GLAECONOMICS

Working Paper 103

London's workforce exposure to generative artificial intelligence

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April 2026

MAYOR OF LONDON

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Greater London Authority
April 2026

Published by
Greater London Authority
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London E16 1ZE

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The author is grateful to colleagues within the GLA for their thoughtful contributions to this research, and to the Institute for the Future of Work (IFoW) for its helpful guidance. All errors and omissions are the author's own.

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Mayor's foreword

Artificial intelligence (AI) is no longer a distant prospect. It is already reshaping how we work, how our economy functions, and how Londoners experience daily life. For a city like London – a global centre for finance, the creative industries, professional services and technology – the implications are profound. AI presents extraordinary opportunities to boost productivity, improve public services and create new, high-quality jobs. But if its adoption is not handled responsibly, it also brings real risks of economic disruption, increased inequality and intense anxiety about what this transition will mean for people's livelihoods.

This report from GLA Economics is an important and timely contribution to that conversation. By examining London's exposure to generative AI (GenAI) across occupations, industries and communities, it provides a rigorous, evidence-based picture of where change is most likely to be felt first. It shows clearly that London's workforce is more exposed to GenAI than any other region in the UK – not because we are weaker, but because our economy is rich in the knowledge-intensive work where GenAI's capabilities are advancing fastest.

Crucially, this analysis avoids easy conclusions. High exposure does not automatically mean job losses, just as lower exposure does not guarantee insulation from change. In many cases, AI is more likely to transform roles than replace them outright, shifting the mix of tasks, skills and judgement required at work. In other cases, where AI poses a genuine threat to jobs, we need to be alert and ready to respond quickly to any adverse impacts on London's labour market. This report helps us to understand those dynamics and where the pressures – and opportunities – are emerging.

At the same time, it is important to recognise the limits of any snapshot analysis in a field evolving as rapidly as this one. AI capabilities continue to advance at pace, and the ways in which employers adopt and integrate these technologies will ultimately shape real-world outcomes. That is why this research is best seen not as the final word, but as the foundation for deeper, ongoing work.

That is also why I am establishing the London AI and Jobs Taskforce. Bringing together workers' representatives, employers, researchers and civic leaders, the Taskforce will build on this report to develop a fuller, more grounded understanding of how AI is already changing work in London – sector by sector, role by role, and community by community – examining what support and mitigations might be needed to ensure we make the age of AI a success in London. The Taskforce's focus will be practical and action-oriented: identifying where the risks of displacement are most acute, where pathways into good work may be weakening, and where London can lead by shaping AI adoption in a responsible and ethical fashion to improve job quality and productivity, and help build a fairer, greener, safer and more prosperous city for everyone.

London has navigated technological change before. Our strength has always been our people – their creativity, resilience and ability to adapt. My approach to AI is rooted in realism: neither uncritical optimism nor fear-driven pessimism, but a clear-eyed commitment to shaping this revolution in the interests of Londoners. With the right evidence, the right partnerships and the right tools in place, we can ensure that AI strengthens the London promise – that hard work is rewarded with opportunity – rather than undermining it.

This report is a vital first step on that journey. I welcome it as an important contribution to helping London face the AI transition with confidence, purpose and fairness.

Sir Sadiq Khan
Mayor of London

Executive summary

Generative Artificial Intelligence (GenAI) is evolving quickly, and the scale, speed and scope of its labour market effects remain uncertain.

- Rapid improvements in AI capability, alongside growing diffusion across the economy, present a major challenge for understanding its labour market impacts in real time. While this report uses some of the latest available exposure measures – based on the capabilities of early-2025 GenAI models – continued advances mean these benchmarks can become outdated quickly.
- Despite this challenge, the fundamental exposure patterns identified here – particularly the occupations and industries most likely to be affected – remain relevant.
- With GenAI adoption increasing, abstract exposure patterns that identify potential labour market impacts must – as shown in this report – be supplemented by broader evidence of observed adjustments in hiring, task composition, progression and workplace adoption.
- The London AI and Jobs Taskforce will take forward the analysis in this report to better understand AI-specific effects on jobs, productivity, inclusion, and job quality.

GenAI has the potential to reshape London's labour market but its overall impact on employment remains uncertain. High exposure, as defined in the report, does not signal definitive job losses, nor does low exposure guarantee job and occupational security.

- At least 46% of London's workers (around 2.4 million people) are in roles where GenAI could automate a share of their tasks, based on the International Labour Organization's (ILO) occupational exposure estimates. This is substantially higher than the UK average of 38%.
- **London's high exposure to GenAI presents both opportunity and risk.** The technology could deliver productivity gains by improving task efficiency, but it may also create a risk of disruption and reduced demand for some roles, even while increasing the need for some new or existing roles.
- In addition to the technology's capabilities, longer-term GenAI labour market impacts will depend on a range of other factors, including adoption patterns, the availability of complementary skills, public trust in AI outputs and business integration strategies, as well as wider economic conditions.

GenAI exposure – and its potential impact – is heavily concentrated within specific occupations and industries…

- Over 300,000 workers – predominantly in routine administrative roles – face the highest levels of exposure and risk of AI automation, as their clerical tasks align most closely with GenAI capabilities.

- Many professional white-collar occupations are also highly exposed, reflecting the language-, digital- and analysis-intensive nature of their work. However, roles requiring high-stakes judgement, accountability and client interaction are considered by the ILO measures to be less directly automatable. They are more likely to be reshaped through augmentation than replaced by GenAI.

- Reflecting their occupational mix, ICT, finance, professional services, and public administration sectors face the highest overall exposure to GenAI, all of which are industries that are fundamental to London's economy.

- Sectors that rely on physical presence, skilled trades, or direct interpersonal care are less directly exposed, though no sector is likely to remain entirely unaffected.

- Additionally, some sectors with relatively low direct exposure to GenAI – such as transport – may see faster change in the future when other forms of AI such as computer vision advance, increasing the potential of robotics and other automation technologies.

...with uneven impacts likely across London's workforce.

- Differences in exposure across groups largely reflect existing occupational patterns, although no group is entirely insulated from potential effects.
  - Workers with higher levels of educational attainment are among the most exposed, reflecting their concentration in professional, knowledge-intensive occupations.
  - Women are overrepresented in highly exposed administrative and clerical roles.
  - Many younger workers, those at the start of their professional careers, are concentrated in high-exposure digital and knowledge-intensive roles. GenAI may also affect "stepping-stone" jobs that traditionally provide entry routes into careers, with implications both for young people trying to gain a foothold in the labour market and for longer-term talent pipelines into more senior roles.

- GenAI also has the potential to widen income inequality, with greater disruption possible in lower-paid administration roles and productivity gains accruing to higher-paid professionals and/or owners of the models.

Exposure alone does not drive labour market change, but early signals from GenAI adoption trends suggest it is beginning to translate into tangible workplace impacts.

- Worker- and business-reported AI adoption has almost doubled over the last two years to between 26%-35% and continues to steadily rise as use cases become clearer, particularly in highly exposed knowledge-intensive sectors.

- Adoption (and intensity of adoption) remains uneven, with larger and more digitally mature businesses leading the uptake. Organisations' ability to manage change and the risks around data protection, quality, and accountability may be slowing use in some settings.

So far, task change within roles appears to be the main employment effect…

- Early adoption evidence to date points to tentative productivity gains, sub-task automation and role redesigns, rather than wholesale job replacement with AI.
- Business-reported impacts of AI adoption on specific roles broadly align with the ILO's occupational exposure patterns, with limited evidence of changes in headcount
- Firms report prioritising training and upskilling of existing staff in complementary skills, and increasingly expect AI expertise when recruiting across a wide range of occupations.

… although new AI-related roles are also emerging…

- Demand for specialist AI roles is growing rapidly, although these jobs remain a relatively small part of the overall labour market.
- AI-focused firms are also expanding quickly, generating new employment opportunities.

… even as demand may be softening for some highly exposed roles.

- There are early signs of slowing recruitment for some of the most exposed administration and professional roles, although the evidence is still inconclusive. This slowdown may partly reflect AI-related change, but it remains difficult to disentangle these effects from the wider labour market cooling of recent years.
- While reported AI-related headcount reductions remain limited to date, employers in some industries anticipate that automation-related efficiencies arising from AI adoption will allow them to reduce their hiring needs or workforce size over time.

Towards a deeper evidence base

- This report serves as a foundational evidence base. While relevant and rigorous, it is preliminary given the pace of GenAI capability evolution. Nonetheless, it represents a stepping-stone towards monitoring and expanding analysis on this topic to better inform the priorities and strategies of the Mayor's Taskforce.

- It also points to the need for further analysis including new methodologies, experiences from other jurisdictions, and interfaces with economic and social conditions.

Overview of London's potential workforce exposure to generative artificial intelligence (GenAI)

London | 2022-2024 employment estimates

GenAI exposure level	What this means in practice	Share of employment (London)	Estimated workers (London)	Example occupations	Groups with disproportionate concentration
High exposure (level 4)	Most tasks closely overlap with GenAI capabilities, with little variation across tasks. Potentially at most risk of automation with a large share of day-to-day work potentially affected	6.0%	313,000	Administrative professionals, Bookkeepers, Brokers	**Workers**: Women, young and older workers, lower education levels **Industries**: Public admin and financial services
Significant exposure (level 3)	Many tasks overlap with GenAI capabilities, but consistency of exposure varies across the role. Some parts of the role are highly automatable, others less so	14.3%	748,000	Software developers, Financial advisors, Economists	**Workers**: Young, Asian, degree level+ education **Industries**: ICT and financial services
Moderate exposure (level 2)	A mix of exposed and non-exposed tasks. AI is likely to affect specific tasks rather than the role as a whole	18.6%	972,000	IT system designers, Management consultants	**Workers**: Men, prime working age, White, degree level+ education **Industries**: Professional services and ICT
Low exposure (level 1)	Overall exposure is low, but a some tasks may be affected by AI tools	6.7%	351,000	Sales roles, Legal associates	**Workers**:Young, Asian, lower education levels **Industries**: Retail and transport
Limited exposure	Most core tasks have little overlap with current GenAI capabilities, so near-term task change is likely to be less significant	54.3%	2,836,000	Care workers, Construction trades, Waiting staff	**Workers**: Older, Black, lower education levels **Industries**: Healthcare, education and construction

Note: Exposure level reflects the degree to which current job tasks overlap with existing GenAI capabilities. It does not indicate job losses or gains.

Table: GLA Economics adaptation of ILO (2025) approach • Source: ONS Annual Population Survey - Pooled Annual (2022-2024) • Created with Datawrapper

Introduction

Artificial intelligence (AI) has emerged as a transformative force for the global economy. Driven by substantial levels of international investment, capabilities have improved exponentially in just a few years.[1,2] This is particularly the case for generative AI (GenAI) tools – including large language models (LLMs) and multimodal systems such as OpenAI's *ChatGPT* and Anthropic's *Claude*.[3] These models can reach human-level performance for a variety of well-defined tasks, including in language, reasoning, analysis, coding and image-generation. Given these developments, policymakers in advanced economies, including in the UK, consider AI's potential as a key lever for reviving productivity growth, with early signs emerging in some sectors.[4,5,6,7]

At the same time, GenAI's rise has sparked debate about its possible effects on the workforce. The International Monetary Fund (IMF) predicts that about 70% of jobs in the UK could be impacted to some extent within the next five years.[8] Despite a growing empirical literature, there remains limited consensus among academics, policymakers, and business leaders as to the likely impact of AI on employment and other labour-market outcomes in the long term. Some emphasise job displacement risks in parts of professional and administrative work as routine cognitive tasks become automatable and employers seek cost efficiencies.[9] Others highlight evidence of human productivity enhancement – or role augmentation – as a result of AI where workers use AI tools to improve the speed and quality of their work, with modest impacts on overall employment levels. Evidence also suggests that the advent of any new technology creates entirely new roles which could counter any potential losses in more exposed parts of the labour market over the longer-term. [10] How these competing forces balance depends on a wide range of factors, including pace of adoption, demand conditions, and public trust in AI-generated outputs as examples. There is, however, agreement that the impacts of AI will not be evenly distributed across the workforce**. Over the long run though, there is substantial evidence and opinion suggesting that new technologies can create as many – if not more – jobs across the economy as they destroy. This outcome is not guaranteed for AI, but it illustrates a possible future to be worked towards.**[11,12]

Given the scale of potential change, more analysis is needed to assess local labour market exposures to GenAI, particularly in London. While some national studies have mapped AI exposure patterns for the UK as a whole, there are few detailed analyses available for labour markets at regional or city level, which often have distinctive occupational mixes. London's economy is highly concentrated in professional, business and ICT services – sectors generally identified as the most exposed to GenAI. For policymakers in London's skills and employment system, such analysis is key to understanding where

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[1] US tech giants pledge billions for UK AI infrastructure during Trump visit | Financial Times (Financial Times, 2025)
[2] Time Horizon for measuring the autonomous capabilities of AI models - METR (2026)
[3] Throughout this report, 'AI' is sometimes used as shorthand for generative AI or 'GenAI'. The analysis is primarily concerned with recently developed GenAI tools and their potential labour market implications. It should also be noted, however, that different LLMs and GenAI tools possess different capacities and capabilities, with Anthropic's latest model (Claude Mythos), for example, exceeding variants such as ChatGPT in terms of overall capability and potential impact.
[4] AI Opportunities Action Plan | UK Government (2025)
[5] OECD estimates suggest UK labour productivity growth from AI could reach 0.4–1.2 percentage points annually over the next decade, placing it second only to the US among G7 economies. (OECD, 2025)
[6] While AI productivity benefits are yet to substantially materialise in UK economic data to date, there are tentative signs emerging in the US. Where is AI showing up in the productivity data? | Financial Times (Keynes, 2026)
[7] The AI productivity take-off is finally visible | Financial Times (Brynjolfsson, 2026)
[8] These estimates are derived using a different methodology to that followed in the rest of this paper. Gen-AI: Artificial Intelligence and the Future of Work (Cazzaniga et al. | IMF, 2024).
[9] Dario Amodei | Anthropic Chief Executive (CNN Business, 2025)
[10] WEF estimates AI and information processing technology could create 11 million jobs, while simultaneously displacing 9 million others. Jobs outlook - The Future of Jobs Report (World Economic Forum, 2025).
[11] The Effects of Automation on Labor Demand | (Aghion et al., 2022)
[12] The impact of technology on the quality and quantity of jobs (ILO, 2018)

additional transition support may be required, and how to enable businesses and workers to harness the potential of GenAI.

This report uses measures of AI exposure at a task level – an approach that provides high-level estimates of which types of occupations are most likely to be affected. It adapts the International Labour Organization's (ILO) 2025 task-based GenAI occupational exposure framework to London, setting out the technical potential for GenAI to perform tasks for each occupation given its early 2025 capabilities.[13] In this context, exposure should be understood as an indicative early signal of where and how change may occur rather than representing a probability or forecast of net job change.

This paper is intended to provide a strong foundation for further work by the new London AI and Jobs Taskforce, which is being established to generate more real-world evidence on how AI is affecting the capital's labour market prior to responding with effective policy measures. Bringing together a wide range of stakeholders, it will help identify both the near-term risks and opportunities for Londoners and guide a focused set of practical policy interventions. A key part of this will be reviewing existing AI-related skills, identifying areas where AI exposure generates risk and uncertainty, and providing training and business support across London. The taskforce will also provide a forum to develop and test targeted policy responses, including measures to support those at greater risk of displacement, improving productivity, and helping employers – including SMEs – to adopt AI more effectively.

Drawing on this work, the taskforce intends to focus initially on three core sectors. The first is *professional and financial services*, given its economic importance to London and its concentration of highly AI-exposed roles across the occupational spectrum. The second is the *creative industries*, including both commercial creative activities such as marketing and design, and culturally creative roles such as media and arts production – each of which are likely to be affected by AI. The third is *transport*, where the evidence suggests limited GenAI impact on London's workforce to date, but where more disruptive effects from wider AI-enabled automation are plausible over the medium term. The taskforce will also pay particular attention to the impact of AI on the career pathways of *young people, junior roles and graduates*.

