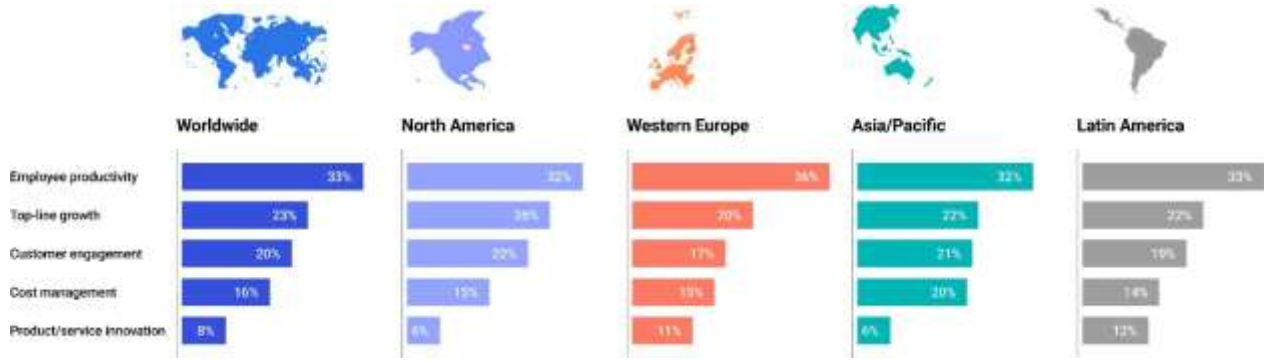
3. Machine Learning Adoption in Service Industries: Macro-Level Evidence

3.1 Scale and Pace of Adoption

Adoption of machine learning in service industries has been on a brisk increase since 2017. In a report by McKinsey Global Institute, around one-fifth of U.S. companies are said to have integrated AI into core business processes by 2023, compared to only one-fifth of companies in 2015 - a five-fold level of increase over eight years (McKinsey Global Institute, 2023). Outsourced financial services industry has been leading the pack: 85% of financial organizations were

planning or already investing in AI-driven tools by 2024 (Decimal Tech, 2024). Within the service economy more broadly, the number of job openings that included AI in their descriptions rose over the last two years by 108% (between 730,000 and 1.5 million job postings) indicating the fast adoption of AI by employers in service delivery roles (JFF / Lightcast, 2025).

Figure: Key business outcomes driving AI adoption across regions



Coherent Solutions. (2026). AI adoption trends you should not miss in 2025. https://www.coherentsolutions.com/insights/ai-adoption-trends-you-should-not-miss-2025

The general growth rate of AI market is expected to be 37.3 percent compound annual growth rate (CAGR) during 2023 to 2030 as the application of ML in the fields of banking, insurance, retail, healthcare administration, legal services, and logistics continues to expand (Skills Coalition, 2024). The amount of AI spending in the health sector alone has increased within the year 2024 and 2025 by 15.1 billion to 19.8 billion (ALM Corp, 2026). Figure 3 - software published by McKinsey Global Institute as part of their skills shift analysis - provides the proportion of companies in every acceptable sector indicating the adoption of AI in core processes, where the acceleration of the service versus manufacturing sector is very acute.

3.2 Aggregate Employment Effects

On a macroeconomic level, the overall impacts of ML in service sectors on employment have been less catastrophic than had been predicted by catastrophe scenarios. According to the 2024 analysis of IMF, about 40 percent of the workforce is meaningfully exposed to AI all around the world, with this number increasing to about 60 percent in high tech, highly digitised economies (IMF, 2024). Nonetheless, the exposure involved in the job is not directly proportional to job loss: the OECD (2021) reported that the occupations considered to be high-risk due to automatization in the 2010s had indeed shown employment increase in the next decade, though not as fast as low-risk jobs.