The rest of this paper is structured as follows:

- **Chapter 1** provides a brief overview of the ways through which AI may impact labour demand and other important factors that will shape its adoption and employment outcomes.
- **Chapter 2** summarises the ILO occupational GenAI exposure framework, its adaptation to London, and its main limitations.
- **Chapter 3** presents detailed occupational exposure estimates for London, including who is most likely to be impacted and the scale of exposure in terms of employment numbers.
- **Chapter 4** examines real-world adoption evidence to date, including survey data and hiring trends, and compares this with the theory-based exposure analysis.
- **Chapter 5** concludes with a summary of main findings, possible policy considerations for London's skills and education system, and the need for further research going forward.
- **The appendices** provide further detail on the ILO methodology, UK adaptation, comparison with alternative approaches, and full SOC exposure scores,.

[13] A Refined Global Index of Occupational Exposure to GenAI (Gmyrek et al. | ILO, 2025)

Chapter 1: How GenAI could affect labour demand

Before estimating London's exposure to GenAI, it is useful for context to set out how this new technology could potentially affect labour demand. This chapter, therefore, summarises the main **theoretical channels** through which employment may be influenced, and the economic, organisational and institutional conditions that will ultimately shape how – and how quickly – these effects materialise. Together, these provide a framework for interpreting the exposure estimates and adoption evidence that follow.

1.1: Channels through which GenAI may affect labour demand

To assess how GenAI – or any new technology – may affect labour demand, it is helpful to focus on the bundle of tasks that make up different jobs. All occupations consist of a diverse range of activities, and new technologies rarely replace an entire role at once. Instead, their capabilities overlap with specific tasks within a job, which in turn can affect demand for that role.

A **task-based approach** therefore offers a more realistic way of understanding potential impacts. It recognises that some tasks may be automated, others may be enhanced, and some may remain largely unchanged. However, it is not enough to consider individual task exposure alone.[14] Because jobs are made up of bundles of tasks, the effect of technology on demand depends partly on whether those particular tasks can be separated from the rest of the role without losing too much value. Where tasks are tightly linked through shared context, judgement, communication or accountability, the integration of new technology may improve performance in part of the job without removing the worker from it. Where tasks are easier to separate, the technology may narrow the human role by taking over specific components while workers focus on the remainder.

Drawing on this broader task-based framework, the OECD (2023) highlights **three main channels through which the adoption of a new technology can influence employer demand for labour** (also illustrated in Figure 1.1)[15,16,17]:

i. **New task creation (*technology generates new labour demand*).**
New technologies often create new types of work. As GenAI develops and spreads, new firms, roles and specialist tasks emerge to design, build, implement, regulate and maintain these systems. Over time, entirely new occupations may develop alongside the technology itself.

ii. **Automation of tasks (*substitution and potential displacement risk*).**
Some well-defined tasks that were previously carried out by people can be fully automated by GenAI. This reduces the amount of labour required for those activities and may allow firms to lower costs or operate more efficiently. In practice, this may appear as slower recruitment, fewer replacements for staff who leave, or changes to job design. Where workers cannot be redeployed to other tasks – and where demand for output does not expand – this can lead to job displacement or redundancy.

iii. **Augmentation of tasks (*human-technology complementarity transforms role*).**
In most cases, technology does not replace entire roles because of human-task bottlenecks – tasks that require judgement, interaction or oversight that GenAI cannot reliably replicate. Instead, workers use GenAI as a complementary tool to perform tasks more quickly or to a higher standard. In practice, this can also often involve refining and validating AI-generated

[14] Weak Bundle, Strong Bundle: How AI Redraws Job Boundaries (Garicano, Li and Wu., 2026)
[15] Employment Outlook – Artificial Intelligence and the Labour Market (OECD, 2023)
[16] Artificial Intelligence, Automation and Work (Acemoglu and Restrepo, 2018)
[17] Why Are There Still So Many Jobs? The History and Future of Workplace Automation (Autor, 2015)

outputs. This form of human–technology complementarity can materially change job content, reducing time spent on routine or drudge tasks and increasing focus on more complex activities that rely on distinctly human capabilities.

However, role change as a result of AI (augmentation) does not have a single, predictable effect on employment. Its impact depends on whether AI does lead to productivity gains and how such gains are translated into business decisions and market outcomes. [18] For example, where AI reduces costs or improves quality, firms may choose to lower prices, improve services or expand into new markets. If this results in higher demand, output can increase, and employment may grow in complementary roles – even if some tasks are automated (often described as *scale effects*). However, productivity gains do not always lead to expansion. In some cases, demand may not increase significantly, or firms may choose to raise markups rather than grow. Under these conditions, employers may be able to meet existing demand with fewer workers. This can result in slower hiring, redeployment, or reductions in staff numbers.

In practice, these dynamics can occur simultaneously across different firms and sectors. The balance between new task creation, automation and augmentation – together with business strategy, market conditions and demand responses – shapes overall employment outcomes. **Because these forces vary across the labour market and exhibit different impacts by industry and profession, the impact of AI adoption on London's labour market remains uncertain.** While there are likely to be both winners and losers as a result of AI, it is important to note that labour market outcomes will also depend on its diffusion, workforce skills, firms' strategic choices, and wider economic and institutional conditions, as well as a range of other factors discussed in Section 1.3.[19]

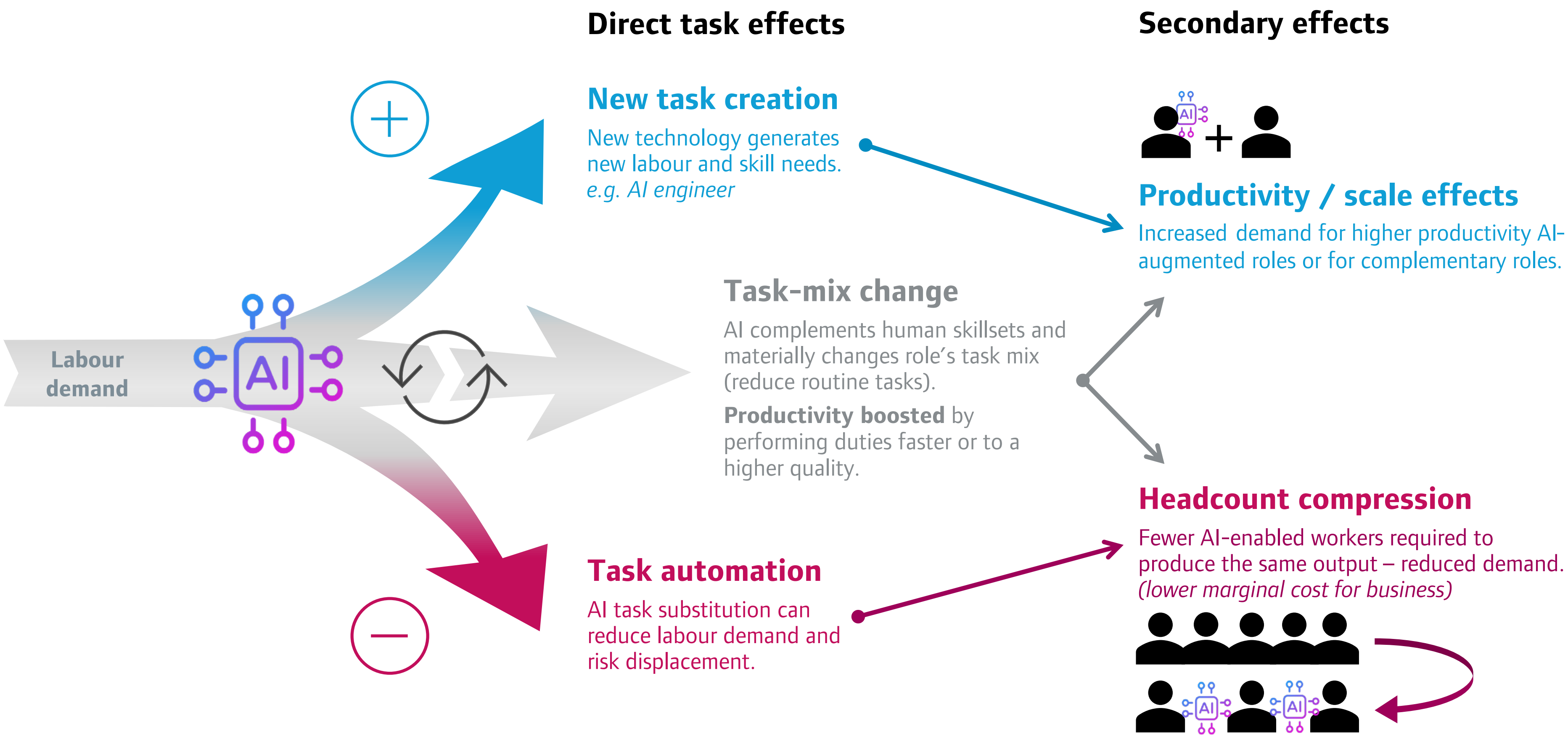
In the following chapters, this report adopts a task-based approach to identify high-level signs of GenAI's labour market impact. It does not delve deeper into the channels discussed above, nor does the data clearly reveal how tasks within an occupation are evolving as a result of GenAI. This is because task-based exposure alone does not shape and determine labour market impacts. As a result, this report best serves as a foundation for more comprehensive analysis involving a broader array of data and information.

[18] New workplace technologies can reshape both the content and quality of work. AI may enhance job quality by automating routine cognitive tasks and enabling workers to focus on more meaningful or complex activities. However, it can also lead to work intensification, greater routinisation and reduced autonomy, with potential negative effects on stress and wellbeing. Ultimately, the impact of automation and augmentation on job quality depends on how technology is implemented and how productivity gains are used in practice (OECD, 2023; Pissarides Review, 2025).

[19] The Labor Market Impacts of Technological Change (Autor, 2022)

Figure 1.1: High-level example of how AI could impact employer demand for labour through a variety of channels

Dynamic changes in occupational tasks result in ambiguous net employment effects



Note: *Productivity can rise substantially when AI effectively reduces the time taken to perform routine tasks, but it can also remain the same or fall where outputs require significant levels of human checking or reworking.

Source: GLA Economics (authors' adaptation based on the international literature on new technologies, AI, task theory, and labour demand).

1.2: How GenAI differs from earlier technological waves

The mechanisms described above are not unique to AI. Historically, general-purpose technologies have created and displaced tasks, with overall employment effects shaped by their capability, pace of adoption and a range of other factors (Section 1.3). In many cases, these adjustments unfolded gradually over extended periods. GenAI, however, combines several features that may influence both the speed and breadth of its labour market impacts.

Unlike many earlier technologies that primarily transformed physical or routine activities, GenAI has demonstrated **capability across a broad range of complex cognitive and knowledge-intensive tasks**, including drafting, analysis, coding, and reasoning. As a result, any potential AI-related shocks may affect professional occupations across broad swathes of the economy– roles previously considered less susceptible to automation risks.

Its development trajectory also differs from many past innovations. AI model **capabilities have advanced exponentially** since late 2022, supported by significant global investment and intense competition among providers.[20,21] The recent emergence of more autonomous – or *'agentic'* – GenAI systems, for example, has further expanded the range of tasks that may be performed with limited human input, increasing both the scope for possible productivity gains and the potential breadth of labour market disruption.

These developments are occurring alongside relatively **low barriers to experimentation** through user-friendly interfaces and accessible pricing. This ease of use may shorten the lag between technological breakthrough and practical diffusion.[22] Firms and individual workers can test and easily deploy these tools with limited upfront investment, even if large-scale transformation still requires organisational change.[23]

Taken together, these features suggest that GenAI's effects could be both wider in scope and quicker to materialise than earlier technological waves. However, realised employment outcomes will ultimately depend on how firms, workers and institutions respond.

1.3: What factors will shape AI adoption and employment outcomes

While GenAI may have broader and potentially faster-moving effects than previous technological waves, technical capability alone does not determine labour market outcomes. Whether exposure translates into displacement, role augmentation or job creation depends on how workers, firms, and wider societal institutions respond in practice.

Table 1.1 sets out some key determinants likely to influence both the pace of AI adoption and its impact on employment. These factors can help explain why similar levels of exposure may produce different outcomes across sectors and regions. For London, their interaction will shape how exposure to GenAI capabilities will translate into realised labour market outcomes across its diverse sectors and occupations.

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[20] Recent evaluations suggest frontier AI models can now produce expert-quality work on a significant share of real-world professional tasks. (Patwardhan et al., 2025). However, this evaluation covered only precisely specified, self-contained digital tasks. In real world situations, there is typically greater ambiguity and context specific challenges.

[21] Time Horizon for measuring the autonomous capabilities of AI models - METR (2026). While capabilities have improved dramatically, there remains a high degree of variability in successful task completion rates, especially for more complex tasks, which therefore necessitates human oversight.

[22] The Rapid Adoption of GenAI (Bick et al., 2025)

[23] In short, these more advanced and specialised AI systems enable software agents to plan, use tools, and carry out multi-step workflows with minimal direct human input. However, there remains significant uncertainty over how reliably such systems can perform complex real-world tasks without oversight across domains, and how quickly they can be deployed safely at scale. AI agents: from co-pilot to autopilot (Financial Times, 2025)

Table 1.1: **Example of factors determining AI adoption and consequent employment outcomes**

Factor	Relevance for employment outcomes
Worker-occupation level	
Degree of task–technology overlap	The greater the overlap between AI capabilities and a role's core tasks, the higher the automation potential. However, task bottlenecks can prevent full substitution and lead instead to partial automation or augmentation, although impacts vary by sector.
Worker trust in AI accuracy and reliability	Workers' confidence in the reliability and accountability of AI outputs affects how extensively tools are used in practice. Concerns about errors, bias or reputational risk may limit reliance even where technical capability exists.
Scope for task reorganisation and redeployment	How easily tasks can be reorganised between people and AI affects whether impacts are more likely to be augmentation or displacement. Outcomes also depend on workers' ability to transition into less exposed roles, based on their existing skillsets.
Complementary skills and AI proficiency	Workers' digital and AI expertise, subject-matter knowledge, and judgement skills shape whether AI mainly supports their work or replaces some tasks. These skills also determine how productively workers can use AI in practice.
Business level	
Adoption and integration intensity	Employment impacts depend not only on technical feasibility but also on how quickly AI is adopted and how deeply it is embedded in core workflows. Wider diffusion and use at scale are more likely to generate meaningful productivity change and knock-on labour demand effects than limited or experimental use.
Strategic objective	Firms deploying AI primarily to reduce costs may reduce employment, while those using it to improve productivity, quality or expand output may support job creation.
Organisational capability	Realising productivity gains from AI requires complementary investment in culture change, management practices, workflow redesign, and data/digital readiness.
Market competition	In competitive markets, productivity gains are more likely to translate into lower prices and higher output, supporting labour demand. In more concentrated markets, gains may accrue as higher profits with weaker employment effects.
Wider economic and institutional level	
Public trust in AI outputs	Public confidence in AI-generated outputs influences adoption in sensitive sectors such as legal, health, education and finance. Low trust – where society is less willing to permit unsupervised AI use – can slow diffusion regardless of technical capability.
Security and regulatory compliance	Exposure to data protection, security, copyright/IP and liability risks may delay or constrain adoption, particularly in knowledge-intensive sectors. Clearer regulatory frameworks can reduce uncertainty and support diffusion.
Macroeconomic conditions	Growth, demand and financing conditions influence firms' incentives to invest in AI and whether productivity gains feed through to employment growth. Geopolitical shocks could also affect adoption by disrupting global energy markets.
Demand responsiveness	Where consumer demand for AI-enabled goods and services is responsive to price changes, productivity gains may expand output and employment. Where demand is less responsive, labour-saving effects may dominate.
Collective bargaining and representation	The strength of worker representation and collective bargaining arrangements can influence how AI is introduced, how gains are shared, and whether retraining or redeployment measures accompany adoption.
Infrastructure and capacity limits	Concerns over AI infrastructure's energy and water demands, grid connection limits, and constrained computing power (e.g., GPUs) may raise costs and slow adoption.

Chapter 2: Overview of occupational exposure estimation

In recent years, several approaches have been developed to assess which occupations are most likely to be affected by GenAI. While these methods vary in design – and therefore have different strengths and limitations – there is broad agreement that **exposure scores are not predictions of jobs gained or lost, nor do they definitively indicate augmentation or productivity gains as employment outcomes**. Rather, they indicate the technical potential for tasks within roles can be automated by GenAI. Even where methods distinguish between automation- and augmentation-prone roles, realised employment outcomes will depend on wider factors.