One of the most stringent econometric evaluations so far is presented in the IMF Working Paper No. 2024/199. The study estimates using a shift-share measure of the difference in the AI adoption rate in the U.S. commuting zones between 2010 and 2021, which revealed that the commuting zones with more AI adoption saw a notably major drop in the employment-to-population ratio. Most importantly, this adverse labor impact is concentrated amongst middle-skill employees, i.e. having a high school diploma and some college education, by non-STEM jobs and employees at both extremes of the age distribution. The IMF working paper reproduced as figure 4 graphically illustrates these heterogeneous employment impacts as a function of occupational skill group and level of education; a graph that makes visually clear that the decline in employment to population is greatest among the so-called mid-skill group, that consists of the some college and high

school graduate group.

At the firm level, a study by MIT Sloan, with 58 million LinkedIn profiles and 14 million job postings in the period 2010-2023, comes to the conclusion that as AI can do most tasks within a position, the proportion of workers holding that position in a company drops by about 14 percent (Schmidt, Hampole, Papanikolaou and Seegmiller, 2 By having the effect of AI concentrated in a limited number of tasks in a job - other jobs still undertaken by that job - the net effect on the job is to create bigger jobs of the type of work being outsourced as the newly prime jobs migrate to the other set of tasks. It is important to note that this result highlights task-level heterogeneity in occupations as a mediating factor with vital displacement and augmentation outcomes.

The Future of Jobs Report 2025 published by the World Economic Forum, based on questionnaires of employers covering over 1,400 jobs and businesses across all regions in the world, estimates that 92 million jobs will be eliminated by 2030 and 170 million new jobs will be created, a net increase of about 78 million jobs per year. But there is hidden inequality in this net figure: 41% of employers around the world intend to cut on their workforce in the areas with AI automateers in five years (WEF, 2025). The published projection chart shown by WEF in figure
5 is extensively used in policy argument, and shows that the symmetrical nature of this displacement-creation dynamic is asymmetric (with new positions being concentrated to STEM jobs and green economy jobs that most mid-skilled workers would not had formal degrees).

4. Sector-Specific Evidence on Mid-Skill Labour Demand

4.1 Financial Services

The sphere of fin-tech has been on the leading edge of ML implementation in the service economy, as customer personalisation, financial fraud detection, credit scoring, anti-money laundering, document review, and algorithmic trading, all have been implemented using ML. One of the most acute effects on the labour market of this sector has been documented as those affecting the mid-skill workers. The skill shift analysis provided by McKinsey (2018, updated 2024) categorically refers to a group of bank tellers and accountants as well as brokerage clerks facing job depletion as a result of introducing ML-driven automation.

According to the BLS, the jobs in insurance underwriting will decrease by 4% over the next 10 years but this will lead to numerous losses of jobs because robots with the ML risk model consider thousands of variables at a time and perform equally or better than a human expert on a standardised actuatory exercise (Gaper.io / BLS, 2024). In larger sense, in the 54% of the banking jobs would be highly automatable at or around 50 (Bloomberg; cited in DemandSage, 2026), and McKinsey (2024) have estimated that close to 30% of the whole banking job market would be automatable by 2030, an estimate that captures large sectors of mid-skill clerical, processing, and

An actual example is given by After JPMorgan Chase deployed its COIN (Contract Intelligence) ML system to explore legal documents - a job that usually took about 360,000 hours of legal and paralegal labor each year in the past. This review process used to be done manually but was automated in the system which minimized the amount of human involvement and error rates (Decimal Tech, 2024). In a parallel manner, automation of loan processing procedures is predicted to increase by about 35 percent of volume today to 80 percent in the next decade, accompanied by similar cuts in the volume of loan processing and underwriting performed by mid-skill workers (DemandSage, 2026). Figure 6, which was published by McKinsey Global Institute in their seminal analysis of the skill shift, shows projections of changes in demand of banking-sector skills by the year 2030 - with a reduction in the basic cognitive and administrative categories of skills (where mid-skill positions are found) and an increase in the technological, social-emotional, and higher cognitive categories of skills.

But it is not a displacement only story when speaking of financial services. The OECD employer survey in the workplace on AI (2022) discovered that of the companies in the finance industry that are adopting AI, 64% answered that they were

retraining or upskilling their current employees instead of necessarily cutting jobs (OECD Employment Outlook, 2023). The new mid-to-high skill job titles include AI ethics managers, model risk validators, no-code application specialists, and customer experience strategists with a learning curve that incorporates both domain knowledge and technical understanding.

4.2 Retail and Customer Service

Customer service may be the service sub-sector whereby, mid-skill displacement is most pronounced and quantitatively important. Chatbots, virtual assistants, and systems using NLP have increasingly replaced more and more routine query resolution, which is the backbone of the call-centre and customer representative jobs. According to the JFF and Lightcast analysis (2025) that surveyed 279.87 million job ads in the U.S. in 2010 2024, fast growth ASR in AI-related mentions in job ads suggests that the expectations of employers regarding the role are rapidly changing, even in areas where overall employment volumes are yet to crater, such as 12 mentions to 87 The modernized Jobs Lost, Jobs Gained analysis by McKinsey (2024) clearly predicts decreasing the customer service representatives as well as office workers and production workers, and predicts an increase in demand in STEM and healthcare occupations. This division
-a fall in mid-skill service jobs and an increase in high-skill technical jobs is what labour market represents RBTC to service sectors. This occupational demand bifurcation is graphically shown in figure 7 of the 2024 update by McKinsey analysis, which projects the changes in employment by broad occupational groups to 2030.

The same is stratified in retail, in general. By 2025, cashiers are estimated to be at risk of automation (65%), and retailers showing greater levels of AI implementation have been found to have four-fold productive growth rates than that of low-AI implementers (ALM Corp, 2026). The collective retail field still has large numbers of people working there, yet the distribution of tasks in retail jobs is transforming: AI does the tasks of tracking inventory, demand predictions, and checkouts, whereas human workers are being expected to do the tasks of customer service and interface with complex problems and product knowledge, a task shift that is moving better toward workers possessing more interpersonal and adaptive abilities.

4.3 Healthcare Administration

It can be a good teaching case in healthcare: although clinical care jobs cannot be substantially replaced by ML (and are estimated to be significantly expanded by demographic aging), healthcare administration, which is also a large mid-skill employer, is experiencing considerable ML pressure. According to McKinsey (2018/2024), the impact of automating medical records and healthcare administrative processes through AI will be a decrease in demand of office-support employees, although the overall clinical workforce will have a robust increase.< The most exposed mid-skill jobs include medical billing co-ordinators, records personnel and prior authorisation processors.

This dichotomy in healthcare is confirmed by the U.S. Bureau of Labor Statistics Occupational outlook 2024 34 (released January 2026): AI systems will severely reduce the need to have healthcare work in healthcare administration support capacities but nurse practitioners will have a 52 percent growth in the number of positions between 2023 and 2033, compared with all occupations, on average By 2025, AI in healthcare has reached a spending of 19.8 billion and a significant portion of this spending was on administrative automation over clinical augmentation.

4.4 Legal Services

The most vivid instances of ML displacement within a single type of occupation are provided in legal services. Document review - traditionally the largest component of paralegal time billed, and a quintessential mid-skill legal service component - has been effectively automated by eDiscovery AI systems like Relativity and Logikcull at large law firms. In 2024, KPMG documented that AI-based contract review saves 80% of the time spent on contract review and decreases the error rate by 40% as compared to human reviewers (Gaper.io, 2024). The document review sector which has been

outsourced to generate revenue on the tune of 3.5 billion in 2022 is starting to shrink with AI review turning into the default at large companies. By 2026, paralegals are at risk of automation of around 80% (DemandSage, 2026).

But in the upper tiers of the legal industry, AI is being used as a complement to rather than a direct replacement. The litigation strategy, dealing with a client, courtroom advocacy, and sophisticated negotiation are very human-oriented. This is the trend of replacing mid-level, ordinary, cognitive work in document handling, with maintenance and expansion of high-skilled, professional jobs, which appears in both legal and financial professional services, and supports the RBTC account of within-sector polarisation.

5. Task-Level Mechanisms: Why Mid-Skill Workers Bear the Brunt

5.1 The Routineness of Mid-Skill Service Tasks

The theoreticized process between adoption of ML and mid-skill displacement is based on the routineness of the duties undertaken in occupations of the mid-skill service. Routine jobs, ad-hoc jobs are deserving of middle salary jobs, so that routine jobs, which are codifiable, repetitive, and rule-following, are disproportionately assigned to middle-wage jobs, as the RBTC literature records (Autor et al., 2003; Goos et al., 2014). In services, such as in the clerical, administrative, and semi-professional tasks that define mid-skill jobs, this is the most prone to substitution by ML.