2.1: Selected methodology: International Labour Organization (2025)

Following an assessment of the various approaches – see Appendix 2 – this report adapts the **ILO's task-based GenAI exposure framework** (Gmyrek et al., 2025) for its core occupational analysis. While this approach produces broadly similar exposure trends as others, it was selected because it:

- Follows a **task-based approach** that **rates how well AI – specifically GenAI – can perform specific work tasks under real workplace conditions.**
- Provides **granular, occupation exposure scores,** that are broadly translatable to the UK labour market context (via ISCO→SOC crosswalks).
- Offers some **directional guidance** on whether exposure is likely to take the form of automation or augmentation.
- Is among the **most recent methodologies developed**, and therefore likely to capture GenAI's current (early-2025) capabilities, which have evolved considerably even since some slightly older approaches were developed.

Box 2.1: Methodological summary of ILO task-based GenAI exposure framework (2025) [24]

Task-led foundation. Starting from ~30,000 tasks aligned to the ISCO-08 taxonomy, tasks are assessed for their susceptibility to GenAI capabilities.

Human judgements, then scaled with AI. Worker judgements of GenAI's ability to automate tasks in real workplace settings are combined with expert review to build a vetted set of task ratings. Two large language models are then used to score the remaining tasks consistently, using that validated set as a guide.

From tasks to occupations. Task scores are aggregated to ISCO-08 unit-group occupations. Two summary statistics are key: the **mean** (overall GenAI exposure level) and the **dispersion** – or variability – (how concentrated vs patchy exposure is across an occupation's tasks).

Exposure levels with directional guidance. Occupations are grouped into 'exposure levels' that reflect the **degree** and **consistency** of exposure. Higher and more uniform exposure is interpreted as more automation-prone; lower or more variable exposure is more consistent with augmentation (non-automatable tasks act as bottlenecks that keep people in the loop).

[24] A full description of the ILO methodology, comparisons with other exposure methodologies, its limitations, and technical notes on its adaption to the UK labour market setting are set out in Appendices 2 and 3.

2.2: Interpreting occupational exposure results

The ILO framework assigns exposure levels based on the technical potential for GenAI to automate tasks within each occupation (see Table 2.1). These scores are not forecasts of employment change.

Higher and more uniform exposure across an occupation's tasks suggests greater scope for role redesign and automation, while mixed exposure indicates a stronger likelihood of augmentation. However, realised labour market impacts will depend on the wider adoption factors discussed in Chapter 1.

Table 2.1: **Definitions and interpretation of GenAI exposure levels**

GenAI Exposure level	Interpretation	Example occupations
Exposed: Level 4 *(High task exposure, Low task exposure variability)*	High and consistent exposure to GenAI across tasks within the occupation. Most current tasks in these jobs have a **high potential of automation**, with little variability in task-level exposure.	Administrative / clerical roles, Bookkeepers, Brokers
Exposed: Level 3 *(Significant task exposure, high task exposure variability)*	Above-moderate occupational exposure. Even though some key tasks remain less exposed, the overall potential of automation of the current tasks with GenAI is growing in these occupations.	Economists, Software developers, Accountants
Exposed: Level 2 *(Moderate task exposure, high task exposure variability)*	Moderate occupational AI exposure, with high task-level variability. These occupations include a mix of some tasks that are exposed to GenAI and others not at risk, making the impact uneven.	Management consultants, Marketing professionals, IT system designers
Exposed: Level 1 *(Low task exposure, high task exposure variability)*	Low overall GenAI exposure at the occupational level, but high variability across tasks. Some tasks within these occupations have an elevated automation potential, even if the occupation as a whole remains strongly reliant on tasks that have a low potential of automation.	Sales assistants, Laboratory technicians, Legal associate professionals
Limited Exposure All other occupations *(Low task exposure, low-mod task exp. variability)*	Occupations with minimal-low GenAI occupational exposure, where most tasks remain relatively unaffected. Low-moderate task exposure variability, also makes these occupations **less likely to be impacted by AI automation, although not immune**.	Carpenters, Care workers, Primary school teachers

Note: Occupational GenAI exposure scores are not forecasts of jobs losses. Rather they indicate only the technical potential for tasks within roles to be automated by GenAI.

Limitations: The ILO methodology, like other occupational exposure approaches, is best interpreted as an early-warning signal of where job content may change, rather than as a prediction of job loss or realised adoption. [25] These approaches are also time-sensitive: the 2025 ILO index captures GenAI capabilities at a particular point in time and may therefore date relatively quickly as AI systems continue to advance rapidly, including through more agentic applications. However, these developments are more likely to affect the scale, depth and pace of impacts than the broad ranking of the most exposed

[25] Workers' exposure to AI: What indicators tell us – and what they don't (ILO,2026)

occupations and industries, since they continue to overlap with many of the same areas of cognitive and language-intensive work.

Because the ILO approach works at the level of occupations and static task profiles, it does not fully capture within-occupation differences such as seniority, specialisation, or how tasks are allocated across workplaces. It also cannot show the relative importance, frequency or sequencing of tasks, even though these shape whether AI changes a role in practice. More broadly, exposure scores reflect technical feasibility more than realised deployment, and so abstract from many of the organisational, economic and institutional factors that shape adoption. They also involve a degree of uncertainty, including worker-expert judgement in mapping AI capabilities to different tasks. Finally, mapping occupational exposure scores from the ISCO taxonomy to UK SOC is imperfect and can introduce some inaccuracies.

Chapter 3: Quantifying London's occupational exposure to GenAI

Using the task-based occupational exposure methodology and the exposure levels outlined in Chapter 2, this chapter sets out the scale and shape of London's workforce exposure to GenAI, highlighting the characteristics of those most likely to be impacted.[26,27]

3.1: London's overall exposure

The analysis suggests that at least 46% of workers in London – almost 2.4 million people – are in occupations classified as exposed to GenAI (exposure levels 1–4), meaning some tasks in these roles have potential to be automated or transformed by current GenAI capabilities. Around 6% of workers (313,000) are in Level 4, the highest-exposure group, where most tasks could be automated using current GenAI capabilities. A further 14% (748,000) are in Level 3, where exposure is high but varies across tasks, with some key tasks remaining less exposed. Together, these groups make up just over one-fifth of London's workforce and are the most likely to experience earlier and more pronounced role changes as GenAI adoption grows.

While 54% of workers are in roles assessed as having limited exposure – where their core tasks do not typically overlap strongly with GenAI's current capabilities – this does not imply no impact. GenAI may still be used in supportive ways that could improve productivity, and rapid advances in capability mean that exposure estimates may change over time.

Figure 3.1: Almost half of London's workforce is in GenAI-exposed occupations (Levels 1–4)
London | 2022-2024 employment estimates

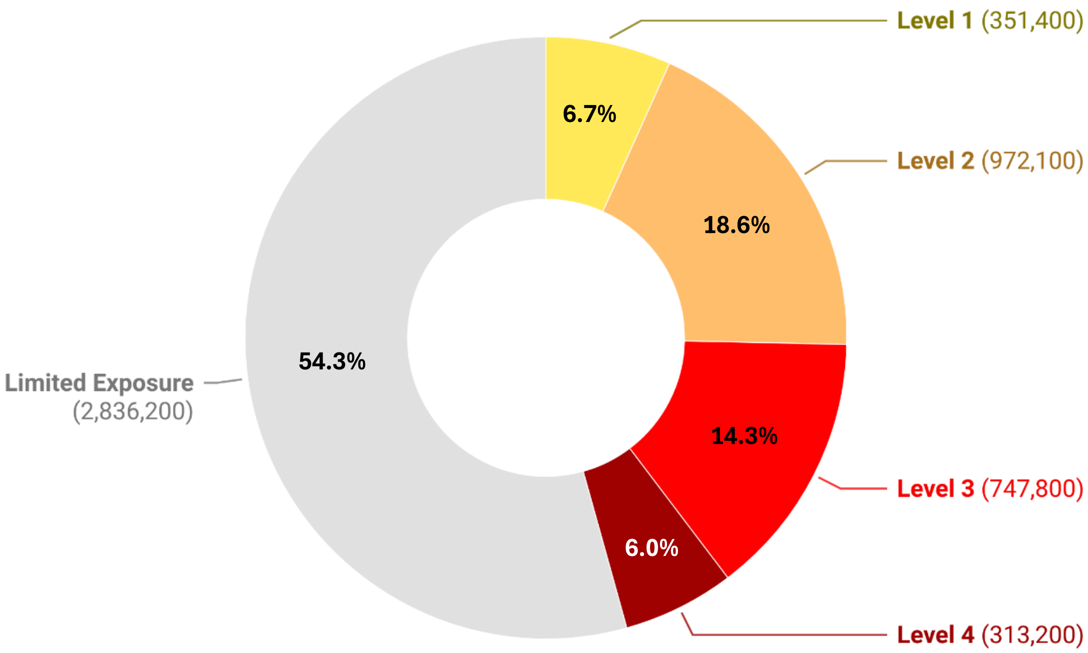


Chart: GLA Economics adaption of ILO (2025) approach • Source: ONS Annual Population Survey - Pooled Annual (2022-2024) - Percentages may not sum to 100% due to rounding. Location is place of employment. • Created with Datawrapper

[26] Occupational employment estimates are derived from the ONS' three-year pooled Annual Population Survey dataset, 2022-2024. APS-based estimates may differ from other employment statistics due to differences in coverage, location classification (which is employment location here), weighting and definitions. More information on this data is included in Appendix 3.
[27] See Appendix 4 for additional charts showing the share of workers within each exposure group by characteristic.

3.2: Occupational exposure

The exposure analysis suggests that the potential impact of GenAI is uneven across London's workforce and highly concentrated in specific occupational groups.

Administrative and clerical occupations are the most exposed. All roles in this group show some degree of exposure, with 61% in Level 4 and a further 27% in Level 3. Admin roles account for almost 90% of all workers in the highest level of exposure (Level 4). This reflects the text- and process-based nature of much administrative work – such as drafting and managing documents and emails, scheduling, data entry and summarising – which maps closely to GenAI's strengths. Because many tasks are routine, clearly defined and carried out digitally, AI tools can automate or accelerate substantial parts of the work with relatively few physical or contextual constraints. As a result, these roles have higher potential for disruption.

In absolute employment terms, the largest concentrations of exposure sit within professional and associate professional occupations, which include large shares of roles in Levels 2 and 3. Exposure is particularly concentrated among IT, business and finance professionals. Many of these jobs involve language- and analysis-intensive tasks – such as drafting, research synthesis, coding and documentation – that align well with GenAI capabilities. However, they also involve tasks requiring judgement, accountability, client interaction, ethics and context-specific knowledge, which are less directly automatable. In practice, this implies variation within roles: some tasks may be streamlined or partially automated, while others are more likely to be augmented with human oversight. Labour market adjustment is therefore more likely to involve task change and productivity gains than wholesale displacement, although outcomes will vary by specialty and setting. In some Level 3 professional roles, these gains could also translate into labour-saving effects (headcount compression) over time if firms can meet demand with fewer staff.

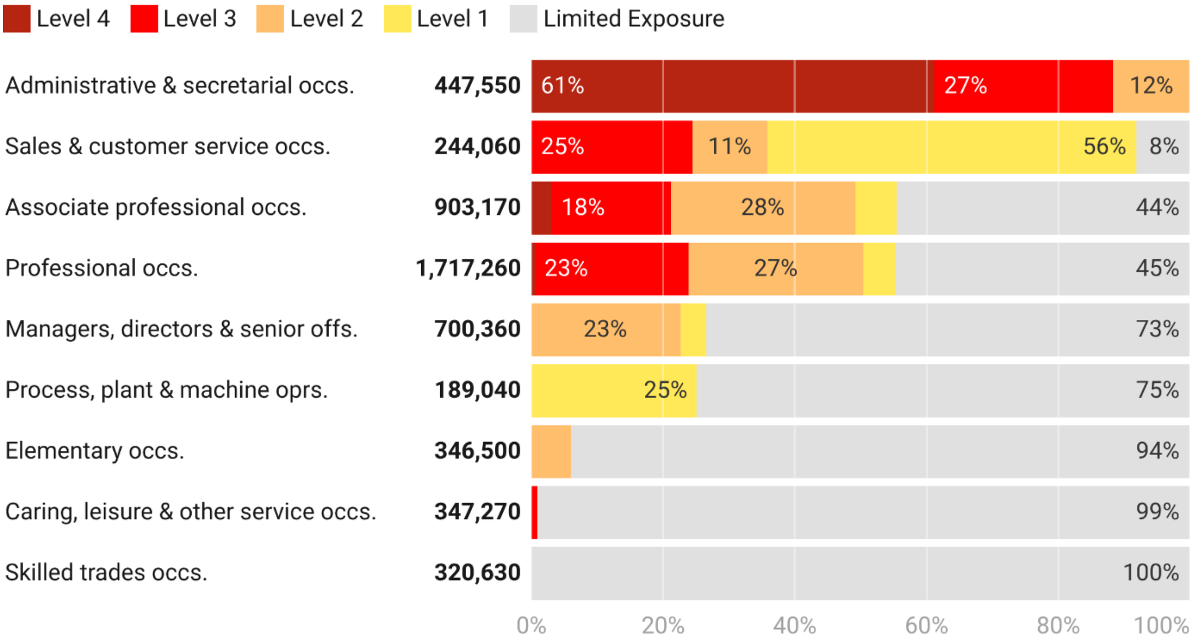
Disruption may also be felt in some professional occupations through indirect effects, as many highly exposed administrative and associate professional roles act as stepping stones into professional careers. If opportunities in these entry roles decline as a result of AI automation, progression pathways could weaken and, over time, reduce the supply of workers into less exposed mid- and senior-level professional roles.

By contrast, elementary occupations, caring roles and skilled trades generally have lower exposure because core tasks are typically physical, in-person and context-dependent. In elementary roles, work often centres on on-site duties with limited text or data processing, so impacts are more likely to be indirect (for example, improved instructions, translation, or shift scheduling). In caring roles, essential work relies on empathy, interpersonal judgement, safeguarding and hands-on support; GenAI may streamline record-keeping and care planning, but it does not substitute the relational or physical elements of these occupations. In skilled trades, performance depends on manual dexterity, site-specific problem-solving and safety compliance, with AI more likely to assist with diagnostics, documentation and access to technical information than automate core tasks. Overall, GenAI may improve efficiency at the margins in these roles, but widespread automation is less likely given the nature of the work.

Figure 3.3 presents a more granular occupational view of London's workforce exposure, with 4 of the top 5 largest occupations of employment being meaningfully exposed to GenAI.

Figure 3.2: Administrative roles at most risk of GenAI disruption, with large numbers of workers in professional roles also exposed

Distribution of GenAI exposure levels across broad occupational groups
London | 2022-2024 employment estimates | Major SOC 2020 groups



*Note: Numbers in **bold** are the estimated number of total workers in each category.*

Chart: GLA Economics adaptation of ILO (2025) approach • Source: ONS - Annual Population Survey - Pooled Annual (2022-2024) • Created with Datawrapper

Box 3.1: Understanding GenAI exposure for programmers and software developers

Programming includes many structured, language-like tasks – such as drafting or converting code, writing tests, straightforward debugging, and producing documentation – that map closely to what GenAI tools can already do well. In practice, impacts vary by task: some sub-tasks are increasingly automatable, while others are best treated as AI-generated first drafts that still require human oversight. Where integrated effectively, coding assistants can shift developers' time towards higher-value activities such as system and architecture design, integration, security, complex debugging and stakeholder communication.

Experimental and field evidence broadly matches this pattern. AI coding assistants are among the most widely adopted GenAI applications and can substantially speed up well-scoped or repetitive tasks (often ~25%+ faster), with the largest gains reported among less experienced developers.[28,29] However, productivity gains are not automatic, particularly for experienced developers working on complex tasks where low-quality or incomplete outputs can increase time consuming reviews and correction. [30] It may also introduce defects or security weaknesses without appropriate safeguards. Realised benefits therefore depend on strong quality assurance, testing and secure-coding practices.

As routine coding becomes faster, bottlenecks may shift to other parts of delivery – such as product decisions, quality assurance and security review – changing the mix of skills needed. Moreover, because many exposed tasks sit in junior and entry-level work, wider automation could also reshape career entry routes and "learning-by-doing", with implications for how new developers build experience and how firms structure progression pathways.

[28] The Effects of Generative AI on High-Skilled Work: Evidence from Software Developers (Cui et al., 2024)
[29] The Impact of AI on Developer Productivity: Evidence from GitHub Copilot (Peng, et al, 2023)
[30] Measuring the Impact of Early-2025 AI on Experienced Open-Source Developer Productivity - METR

While these findings are preliminary given the rapid evolution of events in this sphere, the emerging picture for programmers is one of uneven task displacement and role transformation. Productivity gains in some activities can complement higher-value work, but they could also reduce hiring needs over time, compress team structures, and reshape junior entry routes and career progression.

Figure 3.3: Many of London's largest occupations of employment are exposed to GenAI

Largest 25 occupations of employment by GenAI exposure level
London | 2022-2024 employment share estimates | SOC 2020 4-digit

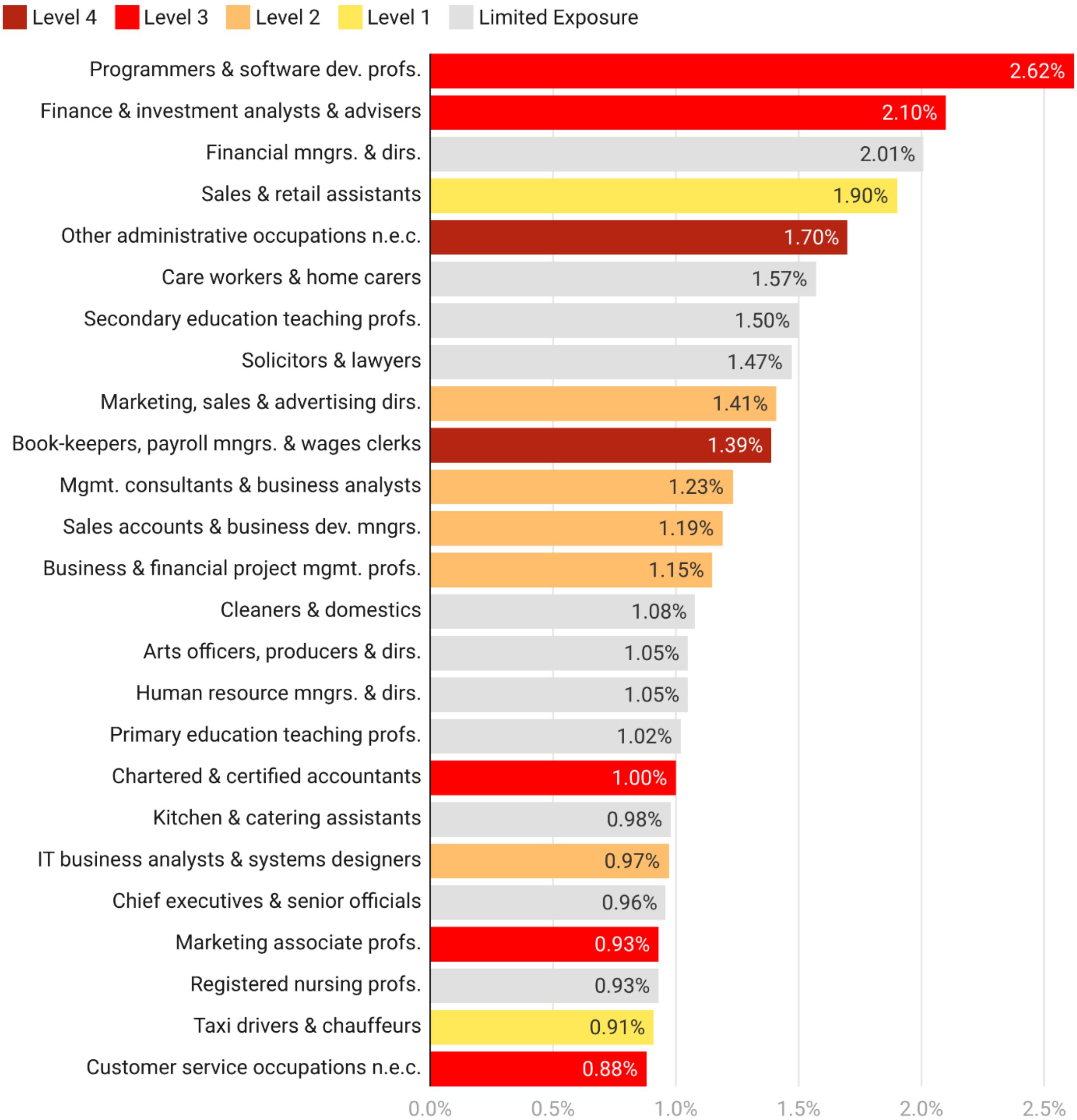


Chart: GLA Economics adaptation of ILO (2025) • Source: ONS Annual Population Survey - Pooled Annual (2022-2024) • Created with Datawrapper

3.3: Industry exposure

Based on its occupational mix, the analysis suggests that London's **information and communication (ICT) industry has the highest overall exposure to GenAI**. Around 77% of workers in the industry are exposed to some degree, with the largest shares concentrated in Levels 2 and 3 (37% and 32%

respectively). This reflects the prevalence of digital, information-processing and language-based tasks across many roles in the sector, including code generation, help-desk responses, documentation, testing and other forms of routine content generation or review. However, full automation is constrained by task bottlenecks around problem-solving, system oversight, integration and quality assurance, implying that the most likely effect is a combination of partial task automation and augmentation-led productivity gains.

Similarly, the **financial and insurance industry also has a very high degree of overall exposure to GenAI** (also 77%). However, a larger share of workers in the industry are concentrated in the highest exposure categories, with 35% and 11% in Levels 3 and 4 respectively. This reflects the close alignment between GenAI capabilities and many of the sector's core activities, including document drafting and review, risk and compliance checks, reporting, claims handling, data analysis and client communications. As a result, the industry appears particularly well placed to realise productivity gains from adoption, although in some functions this may also translate into role redesign, slower hiring or headcount pressure where tasks are easier to automate and demand does not expand sufficiently.[31]

Figure 3.4: Workers in London's industrial strengths are the most exposed to GenAI

Distribution of GenAI exposure levels across industries

London | 2022-2024 employment estimates | Selected SIC industries

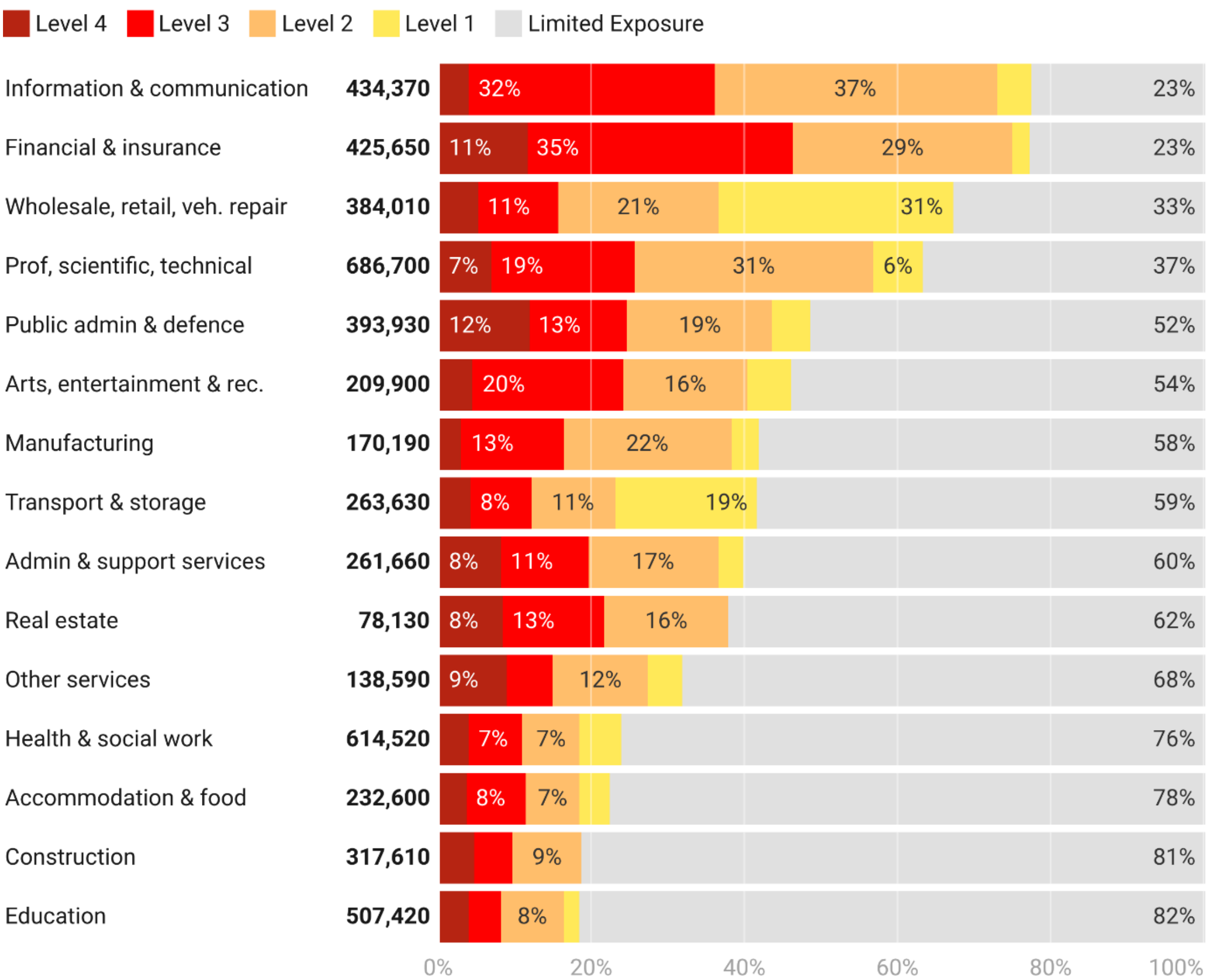


Chart: GLA Economics adaptation of ILO (2025) approach • Source: ONS - Annual Population Survey - Pooled Annual (2022-2024)

[31] Wall Street hunts next casualty from AI threat to white-collar work (Financial Times, 2026)

At the other end of the spectrum, industries including **education, construction, hospitality and healthcare display relatively low-levels of exposure to GenAI, albeit not negligible**.[32] Consistent with the earlier occupational analysis, these industries are primarily employing roles focused on physical, in-person and highly context-dependent activities which GenAI is less directly applicable to.

Within each of these lesser exposed industries however, there are **back-office administration and customer-contact** functions which are highly exposed to AI. As illustrated by Figure 3.4, approximately 4-5% of workers in each of these sectors have a Level 4 degree of exposure and an even greater share in Level 3. In terms of scale, healthcare and education combined account for almost 43,000 workers – or 14% – in Level 4 exposed roles. As such, even these generally less exposed sectors are unlikely to be immune from the effects of GenAI. Additionally, while high-stakes accuracy, safeguarding and on-site variability mean adoption will stay somewhat cautious – and well below that of ICT and finance industries – AI exposure and its application may rise gradually in the future as system integration improves and use cases discovered.

Transport provides an important example of this distinction. Viewed through a GenAI lens, the sector appears less directly exposed because many core roles involve physical operation, real-time monitoring and on-site co-ordination rather than language-intensive desk-based tasks. However, this should not be read as low exposure to technological developments more broadly. ONS estimates published in 2019 using a broader pre-GenAI automation framework suggested that several transport occupations already faced relatively high automation probabilities over the longer term.[33] More recent research has identified automated driving, fleet management and safety monitoring as areas where advances in computer vision, sensor fusion and robotics could reshape tasks over time, potentially accelerated by GenAI capability.[34] However, automation in the sector in the UK remains largely confined to trials and controlled environments, so this is better understood as a medium-term source of change than an immediate one.

Box 3.2: Applications of GenAI in sectors of limited exposure: health and education

While healthcare and education are not typically considered sectors with a high concentration of GenAI exposed roles, early applications are emerging within them that are focused on supporting frontline professionals and improving administration efficiency.

In healthcare, the NHS is piloting AI-assisted diagnostic tools, administrative automation and predictive systems to help identify patients at risk of deterioration or repeat admissions, with the aim of freeing clinicians' time for direct care.[35,36]

In education, UK schools and colleges are beginning to use AI tools to support lesson planning, resource creation and marking, and to offer more personalised learning support, within clear data governance frameworks. International evidence suggests these tools can augment teaching while preserving teachers' agency and can help less experienced tutors improve the quality of support and student outcomes.[37]

These examples illustrate how GenAI could being integrated as a productivity-enhancing and decision-support tool in public services, while maintaining professional oversight and accountability.

[32] Some SIC industries have been omitted from this analysis on account of small sample sizes, including agriculture and utilities. UK level analysis suggests these too have very low exposure to the capabilities of GenAI.
[33] Which occupations are at highest risk of being automated? - Office for National Statistics (2019)
[34] AI in mobility: Progress in Implementing the European Union Coordinated Plan on Artificial Intelligence (Volume 2) | OECD
[35] Artificial Intelligence - NHS Transformation Directorate (2025)
[36] Generative AI in Healthcare as a Driver of Economic Growth in the UK (Healthcare, 2025)
[37] OECD Digital Education Outlook (2026)

3.4: Regional and sub-regional exposure

While the primary focus of this analysis is London, it is useful to also set the findings in a national context (Figure 3.5). Reflecting its concentration of professional, technology and business service activity, **London is the UK's most highly exposed region to GenAI**, with 46% of workers meaningfully exposed, compared with 38% nationally. The exposure is particularly acute among those mainly professional occupations in Levels 2 and 3, accounting for 20% and 21% respectively of all workers in those roles nationally (see Appendix 4).

Outside London, the next most exposed regions are those closest to it – the South East and East of England – which also have relatively large professional and technology clusters and higher shares of graduates. These, and proximity to London, are likely factors in pushing their occupational exposure above the national average.