The general equilibrium model by Acemoglu and Loebbing (2024) is calibrated to the

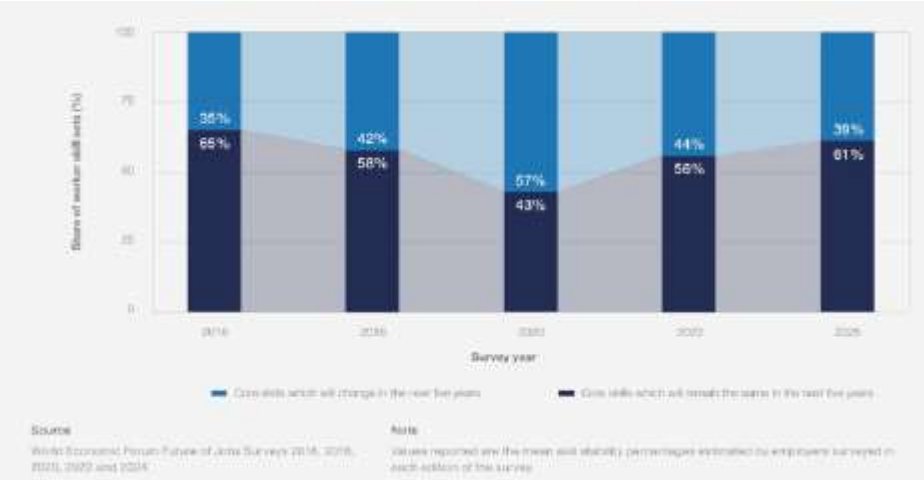
U.S. economy showing that it is more profitable to automate middle-skill tasks than either low-skill tasks (or full-automation of the high-skill tasks) since, below the wage-level, one will not have that cost-advantageous price elasticity of machines, but at the same time, full- The overall equilibrium mechanism behind the empirical job polarisation pattern is this pattern of interior automation, in which machines replace the middle of the complexity distribution. Figure 8, Acemoglu and Loebbing (2024), is a simulation of the model of the distributional effect of employment and wage polarisation in the interior automation - representing in distributional terms the U-shaped effect in formal theory.

The OECD AI Papers No. 14 (Green, 2024) gives empirical estimates of the increasing and decreasing skills required in jobs with high exposure to AI. The most widely sought skills in high-AI-exposure jobs are management and business skills project management, finance, administration and clerical. The proportion of vacancies in highly AI-commonly careers in need of using at least one emotion, cognitive, or digital skill grew by 8 percentage points over the period considered, suggesting even inside the mid-skilled jobs, employers are changing the tasks demands toward the less routine and more human-appropriate capabilities.

5.2 ML's Expansion of Automatable Cognitive Tasks

The shift of the assortment of automatable tasks (critically) is the difference between ML and older automation. The earlier rule-based automation was restricted to tasks that were fully defined and could be coded. ML - deep learning and speech recognition, in particular, can now process unformatted data, speech, images, ambiguous user input. This implies that even non-routine cognitive tasks in mid-skill jobs (answer diverse customer inquiries, evaluating insurance claims based on incomplete data, or filing legal records as relevant) are becoming included in the scope of ML.

Figure: Share of core skills expected to change vs remain stable (2016–2025)



With the above demonstrating rapid increase in skill disruption peaking in 2020 (57 percent), it reflects the accelerating nature of the reskilling needed in AI-exposed jobs.

Generative AI might impact 10% or more of the U.S workforce, and potentially 50% or more of the workforce as estimated by Eloundou and colleagues (2023). Figure 9 of Eloundou et al. (2023) and later repeated in the OECD Employment Outlook (2023) provides a task-level exposure of AI at occupational category levels - high expose tasks are not limited to low-skilled manual jobs, but are now broadly distributed within the middle-skill cognitive range of the service sectors.