Figure 3.5: London has the highest exposure of any UK region, reflecting its industry mix
Distribution of GenAI exposure levels across UK regions
London | GenAI exposure | 2022-2024 employment estimates | ITL1 regions

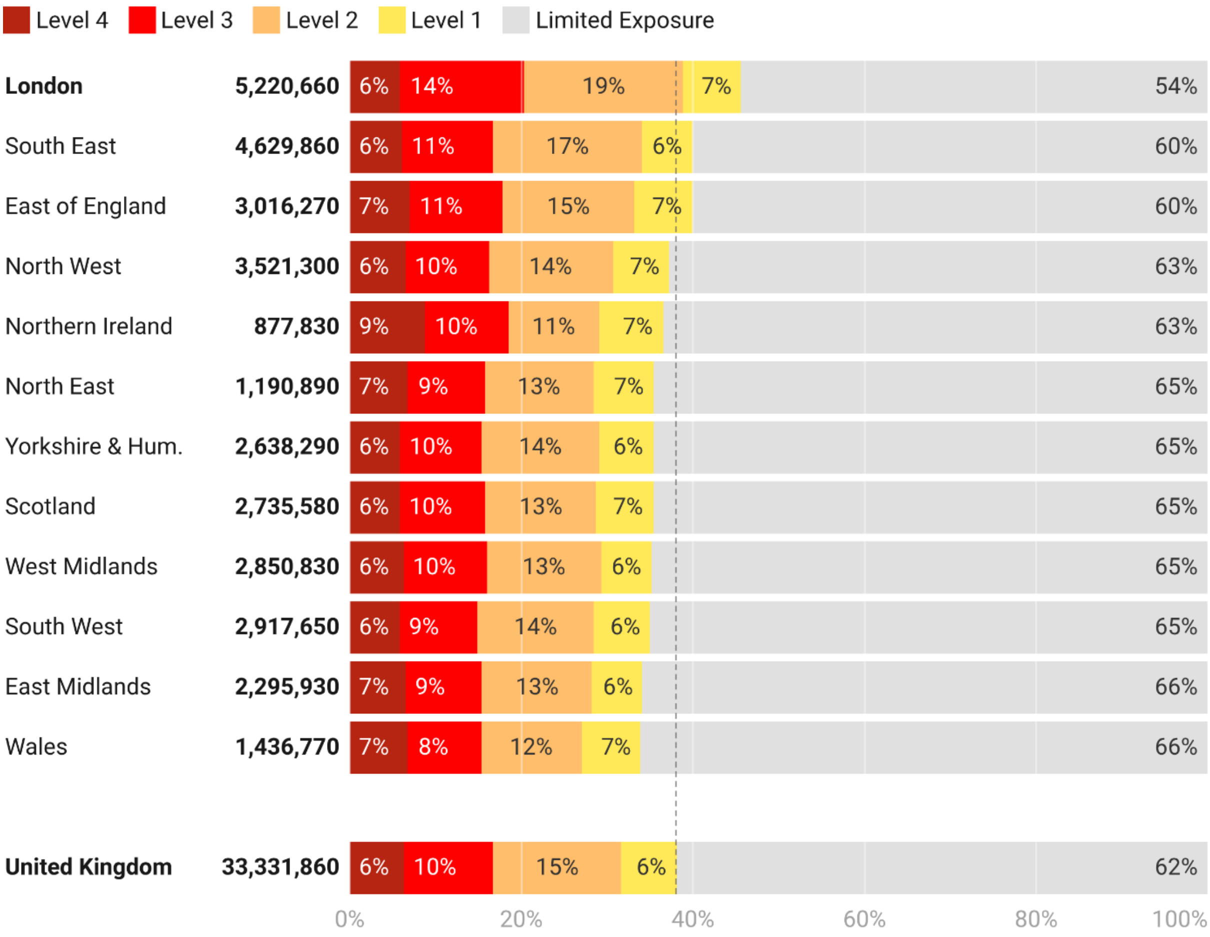


Chart: GLA Economics adaption of ILO (2025) approach • Source: ONS Annual Population Survey - Pooled Annual (2022-2024) • Created with Datawrapper

Exposure within London is also uneven. Local authorities in or close to the capital's central activities zone account for the majority of exposed workers, consistent with the concentration of white-collar professional jobs, although exposure rates are broadly similar across London's other sub-regions.[38]

Figure 3.6: London's central business district accounts for by far the most exposed roles

Distribution of GenAI exposure levels across London's sub-regions
London | 2022-2024 employment estimates | Sub-regional partnership (SRP) regions

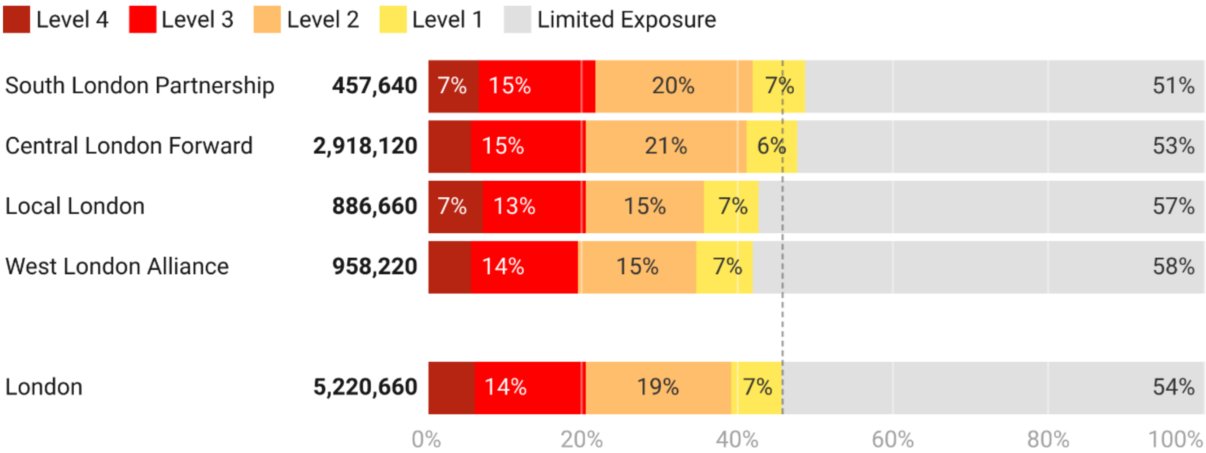


Chart: GLA Economics adaption of ILO (2025) approach • Source: ONS Annual Population Survey - Pooled Annual (2022-2024) • Created with Datawrapper

3.5: Exposure by highest level of educational attainment

An individual's education strongly shapes their occupation and, in turn, their exposure to GenAI. In London, 62% of workers hold degree-level qualifications (Level 6+), and many work in knowledge-intensive roles where tasks involve writing, analysis, coding or documentation. Because these activities align with current GenAI capabilities, **degree-holders are more likely to be in exposed occupations** (51%), leaving them well placed for potential productivity gains but also more likely to experience job redesign.

Among graduates, exposure is concentrated in Levels 2 and 3 (23% and 17%), where task exposure varies within roles and impacts are more likely to involve augmentation than uniform displacement. A smaller share (5%) of degree-holders are in Level 4 roles, where exposure is consistently high. Given uncertainty – especially for highly exposed roles – both the largest productivity gains and the sharpest disruption could be felt among highly-educated workers.

High exposure is not confined to graduates. The highest shares of Level 4 exposure are among those with lower educational attainment, A-levels and GCSEs (9% and 8%), reflecting the task profile of many administrative and some associate-professional roles. By contrast, workers with other or no qualifications are more often in low-exposure occupations (69%), which typically involve physical, in-person or context-dependent tasks, and therefore less likely to require higher levels of formal education.

[38] London's 33 local authorities are each part of one-of-four sub-regional partnerships (SRPs). These SRPs serve a vital administrative function within local government by convening key stakeholders to collaboratively address London's strategic economic and social issues, including skills, employment, infrastructure, healthcare and land use.

Figure 3.7: London's most highly educated are among those at the sharpest edge of change
Distribution of GenAI exposure across worker educational attainment levels
London | 2022-2024 employment estimates

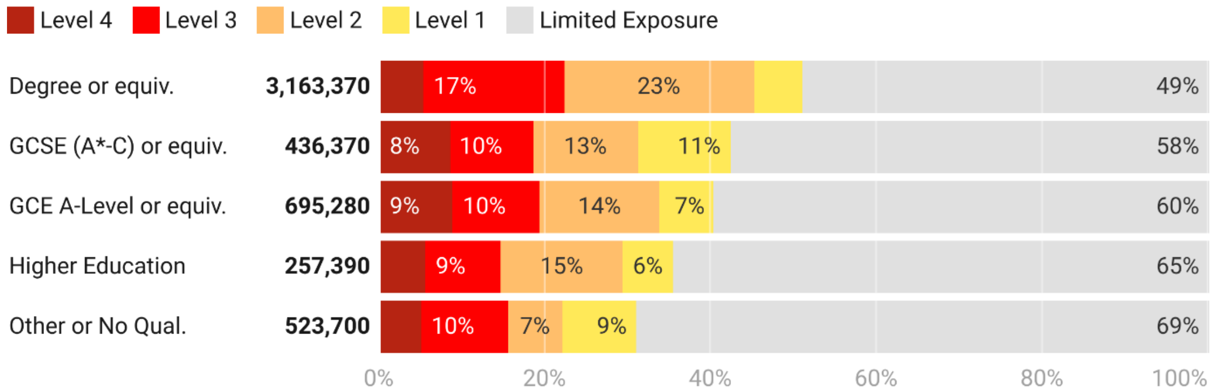


Chart: GLA Economics adaptation of ILO (2025) approach • Source: ONS Annual Population Survey - Pooled Annual (2022-2024) • Created with Datawrapper

3.6: Exposure by personal characteristics

Figure 3.8 explores how GenAI exposure varies across workers' personal characteristics, highlighting the groups, based on their occupation of employment, that are most vulnerable to GenAI, as well as those that are most likely to reap the benefits of its adoption.

Age

Younger Londoners are more likely to work in GenAI-exposed occupations. In London, around 52% of workers aged 16–29 are in occupations with substantial exposure to GenAI, compared with 47% of those aged 30–49 and 39% of those aged 50+. Around a quarter of 16–29 year-olds fall within the two highest exposure levels.

These differences largely reflect education differences and occupational sorting. As higher-education participation has expanded over time, younger cohorts have been more likely to enter knowledge-intensive and digitally oriented professional roles – such as in ICT, finance and professional business services – where day-to-day tasks align more closely with GenAI's capabilities. Many younger workers also enter their professional careers through highly exposed administrative and support occupations. These traditional entry point roles act as 'gateway' or 'stepping-stone' occupations into higher-paid professional careers by helping people build experience, workplace knowledge and important transferable skills.

Furthermore, exposure is not uniform within occupations, with GenAI typically being best-suited to routine, codifiable tasks that are more common in **junior and entry-level work**. This may make the labour market impacts on younger workers more acute, even when the occupation as a whole is not fully automatable.[39] However, younger workers may also be better placed to adapt, as those earlier in their careers tend to be more occupationally mobile, more amenable to developing new skillsets and less

[39] While evidence of material impact of AI on younger workers is limited to date and confined largely to anecdotal accounts, the potential of serious disruption to young workers represents a significant long-term risk. International evidence strongly indicates that disruptions during a person's early career – specifically involuntary job loss or prolonged unemployment upon entering the labour market – can result in significant 'scarring' effects. These effects often lead to poorer, long-lasting negative employment, social and health outcomes, including lower wages and increased risk of future unemployment. The persistent effects of initial labour market conditions for young adults and their sources (von Wachter, 2020) and The career effects of labour market conditions at entry (OECD, 2020)

locked into established specialisms. In parallel, younger workers also tend to be digital natives and therefore are generally quicker to adopt new technological tools. There are examples where AI's capability has been shown to generate strong productivity gains for less experienced or lower performing workers where AI is used to complement day-to-day work. [40]

By contrast, older workers (aged 50+) are more likely to be in roles where core tasks are physical, in-person or context-dependent – such as care or skilled trades – which lowers their average exposure. However, a meaningful minority of older workers remain in highly exposed occupations. For these workers, adjustment may be more challenging if participation in ongoing training is lower or confidence with new digital tools is more uneven. Conversely, however, experienced workers may be best positioned to critically interpret and effectively apply AI-generated insights where adopted.[20]

Sex

While both sexes in London have similar overall levels of exposure, **women are more likely to work in highly AI-exposed roles compared to men**. Around 8% of women working in London are in roles most exposed to GenAI automation (Level 4) compared to 4% of men. Indeed, women account for almost 60% of jobs in these most exposed roles, compared to 45% across the whole workforce (see Appendix 4). Women's greater labour market exposure to GenAI stems from the fact that women are generally more likely to be in careers in administrative and customer service occupations, where GenAI is highly capable.[41]

Compared to the national gender split, the largest difference is related to male exposure to GenAI, where 64% have limited exposure to AI in the UK compared to 54% in London. This difference reflects London's sectoral mix which is much more focused on professional activities, than construction or agriculture, which are traditionally male dominated fields that are less impacted by GenAI.

Ethnicity

Workers of Asian ethnicity are more concentrated in GenAI-exposed roles (53%), including a higher share in the top exposure bands (around 7% in Level 4 and 20% in Level 3). White workers, the largest ethnic group, also face relatively high exposure (47%). By contrast, overall exposure among Black workers is lower (34%). These differences are likely linked to longer-standing patterns of occupational sorting and unequal access to opportunity, including differences in education and pathways into higher-paid professional work. UK evidence also suggests that some Asian groups are more strongly represented in professional, digital and IT-related occupations, which helps explain their higher average exposure, since these roles often involve language-, data- and analysis-intensive tasks that align more closely with current GenAI capabilities.[42]

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[40] The effects of generative AI on productivity, innovation and entrepreneurship (OECD, 2025)
[41] Occupation by sex (ONS, 2022)
[42] Work, pay and benefits - Ethnicity facts and figures (ONS, 2022)

Figure 3.8: Younger, female and Asian workers are more likely to be employed in highly exposed roles, reflecting existing occupational sorting patterns

Distribution of GenAI exposure levels across worker's individual characteristics
London | 2022-2024 employment estimates

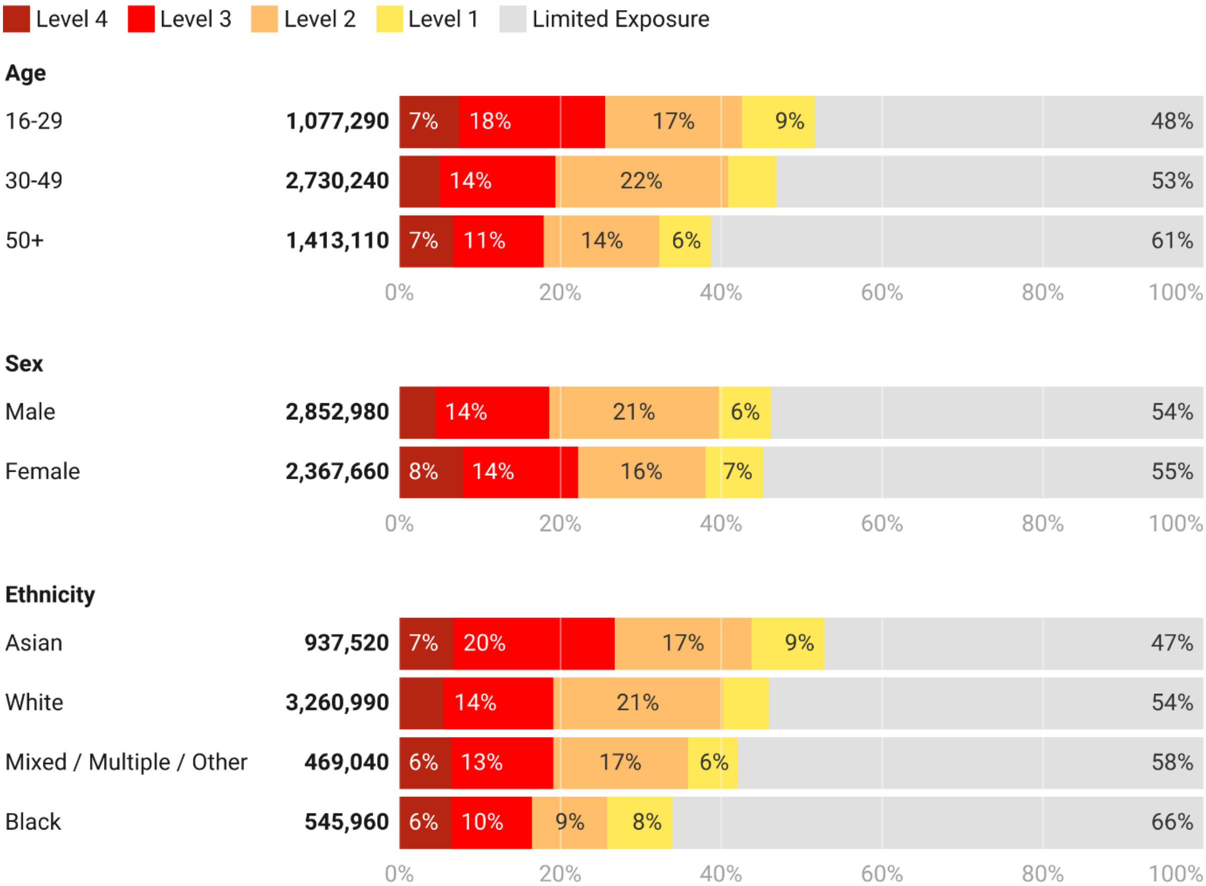


Chart: GLA Economics adaptation of ILO (2025) approach • Source: ONS Annual Population Survey - Pooled Annual (2022-2024) • Created with Datawrapper

3.7: Exposure by median earnings percentile

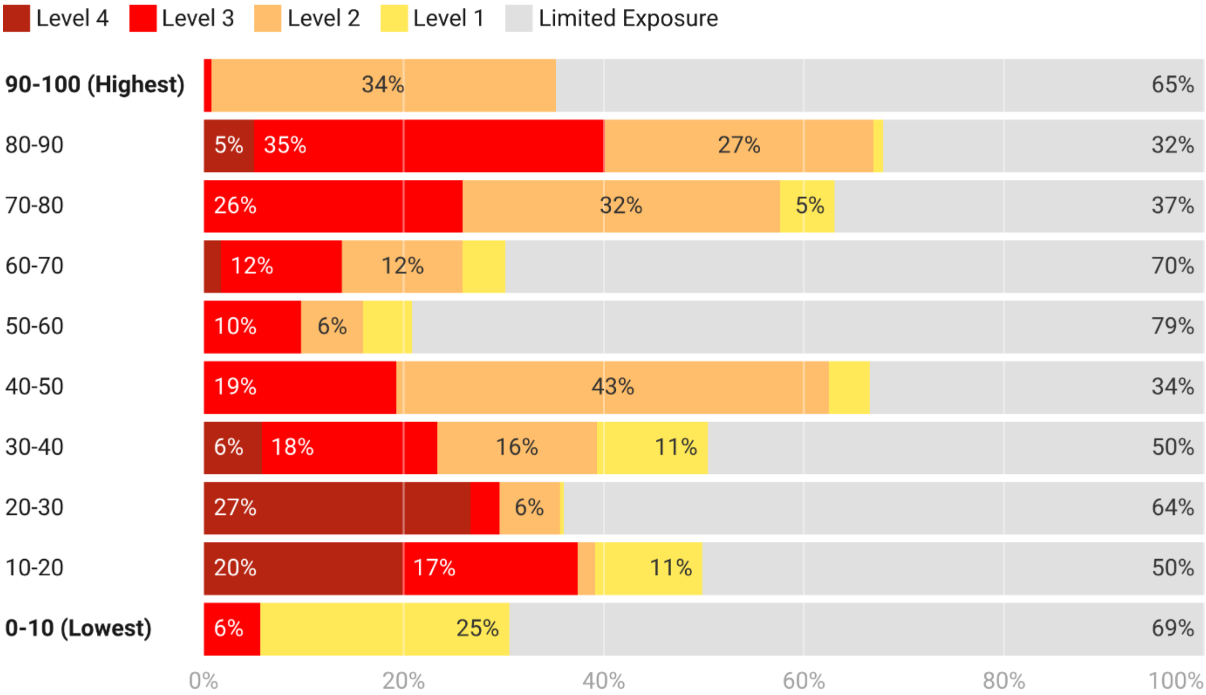
London's lowest and highest earners face the greatest exposure to GenAI disruption, albeit with potentially different outcomes. Many higher earners (around the 70th–90th percentiles) work in professional roles within exposure Levels 2–3, where GenAI is more likely to change how work is done rather than to replace roles outright (although employers could still seek to limit headcount growth in some higher-paid functions depending on impacts over time). This complementary use of AI can raise productivity and reinforce wage advantages if gains accrue mainly to already high-paid work.[43] Moreover, degree-educated workers in higher-paid professional roles are often more likely to possess transferable, in-demand skills, as well as the resources to pivot more easily into alternative career pathways if adversely affected.[44] In contrast, lower skill administrative roles which have the highest risk of AI automation (Level 4) are generally at the lower end of the income distribution (10th-30th percentiles) and may struggle more to transition. If AI adoption leads to lower demand for these jobs, disruption may risk increasing wage inequality.

[43] AI Adoption and Inequality | IMF (Rockall et al, 2024)
[44] Measuring US workers' capacity to adapt to AI-driven job displacement | Brookings (2026)

In addition to potential *across* occupation wage changes, the international evidence also suggests that AI may narrow wage gaps *within* occupations if it helps lower-performing workers catch up.[45] Outcomes will therefore also depend on how widely AI skills and access spread. Where uptake and training are uneven, an 'AI divide' can emerge that concentrates benefits among those best placed to use the tools, or quickest to adopt them. Overall, the direction of wage effects is uncertain, but the distribution of exposure in London makes unequal outcomes a credible risk.

Figure 3.9: GenAI impacts could be felt most acutely by the highest and lowest earners

Distribution of GenAI exposure levels across median earning deciles
London | 2022-2024 employment estimates | 2025 median earnings percentile (UK)



The earnings data used to produce this figure is taken from an ad-hoc UK ASHE release and includes figures which would usually be suppressed on quality grounds where the CVs are greater than 20%, and are therefore considered unreliable for practical purposes. ~10% of occupations have unreliable median earnings data and the figure should therefore be interpreted cautiously.

Chart: GLA Economics adaptation of ILO (2025) approach • Source: ONS Annual Population Survey - Pooled Annual (2022-2024) and ONS Annual Survey of Hours and Earnings (2025) • Created with Datawrapper

Box 3.3: How do the ILO occupational AI exposure results align with other approaches?[46]

ILO derived exposure results broadly align with the findings from alternative approaches. That being, that the most GenAI exposed roles are typically language- and information-heavy (professional, associate professional, admin, ICT), best aligned to GenAI's capabilities.

However, available exposure indices can vary considerably in some areas depending on the specific method used. The ILO's task-based exposure scores, tend to be somewhat more conservative (lower) than capability-proximity measures – such as those constructed by Felten et al. (2021; 2023) – because it leans on workplace judgements about what tasks current GenAI tools could technically automate in practice. Non-automatable bottlenecks, oversight, and high-stake risks keep humans in the loop, even where technical potential for automation is possible. It also down-weights automation potential when an occupation's tasks have varying levels of exposure (some automatable, but many not) and aggregates

[45] Artificial intelligence and wage inequality (OECD, 2024)
[46] See Appendix 2 for further discussion of alternative AI exposure estimation approaches.

tasks equally within occupations, so a few relatively easy-to-automate subtasks do not determine the entire roles exposure.

A key caution around exposure measures as a whole is that they do not equate to realised labour-market impact. More recent literature highlights that while exposure analysis remains important, a broader empirical layer has emerged around it. The literature now contains more vacancy studies, administrative and linked worker-workplace evidence, direct firm and employer evidence, and platform-based evidence. This means the debate is slowly moving from abstract exposure towards observed adjustment in hiring, task composition, progression and workplace change.

For example, vacancy data can provide useful insights as it fits between abstract exposure estimates and realised employment outcomes. They can show changing employer demand, new combinations of skills, shifts in hiring intensity, and changes in the wording and content of jobs before those changes show up clearly in employment stocks.[47] While vacancies can detect directional change, they are still incomplete as the data does not cover current incumbents, internal redeployment, promotion chains, and work changes that occur without external recruitment.

[47] Patterns of co-occurrent skills in UK job adverts (Liu et al., 2025)

Chapter 4: Emerging evidence of AI's adoption and impact on the labour market

This chapter examines the emerging, descriptive evidence on how GenAI's technical capabilities are beginning to translate into real-world changes in the labour market. Building on the framework set out in Chapter 1, it considers the different channels through which AI may affect labour demand and assesses how the occupational exposure analysis in the previous chapter aligns with observed patterns of adoption. While this analysis provides early signals on how AI is potentially transforming London's labour market, it should be noted that these are preliminary conclusions that would require additional data and information to provide a comprehensive and more definitive picture of GenAI's labour-market impacts.

The following analytical overview draws on a range of sources, including the *ONS' UK Business Insights and Conditions Survey (BICS),* and timely *job postings data from Lightcast* for **firm behaviour** (both March 2026), as well as *Ipsos polling (commissioned with the Tony Blair Institute)* for **individual usage and attitudes** (June 2025).[48,49] Together, these complementary sources suggest some key adoption trends and challenges emerging for the workforce as a result of AI.

Box 4.1: Accurately measuring AI adoption and its impacts is challenging (caveats)

Who is responding and what is counted matters. In survey evidence, reported use can vary by respondent in an organisation (HR, CTO, corporate admin, specialists) and question design, so figures may mix pilots with production and 'any use' with sustained work-critical practice.[50]

Shadow AI use vs official rollouts. There is often a gap between corporate rollouts and day-to-day practice. Employees may use public AI tools where formal implementations stall (shadow use), creating a mismatch between what companies report and actual usage. Concerns about confidentiality, compliance and managerial acceptance can also suppress disclosure, leading to under-reporting. [51]

Presence vs. intensity/purpose. Most firm surveys record whether AI is present, not how many workers use it, how frequently, or on which tasks – dimensions that matter for productivity, hiring and skills demand. Usage can also vary widely across functions within the same organisation.

Shifting definitions and embedded features. What counts as "AI/GenAI" varies across surveys and over time, and AI features embedded in common software can be overlooked or counted generically, hindering comparability.

Difficult to disentangle AI specific effects. Mainstream GenAI technologies emerged during a period of unique labour market turbulence post the COVID-19 pandemic and so accurately isolating its specific effects on employment or employer recruitment activity is challenging.

These limitations do not invalidate the analysis but do suggest caution. They should be treated as indicative of direction and broad magnitude, not precise measures of work-critical impact. They may also explain differences arising between exposure results and reported adoption.

[48] Business insights and impact on the UK economy | BICS Wave 153 | ONS (April 2026)
[49] What the UK Thinks About AI | IPSOS/TBI Wave3 data (July 2025)
[50] Across both surveys, relatively high numbers of respondents report being *'unsure'* about their use of GenAI, or how they anticipate it has caused (or will cause) an impact to their business, or them personally. As a new and rapidly developing technology, GenAI's medium-term capability and effects remain uncertain, and high survey uncertainty rates across questions should be read as consistent with early-stage diffusion.
[51] Roughly 30% of UK adults do not discuss their use of AI with their colleagues, regardless of their role or level (2025). Ipsos AI polling September 2025

4.1: Who is using GenAI, and how?

While still relatively modest, AI adoption is rising steadily among firms, with the core intention being to improve productivity through more efficient business processes. Differences in compatibility however, mean prevalence is unevenly spread across both firms and industries. As shown in Figure 4.1, the share of UK businesses reporting that they use AI (or are unsure of usage) rose from 9%-16% in late 2023 to 26-35% by March 2026.[52,53,54] Consistent with other research, adoption also tends to be higher among the largest firms (45%-67%) compared to smaller businesses (25%-40%).[55] By industry, ICT, professional services, education, and creative industries are consistently among the highest adopters, while construction, hospitality and transport are typically lowest, consistent with the technology's compatibility with industry activities. This also aligns with the exposure analyses in Chapter 3 and reported use internationally.[56] The most common applications of AI reported were in text generation with LLMs, visual content creation, and data processing, with the primary purpose of implementation being to improve business operations (51%), followed by providing personalised products and services (27%).[57]

Job postings evidence aligns with rising adoption trends, with employer demand for AI expertise also growing rapidly. By end of March 2026, 7% of London's online job postings were explicitly seeking AI-related skills from prospective candidates (Figure 4.4).[58,59] Employer demand for this expertise has grown exponentially since 2024, having more than tripled since the beginning of that year. This growth reflects the increasing adoption of AI by businesses as they gradually devise strategic implementation approaches and industry specific use cases of the technology. Consistent with the occupational exposure analysis, London leads the way in terms of AI skill needs, with demand for AI skills far exceeding that of all other UK regions which is close to 2%. London's particularly high demand reflects its professional services oriented industrial make-up and status as a major international centre for AI and technological innovation.

Individual-level evidence reveals younger, 'white collar' workers are the largest active users of GenAI, with Londoners leading applied use in the workplace. More than half of UK adults (56%) surveyed in June 2025 reported using a GenAI tool in the past 12 months, and around 23% of workers say they use GenAI weekly at work. London stands out, with about 29% reporting weekly workplace use – the highest of any UK region, reflecting its regional sectoral mix.[60] Similar to firms, reported usage of AI in work is highest among workers in ICT, finance, and professional services. AI usage in the workplace is also highly correlated with age, with younger cohorts – the most digitally literate – the largest adopters. The evidence suggests that AI tools are lifting productivity most for inexperienced workers (or lower performers), particularly in language- and data-intensive roles, thereby narrowing productivity gaps within teams.[61]

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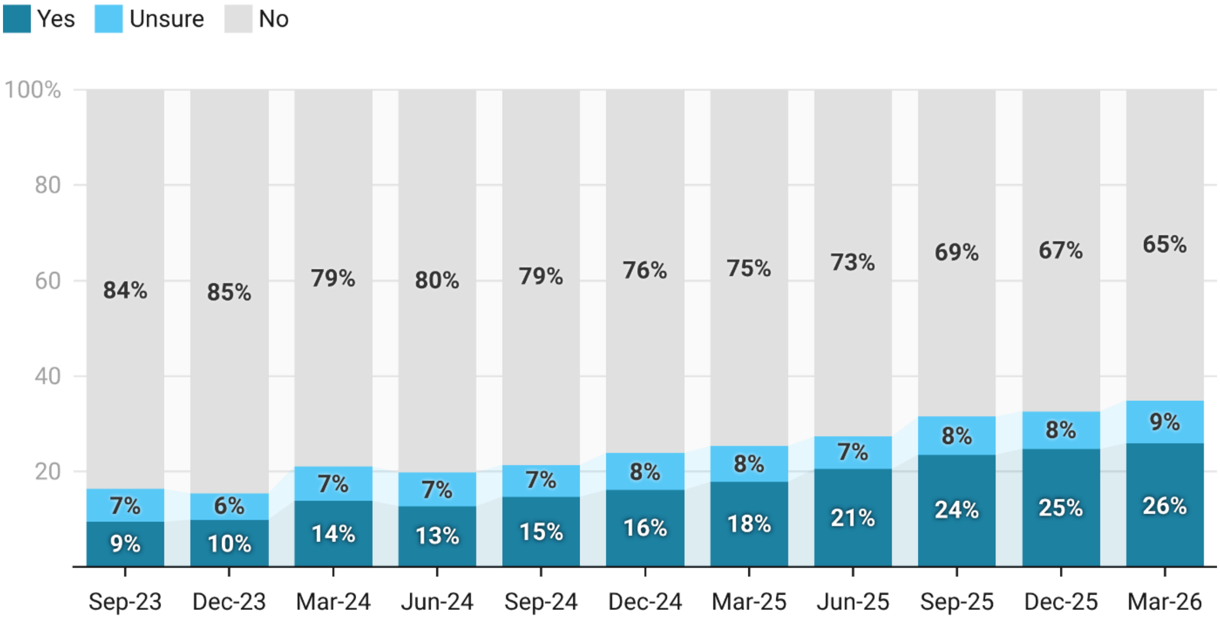
[52] The ONS BICS does not provide weighted firm estimates at regional levels, but given its concentration in ICT and professional services, London is expected to have a higher overall rate of AI adoption among firms.
[53] Broadly similar and complementary findings to the quarterly ONS BICS evidence related to AI adoption are shown in a larger study of UK firms between Feb-May 2025 (AI Adoption Research – DSIT, 2026). However, there can be significant variation in estimated usage rates from study to study (Yotzov et al., 2026).
[54] Data on overall firm AI adoption is imputed from a question on specific usage of different AI technologies. Firms can select multiple technology options, including whether or not they are 'unsure'. This response is interpreted by the authors as being unsure of overall AI usage. In Figures 4.1 and 4.2, the dark blue segments represent a lower bound of usage while the inclusion of the light blue 'unsure' responses is an upper bound.
[55] The State of AI: Global survey | McKinsey (2025)
[56] The State of Generative AI Adoption in 2025 | St. Louis FED (Bick et al., 2025)
[57] Separate UK company survey data reveals broadly consistent adoption trends (DSIT, 2026).
[58] While no formal definition exists of AI related skills, this analysis builds on Lightcast's Global AI skills taxonomy.
[59] According to Lightcast, the top specific AI skills sought by employers in London in Oct-Dec 2025 included 'Artificial Intelligence (general)', 'machine learning', 'Generative AI', 'AI infrastructure', 'Agentic AI', and 'Prompt Engineering'.
[60] A more recent YouGov survey conducted for the GLA between Oct-Nov 2025, found 64% of Londoners used GenAI technologies for work, with 39% saying they used it at least once a week and 10% saying they used it every day.
[61] The effects of generative AI on productivity, innovation and entrepreneurship (OECD, 2025)

Figure 4.1: AI adoption rates are rising steadily among UK firms

Share of businesses using AI technologies
UK businesses | Sep 2023 - Mar 2026 | All business sizes



'Yes' value imputed from question: "Which of the following AI technologies, if any, does your business currently use?"