The Dallas Fed (2026) quantitatively provides a post-ChatGPT employment dynamics update. In the United States, the total employment had risen by about 2.5% since ChatGPT was launched in October 2022, though the employment rate in the 10 percent of industries with the highest exposure to AI began to fall (by 1 percent). Most importantly, the drop is also concentrated among younger workers ages 2225 -the entry level of many mid-skill service jobs-implying that ML is also eliminating the initial steps of occupational ladders by which workers acquire mid-skill competencies and progress. The long-run economic mobility impact of this goes far beyond the existing numbers of displacement.

5.3 The Augmentation Channel

The substitutive effect of ML and mid-skill labour is not a property of the relationship between them. There is a substantial amount of evidence in support of an augmentation channel, wherein the productivity of mid-skill workers who are engaged with by the ML tools is increased. According to the ILO (2025), AI promises to democratise decision-making, which has long been controlled by highly specialised employees: with the help of AI, middle-skilled workers would be able to implement more complex tasks, eliminating skill gaps and increasing overall productivity and job quality. Instead of substituting human labour in large-scale, AI in the mode reduces the gap between unskilled and trained employees.

The best firm-level finding is given by the MIT Sloan study (Schmidt et al., 2025): when AI exposure is confined on a small number of tasks within a job - with all other tasks being retained - job in that job can increase, since workers are pushed towards other jobs. This implies that management choices related to the deployment of ML have enormous implications: those companies that utilize ML to redistribute the workforce instead of merely decreasing the number of employees are more productive and successful in employment at once.

The best micro-level evidence on augmentation maybe is the work of Brynjolfsson, Li and Raymond (2025, Quarterly Journal of Economics). In a large U.S. customer service company in a randomised controlled trial, employees who had

an AI assistant give them real-time suggestions experienced an increase in productivity of about 14% on average, with that amount being highest among low-skilled and recent employees, who could use AI suggestions to reach their competency levels only the experienced workers previously managed. It is a type of within-job upskilling that is made possible by ML augmentation, one of the tangible channels of exploration by which the process of mid-skill displacement can be partially compensated.

6. Wage Effects and Labour Market Inequality

6.1 Wage Polarisation

The penury effect of the use of ML is not limited to the employment levels, but the level of wages. The empirical data continuously seem to indicate wage polarisation as a part and parcel of the employment polarisation. Acemoglu and Loebbing (2024) with a theoretical example show that interior automation raises the skill premium after a threshold of skill and decreases it before - gives the phenomenon of wage polarisation. This is empirically supported both in Europe and the U.S. context.