Chart: GLA Economics • Source: ONS Business Insight and Conditions Survey • Created with Datawrapper

Figure 4.2: AI adoption rates by industry vary, but broadly aligns with exposure

Share of businesses using AI by industry
UK businesses | Mar 2026 | Selected industries

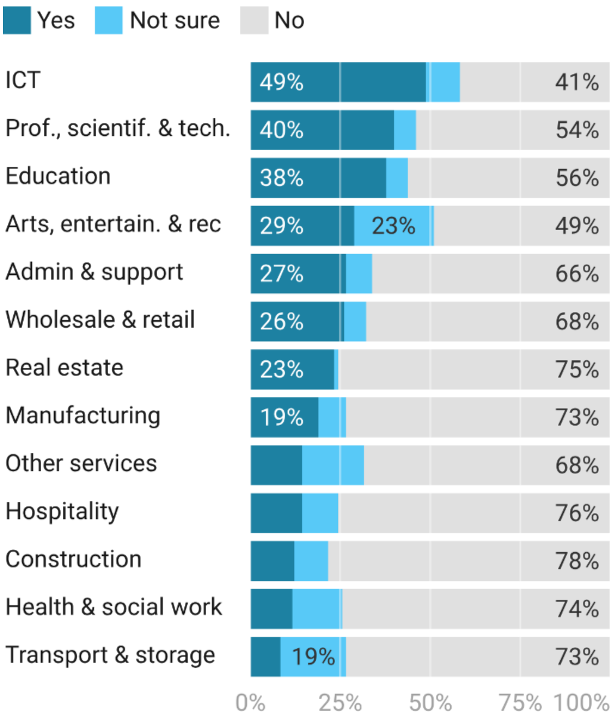


Chart: GLA Economics • Source: ONS Business Insight and Conditions Survey • Created with Datawrapper

Figure 4.3: GenAI tools record strongest growth in adoption among businesses

Share of businesses using AI by use
UK businesses | Sep 2023 - Mar 2026

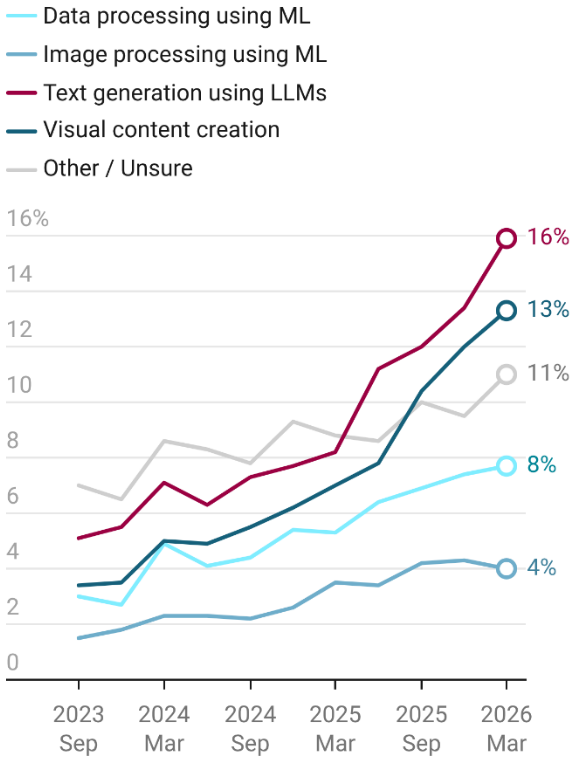


Figure 4.4: Employer demand for AI skills is growing exponentially, particularly in London
Share of online postings that explicitly contain AI expertise
Jan 2019 - Mar 2026 | 3-month moving average | Selected ITL1 regions

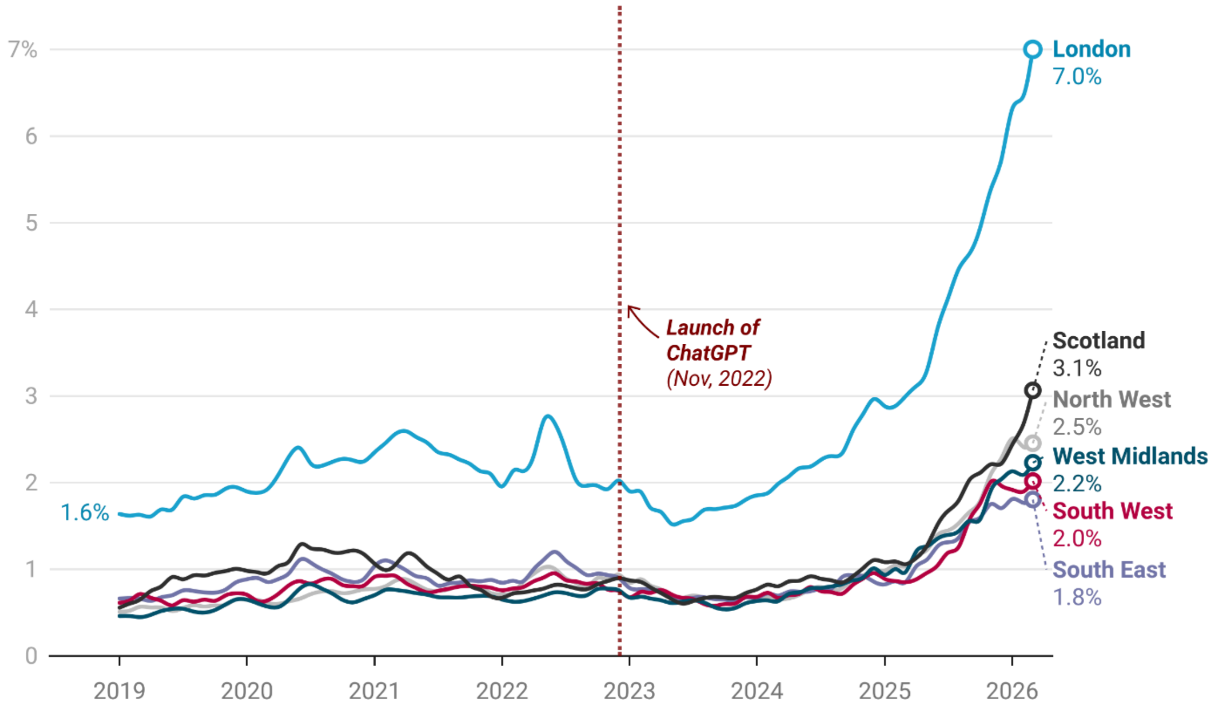


Chart: GLA Economics • Source: Lightcast UK job postings • Created with Datawrapper

4.2: Is GenAI adoption creating new jobs?

While AI adoption may cause short-term disruption and labour-market frictions, the longer-term picture is more nuanced. As set out in Chapter 1, AI has the potential to support employment growth by raising productivity, reshaping work and increasing demand for new skills and occupations, rather than simply displacing existing roles. **Where AI complements workers and boosts productivity, higher growth and labour demand could outweigh the loss of some tasks over time, while also helping to create new roles and sectors.** In the UK, recent modelling suggests that jobs directly involving AI activities will rise dramatically by 2035, though much of this increase is expected to come from existing roles taking on AI-related tasks. [62] Even so, net job growth is still projected through to 2035, especially in professional and associate professional occupations, many of which are highly exposed. [63] Given its concentration in activities related to these roles, London appears well placed to benefit, provided workers can access the skills needed to move into expanding roles.

Consistent with the historical precedent, evidence from job postings shows that employers are increasingly seeking to recruit new AI specialist roles. Online job advert data shows increased demand for previously niche roles, such as *AI engineers, AI strategy directors,* and *AI forward-deployed engineering specialists* (Figure 4.5).[64] Recruitment activity for these roles and associated skill sets has grown rapidly since 2024, reflecting the recent acceleration in AI capability and adoption. Demand for

[62] AI Skills for Life and Work: Labour market and skills projections – (DSIT, 2026)
[63] Skills Imperative 2035 Final Report – (NFER, 2025)
[64] The new hot job in AI: forward-deployed engineers (Financial Times): AI forward deployed engineers (FDEs) are AI specialists installed within a business to help them customise and integrate AI models to meet specific use cases.

specialist AI roles – and related occupations – is also expected to remain strong as firms integrate AI more deeply into business processes.[65]

Figure 4.5: AI is creating demand for new, specialist roles

Monthly online job postings for AI engineers

London | Jan 2019 - Mar 2026 | 3-month moving average

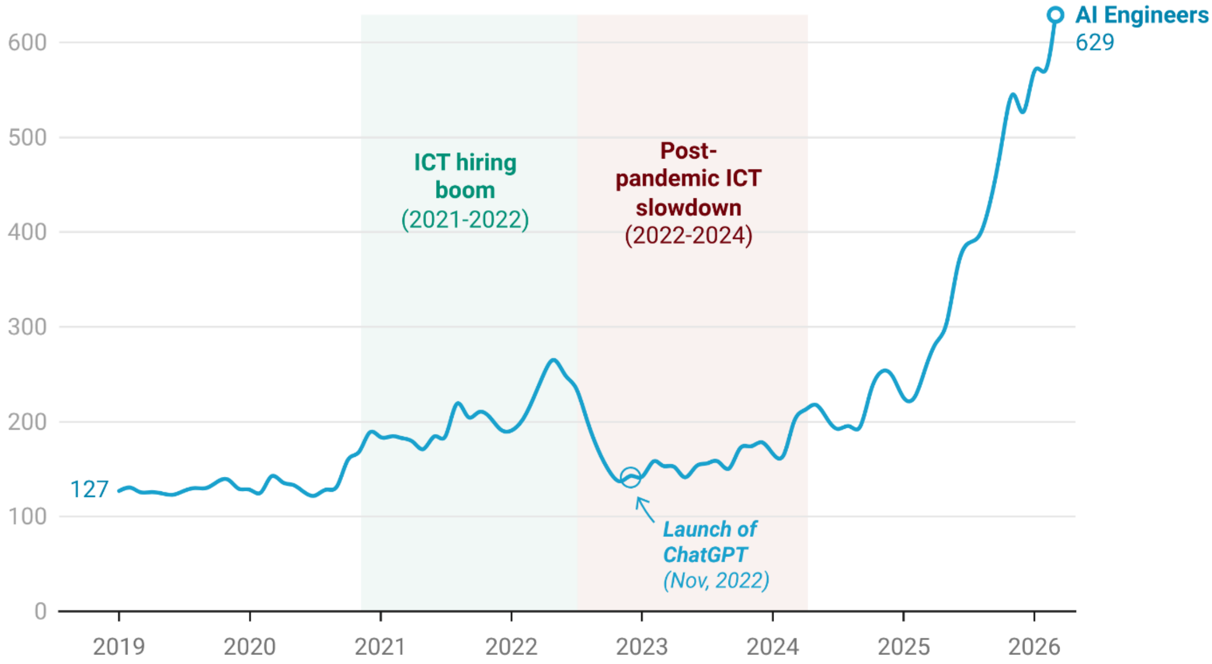


Chart: GLA Economics • Source: Lightcast UK job postings (Lightcast Occupational Taxonomy) • Created with Datawrapper

Survey results provide further supporting evidence with 4% of UK businesses that use AI reporting that they are actively recruiting new staff with artificial intelligence related skills/roles as part of their AI integration strategy (rising above 10% in the largest companies).[66] Shortages of these specialist AI related skills in the labour market is also cited among employers as a major brake to adoption.

The rapid rise in demand for and adoption of AI technologies across the economy has also driven strong growth of the UK's wider AI sector and consequently its overall levels of employment, much of which is located in London (see Box 4.2).

Box 4.2: Growing AI industry in the UK generating new employment opportunities[67]

According to analysis from the UK Department for Science Innovation and Technology (DSIT), the UK's AI ecosystem is growing rapidly. As of 2024, it employed over 86,000 people (+33% from 2022) and includes more than 5,800 'dedicated and diversified' AI companies (+53% from 2022) – more than half which are registered in London (52%), reflecting its international strength as a global AI hub. In 2024, these AI companies are estimated to have generated almost £24bn in revenue, up over £13bn (+125% from 2022). This rapid expansion highlights how AI is creating new jobs both inside specialist firms and across the wider economy. These are not only in technical roles like specialist AI data scientists and ML engineers, but also roles in AI assurance and governance, as well as in product and commercial that help organisations adopt and manage these tools effectively.

[65] AI Skills for Life and Work: Labour market and skills projections (DSIT and Institute of Employment Research, 2026)
[66] Business insights and impact on the UK economy | BICS Wave 153 | ONS (April 2026)
[67] Artificial Intelligence sector study 2024 - GOV.UK – Employment breakdown: 36% (30,670) of employment is estimated to be within 'dedicated' AI companies – where all activity is assumed to be AI related – and the remaining 64% (55,520) within 'diversified' AI companies.

4.3: Is GenAI adoption changing existing roles?

AI adoption is materially changing how work is being done among some occupational groups, consistent with the earlier exposure analysis. In March 2026, UK businesses reported that administrative, creative, data and IT roles had been the most impacted by the AI technologies they had adopted; all roles that generally have a high degree of exposure to GenAI capabilities (Figure 4.6). Similarly, at the individual level, evidence from Anthropic's *Economic Index*, which analyses worker use of its AI model – *Claude* – shows that a wide range of occupations are actively using AI tools to complete their work (particularly for computer and mathematical activities). Some common tasks appear to be being automated, others augmented – where the LLM becomes a collaborative partner – and others that appear unaffected.[68] Looking to the future, individual worker survey responses from those in professional, admin and managerial roles show that 12% of them expect substantial change in their main work activities as a result of AI within 12 months, rising to 28% in five years' time. Higher rates of change were anticipated by those who used the technology most often in their work.[69] While these findings do not imply job displacement, it does at least suggest significant change or disruption is afoot and white-collar workers will need to adapt to this new reality.

Figure 4.6: AI is impacting admin, digital and creative roles most - consistent with exposure

Roles most impacted by AI technology adoption, as reported by industry firms
UK businesses | March 2026 | Selected SIC industries

high low

Sector	Admin roles	Creative, design roles	Data analysis roles	IT roles	Manager roles	Sales & customer service roles	Skilled, manual roles
Manufacturing	17%	20%	8%	10%	8%	5%	2%
Construction	19%	13%	6%		5%	4%	
Wholesale & retail	28%	46%	17%	14%	16%	17%	3%
ICT	23%	32%	29%	40%	13%	11%	3%
Prof. & scientific	31%	33%	39%	14%	15%	10%	3%
Admin & support	19%	23%	22%	12%	9%	3%	1%
Education*	33%	25%	17%		8%	16%	
Arts, ent. & rec	25%	28%	1%		7%	12%	
Transport & stor.	11%	11%	16%		10%	6%	
All businesses	**26%**	**29%**	**22%**	**15%**	**12%**	**9%**	**2%**