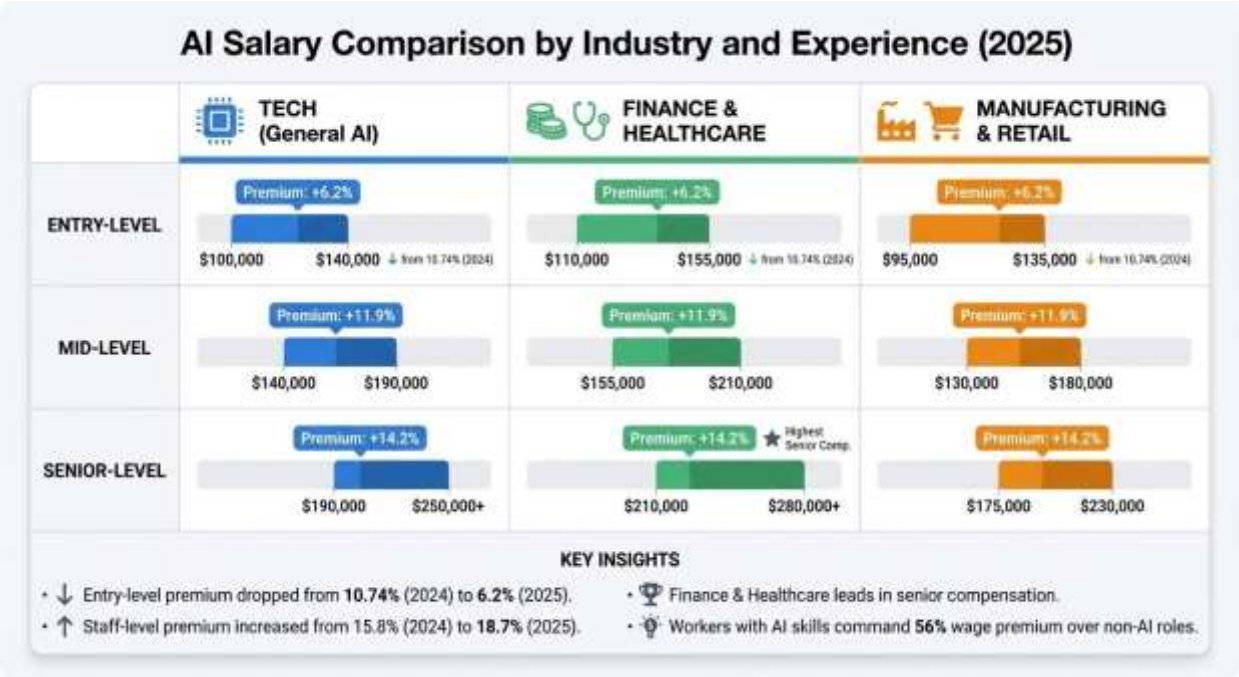
In the U.S., household income showed an increase between 0.403 in 2010 and 0.410 in 2024 due to automation, which raised the Gini coefficient by 40-60 per cent in place of the skill premia and job displacement (SparkCo analysis, 2025). There were a 82.3% versus 88.6% in 2024 and 1990 over decades of displacement in the simple mid-skill jobs, workers aged in their prime labour force participation rate with no college degree or high school diploma (BLS Current Population Survey, 2024). Figure 10 of the OECD Employment outlook 2023 is a graph which illustrates empirically the evolution of real wage growth by occupational skill decile by country, in the OECD countries-the typical wage stagnation and decline in the middle deciles in the middle occupational-skill-service employment.

The Dallas Fed (2026) provides a twist to the post-2022 wage effect. Notable ChatGPT gains Since the launch of ChatGPT, nominal average weekly wages nationwide grew 7.5 percent and the computer systems design sector (highly AI-exposed) grew 16.7 percent. The wages increased 8.5 percent among the top 10 percent of AI-exposed industries more generally. Its trend is aligned with a quality-over-quantity shift: the number of middle-skill jobs will go down, but salaries of those who stay in AI-augmented jobs will be higher, since becoming more productive to retain jobs will increase the bar.

6.2 AI Skills Premium.

The rest of the quantitative indicators of recent data are less obvious, and the rising wage premium based on AI literacy may be regarded as one of them. According to 2025 AI Jobs Barometer by PwC, employees that possess proved AI abilities receive a premium of 25 percent of the salaries of their non-skilled counterparts (ALM Corp, 2026). By 2024, workers most skilled in AI earned a premium 56 percent higher than the median worker, although this represents a huge wage increase on the previous year, and the median pay in AI-thorough-specific jobs amounted to 156,998 in Q1 2025 (DemandSage, 2026). Figure 11 - found in the AI Jobs Barometer (2025) of PwC - shows the trend in the AI skills wage premium by sector and geography, showing how fast the premium is rising since 2022.

Figure: AI salary comparison by industry and experience level (2025)



Source: Acedit. (2026). AI career insights: Salary trends by industry. https://www.acedit.ai/blog/ai-career-insights-salary-trends-industry

With this premium, there will be a split in the middle-skill labor force: those who manage to master the artificial intelligence complementary skills will be able to move up the wage ladder into better-paying and more rewarding jobs, and those who fail are at risk of being removed and earning no higher wages. The OECD AI Papers (2024) report that finding itself in a job subject to AI is experiencing 66% more rapid skill changes than usual that exceeds the normal retraining cycle and poses a structural threat of skills mismatch to the mid-skill workers caught in the middle.

6.3 Gender and Demographic Asymmetries

Distributional effects of adoption of MLs in service industries are not gender-neutral. Available data at ILO reveal that in developed nations, the most at-risk jobs attributed to the impact of AI in robots occupying automated tasks claim 9.6% of positions employed by women in the workforce - nearly three times that occupied by men at 3.2%- due to their presence in mid-salary clerical, administrative, and frontline jobs (ILO, 2025). Across the world, 4.7% of female workplace activities are of the highest risk AI automation category, as opposed to 2.4% of male jobs (DemandSage, 2026). The ILO 2025 Brief includes some visualisation in Figure 12 of these gender differentials in the exposure to AI by occupational categories, explicitly clarifying the extent to which female-dominated middle-skill service positions are at risk of being automated.

Young employees are also overly exposed. The researchers of Stanford report a 13-percent decrease in employment of workers aged 22-25 in jobs affected by AI since the end of 2022 (cited in Dallas Fed, 2026). Such a clustering of effects into young, female and non-college-educated mid-skill workers reflects the occupational sorting that previously positioned these groups in routine-intensive service jobs - and suggests that, in the absence of special action, the adoption of ML will further amplify the already existing inequalities in the labour markets of these countries and not lessen them.

7. Policy Responses: Upskilling, Reskilling, and Active Labour Market Policies

7.1 Employer-Led Upskilling

Upskilling and retraining of their existing employees is the main medium through which the firms in the service industries have reacted to the emerging skills demands brought about by adoption of the ML. According to the survey of the OECD employers (2022) 64% of companies that succeed in the finance industry and 71% of those in the manufacturing industry that implemented AI answered by retraining or upskilling of workers, and it is the most popular firm-level strategy, surpassing the adoption of new workers and the reduction of headcount through attrition and redundancy (OECD Employment Outlook, Out of seven surveyed countries, more than a half of employees who claimed to have used AI reported that they received (or their employer had paid) some form of training.

Both the ILO (2025) and the IJCM (2025) mention that 85% of companies worldwide intend to invest in upskilling, and 63% of them define the lack of skills as the most significant obstacle to transforming the business. The OECD Employment Outlook 2023 (Figure 5.2, reused in the published report) has given the responses of the employer to adjusting skills needs due to adoption of AI with respect to retraining, new hiring, outsourcing, and redundancy as the most common ideas in all the 7 surveyed countries with retraining being the most common strategies used by the employers.

7.2 Active Labour market Policies and Public Policy

Policy measures led by the government include regulatory provisions, investment in training by the government, and active labour market policies (ALMPs). The Digital Skills agenda by the European Commission provided AI-skills proficiency to over 12 million employees in 2023, and the implementation of Digital Skills in the tech-centric service industries created a tangible effect on skill deficits (European Commission, 2025; cited in IJCM, 2025). The vocational education and training (VET) system in Germany has been attributed to dampening polarising effects compared to more flexible labour market such as in the case of the United States and United Kingdom (Goos et al., 2023; cited in IJCM, 2025), meaning that institutions structures influence the degree of mid-skill displacement at a particular level of ML adoption.

In 2024, SkillsFuture Credit scheme in Singapore enrolled 260,000 workers in AI and cybersecurity programs, 54% of mid-career workers had made a job find within six months of training (IJCM, 2025). Norway has partnered with the employer and employee organisations to create industry tailored AI and data science training courses in banking and municipal care, which is an example of tripartite social dialogue that ILO (2025) suggests as a best practice in managing transitions brought about by ML.

According to the OECD Employment Outlook (2023), the governments must make sure they offer sufficient support to those who are most impacted by displacement, especially the middle-educated workers in routine-intensive service jobs, both by providing income support and by poised to offer active re-employment support. Projected by McKinsey (2024), the number of occupational transitions needed in Europe alone could be up to 12 million by 2030, or twice the rate before the pandemic, which will necessitate not only investment in training employers but also redesign of secondary and post-secondary education systems.

7.3 Limitations of Current Policy Frameworks

Irrespective of the size of policy rhetoric, existing systems have major limitations. Training is ranked as one of the top-five policies to technological disruption across only 27 percent of all countries worldwide (IJCM, 2025). The job skills transition rates of AI-exposed jobs are increasing 66 times as compared to the non-exposed job skills and pose a very real concern that training cycles in institute may not match (Gloat, 2025). Moreover, the train-and-hope dynamic of

most employer upskilling schemes is not a response to the structural fact that the adoption of ML is potentially leading to a fall in the overall number of middle-skill jobs in existence - so that reskilling supply must be met by new labour demand that is actually created, and not just redistributed.

According to McKinsey (2024), potential automation of current AI technologies estimates about 57% of the working hours in the U.S., and over 40% of jobs can be fully automated; a technical limit clearly exceeding the realised levels of displacement, but which nonetheless presents the risk that the scale of disruption could be accelerated exponentially with more obstacles to adoption (cost, regulatory, organisational) removed. The ILO (2025) asks social dialogue to be at the heart of transition management: uniting workers, unions, and employers to negotiate collectively the deployment of ML, the tasks that are automated and profits split evenly.

8. Discussion: Uncovering Patterns, Caveats, Future Studies.

8.1 Generative AI Inflection point.

Empirical studies that have been analyzed in this paper are primarily pre-dated to the current phase of wide usage of large language models (LLMs) and other applications of generative artificial intelligence before the end of 2022. Their data, which now is predominantly pre-MBS (MIT) as Schmidt et al. (2025) make this clear, might be already obsolete concerning the current acceleration of the advance of generative AI - and whether the tendency to identify patterns according to which patterns of RBTC polarisation have existed will be maintained in the novel generative AI era, again is an empirical question. Unlike the other parts of the existing ML systems, which might be more susceptible to overstep automation risk in incorrect areas, generative AI can be trained with less information, capable of receiving more unstructured inputs, and is more flexible.

New fears of job displacement in the finance, medical and legal work industries, which rely on experience, are a result of the increasing ability of AI to perform non-routine cognition duties (as the OECD (2023) notes). The 2025 ILO update of its Global Index of Occupational Exposure shows a slightly smaller overall score on automation (mean of 0.29 vs 0.30) but with much less dispersion - the risk is becoming more centralized and predictable but no less important (ILO, 2025). The proportion of employees most frequently spread around the globe is the current proportion of workers engaged in a role that involves some form of generative AI contact.

8.2 The Reinstatement Question

One of the key questions that remain unanswered is whether the effect of reinstatements, the creation of new tasks and jobs as a result of the implementation of ML, will be sufficient to mitigate the dispensation in the intermediate skill range. The waves of change in the technology in history have ultimately created more jobs than it was murdered on a net basis though the changes were very unevenly distributed and over long transition periods to new jobs by the displaced workers.

Research from NBER working paper, Applying AI to Rebuild Middle Class Jobs (2024) by David Autor) suggests that AI can be used to re-employ middle-wage jobs rather than hollow out middle-wage jobs - by use of AI to offer more workers access to knowledge and decision-support traditionally the preserve of high-skill professionals. Now this is a hopeful scenario and is open to deliberate actions about the application of ML by businesses and the society, and not the implications of technological use. Any individual who is exposed to some amount of GenAI, even at a global level like in the example cited by the ILO (2025) in which only a quarter of the workforce is believed to be affected but not most jobs should be replaced but instead changed, also guests the result in a total lack of self-sufficiency when it comes to how the transition must be dealt with.

8.3 Data and Methodological Limitations

One obstacle to second hand research on the subject is data. The AI adoption data provided by the U.S. Census (Bonney et al., 2024) estimated it to be approximately 10-percent of firms, and the business subscription data (Ramp AI Index) stands at approximately 44-percent, which is four times less different between conceptualisations and measures (Stanford Digital Economy Lab, 2025). As of 2023, most econometric studies are founded on data up until now and remain incapable of fully reflecting the entire generative AI effect. The Stanford Digital Economy Lab has very little evidence regarding the actual changes in the workers tasks after they have adopted ML (survey based) and limited evidence regarding longitudinal income of the workers who have been displaced by ML (both survey based identified as a gap in the existing body of knowledge).

Moreover, evidence base is biased towards developed economies, in particular, the United States and Western Europe. The adoption of service sector ML and the impact it has on middle-income economy mid-skilled workers have limited coverage, which will become more crucial as adoption of ML is adopted globally in investment in digital infrastructure and the falling cost of compute power.

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