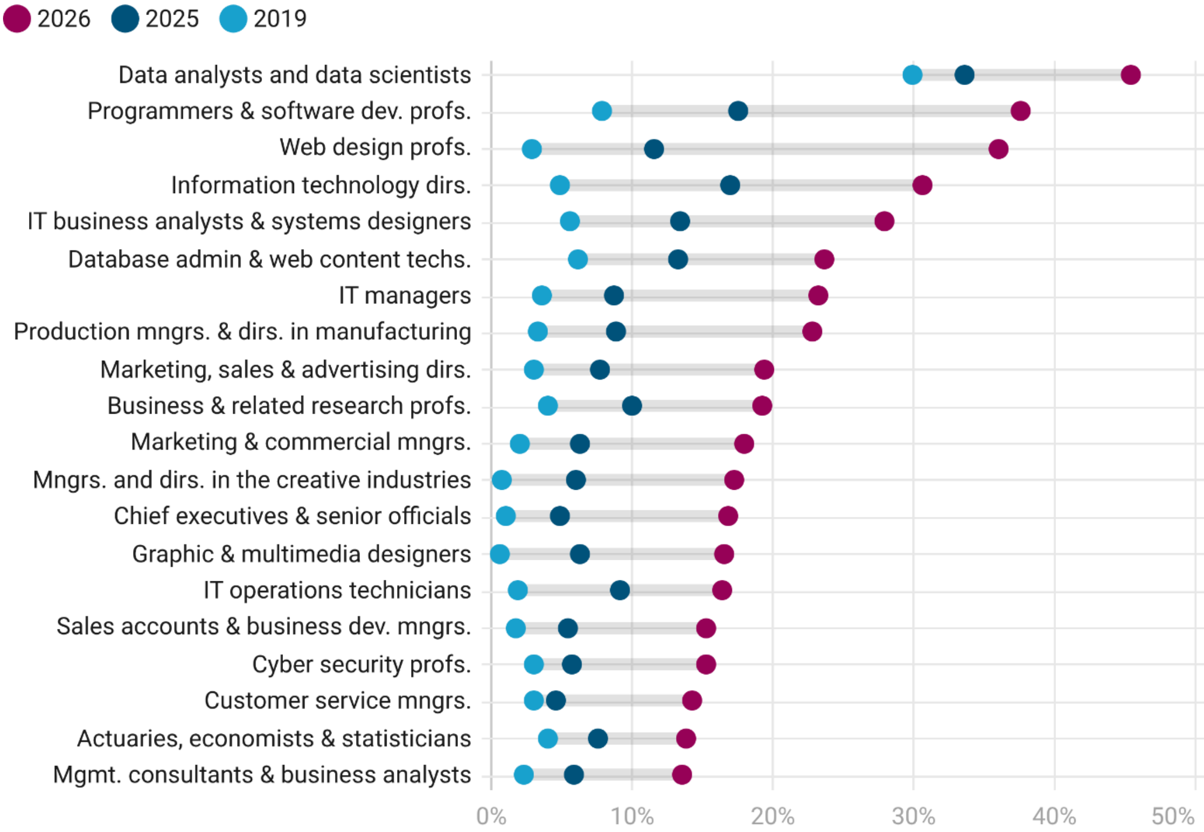
Note: Data is not available for all SIC industries or occupational groups ('' indicates use of data from the previous iteration of the BICS survey in Dec 2025).*
Note: 21% of businesses also reported 'other' or being unsure what roles were impacted. 22% also reported 'not applicable'.
Table: GLA Economics • Source: ONS Business Insight and Conditions Survey • Created with Datawrapper

Employers are actively looking to build an AI-enabled workforce and increasingly expect workers to have the necessary skills. In addition to hiring AI specialist roles, 28% of those UK businesses using AI reported training or retraining existing staff as part of their approach to integrating

[68] The Anthropic Economic Index (Anthropic, 2026)
[69] IPSOS polling found that 21% of those who used AI at least once a week for work expected it to substantially change their main work activities, rising to 39% when looking to five years ahead (July 2025).

the new technology into their workforce (over 40% in larger companies).[70] Similarly, evidence from job postings shows that recruiting employers are seeking AI-relevant skills from prospective candidates across a growing spectrum of roles. At present, demand for these skills is most heavily concentrated among digitally focused roles – such as data analysts and software developers (45% and 38% respectively) – given its ease of integration into their activities. However, its prevalence is also rapidly expanding within other professional and creative design roles, such as marketers and business development professionals, illustrative of the technologies growing general applicability (Figure 4.7). This focus on skills suggests that role augmentation and changing task-mixes within roles, rather than wholesale automation is currently the primary objective of many firms looking to boost their productivity.

Figure 4.7: AI skills are increasingly being sought across a growing spectrum of roles
Occupations with the highest share of postings explicitly requiring AI-related expertise
London | SOC 4-digit occupations | 3-month average (January-March)



Note: Includes occupations with 100 or more online job postings explicitly featuring AI expertise in 3-month period.
Chart: GLA Economics • Source: Lightcast job postings • Created with Datawrapper

4.4: Is GenAI adoption reducing demand for some jobs?

A small share of firms reported reducing overall headcount as a direct result of adopting AI.[71] Approximately 5% of all UK businesses using AI in March 2026 reported it had enabled them to cut overall headcount numbers, with larger businesses reporting higher shares (7%). While a further 17%

[70] Similar trends are reported from tech training providers (Financial times, 2025)
[71] Annual employment estimates for detailed occupations (SOC 4-digit) in the ONS Annual Population Survey (APS) are subject to considerable statistical uncertainty, which limits the ability to identify meaningful changes over time. For this reason, any indications of reduced employment or weaker employer demand in specific occupations are drawn instead from a combination of survey evidence and more timely online job postings data.

said they were unsure of the impact on headline staffing numbers, the majority of businesses (51%) reported that there had been no net change to date.[72]

Firms anticipate future reductions, and workers who use AI are among the most pessimistic about automation risks. Despite the relatively low levels of headcount reductions to date, 11% of firms reported automating or replacing roles with AI technologies as being key to their overall AI workforce integration strategy, which could potentially lead to job losses, role redesigns, or redeployments in the future. Similarly, other employer survey data sources, suggest that 1-in-6 (17%) employers expect AI to shrink their workforce over 2026, with junior managerial, professional and administrative roles most at risk.[73] Expectations are highest in large private sector companies (26%) and public sector organisations (20%). At the individual level, 6% of workers surveyed in mid-2025 anticipated that their job would likely cease to exist in five years' time because of AI, rising to 9% for those who use the technology at least once a week. Together, these findings suggest that both employers and frequent users see credible scope for AI-driven automation in some roles – even if the full employment effects have yet to materialise.

Recruitment activity has slackened in some of the most GenAI-exposed roles, but it remains difficult to separate potential AI effects from broader post-pandemic labour market cooling.[74] As shown in Figure 4.8, occupations with higher exposure to GenAI capabilities have experienced larger declines in recruitment demand relative to 2019 pre-pandemic levels. This pattern also broadly aligns with the occupational areas that employers report as being most affected by AI technologies (Figure 4.6). However, pandemic-related labour market disruption and readjustments coincided with the rapid emergence of mainstream GenAI tools, making it difficult to isolate AI's contribution to these trends, though it remains a plausible contributor. The wider slowdown has also been particularly pronounced in ICT and professional services – sectors where exposure is high – further complicating interpretation.

In an effort to provide clearer insight, Figures 4.9 and 4.10 focus on shorter-term changes during a more stable labour market period. The job postings data suggests that while recruitment demand increased for most exposure groups in the first quarter of 2026 compared with the same period in 2025, demand for the most exposed occupations (Level 4) recovered the least. Looking at individual occupations tentatively shows a similar picture. Although trends vary within each exposure group, many Level 4 occupations cluster in the lower quadrants, indicating potentially weakening recruitment activity. These roles tend to have fewer human-task bottlenecks and are therefore more susceptible to automation, which is consistent with emerging automation signals and employer expectations, though the evidence remains correlational.

A similar, though much less uniform, pattern is visible for some Level 2 and Level 3 occupations. While these roles often include tasks that are harder to automate, weaker demand may still reflect early productivity-related staffing adjustments (including headcount compression), particularly in the more challenging economic environment the UK is currently facing. Other non-AI factors are, however, also likely to be contributing to these recruitment patterns.

Overall, these early trends in employer demand are broadly consistent with the task-based theory and other evidence in this report, although the recruitment data remains volatile, and attribution is uncertain.

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[72] Internationally, there is limited conclusive evidence to date of AI leading to widespread job losses, although some studies point tentatively to clearer effect on entry-level hiring and specific occupations (Brynjolfsson et al., 2025).
[73] Labour Market Outlook – Winter 2025/26 (Chartered Institute for Personnel and Development, 2025). Survey sample of 2,000 UK businesses.
[74] While online job postings can be a useful leading indicator in capturing changes external recruitment behaviour, they do not capture the full labour market adjustment process.

Figure 4.8: Demand for GenAI exposed roles have declined the most post-pandemic

Recruitment activity over time, relative to average pre-pandemic levels
London | Jan 2019 - Mar 2026 | 3-month moving average | Online job postings

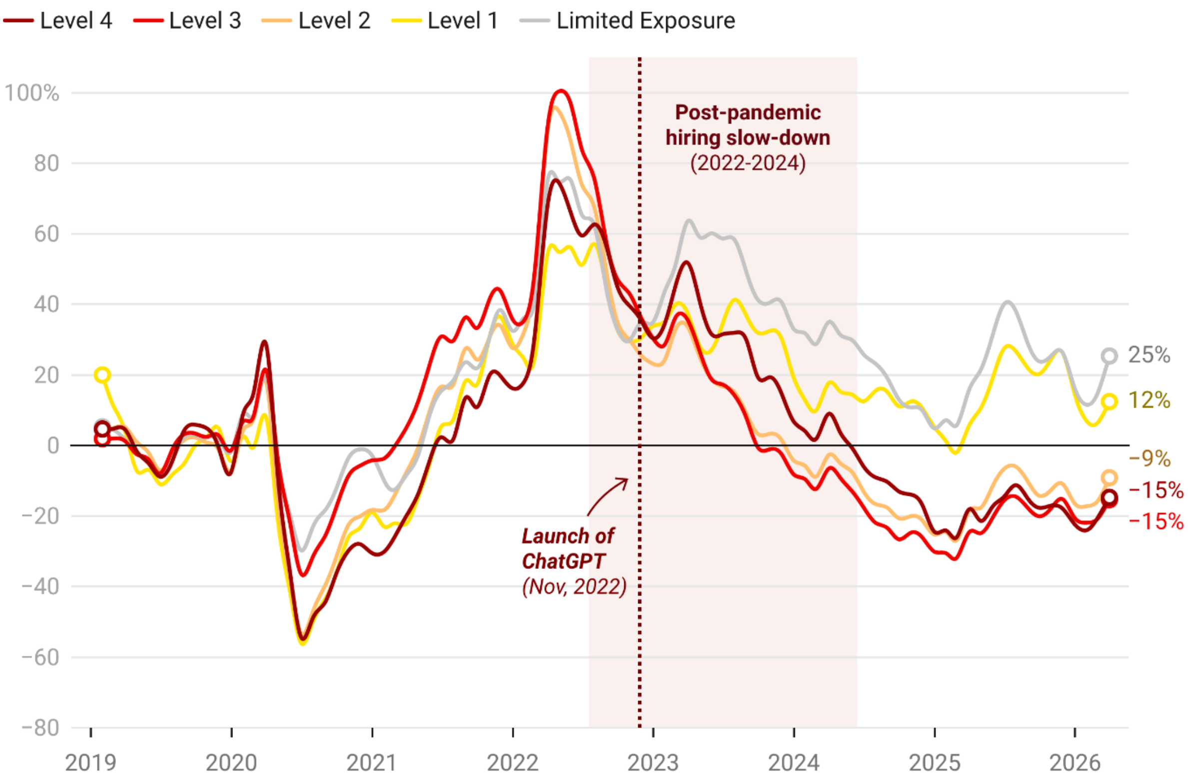


Chart: GLA Economics • Source: Lightcast UK job postings • Created with Datawrapper

Figure 4.9: Demand may be slackening for the most GenAI exposed roles, but difficult to disentangle from wider labour market cooling

Annual change in online recruitment activity
London | Jan - Mar | SOC 4-digit occupations grouped by GenAI exposure level

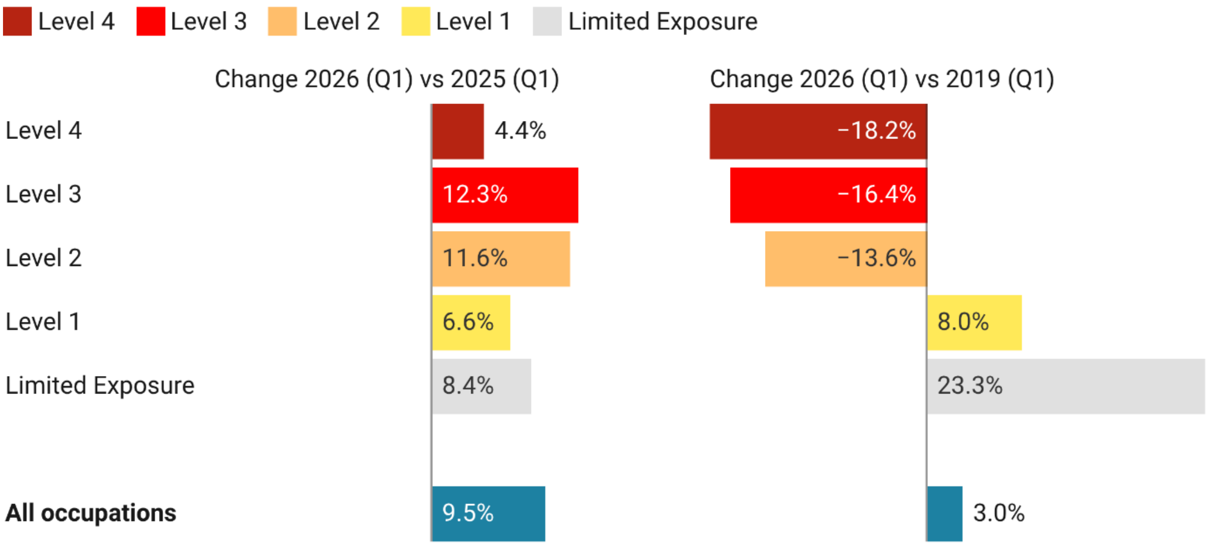
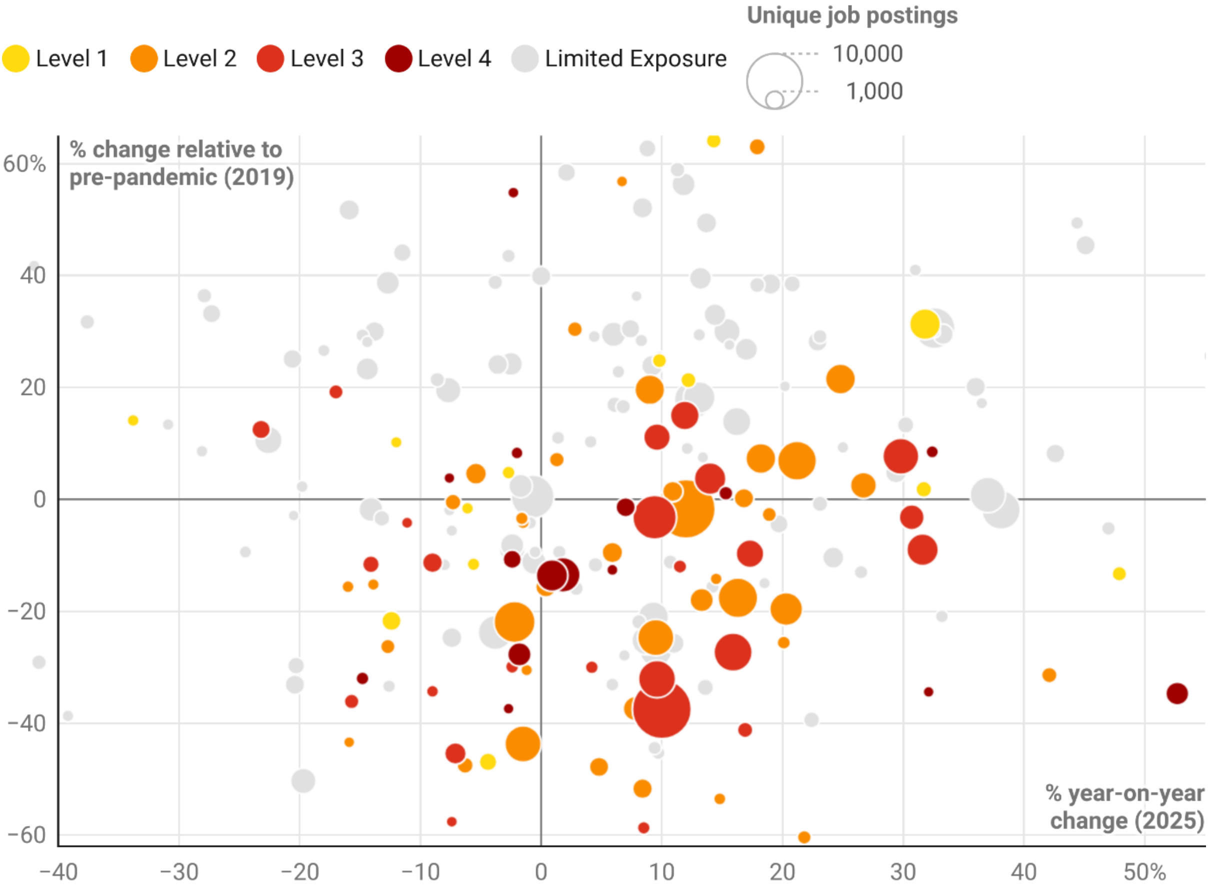


Chart: GLA Economics • Source: Lightcast UK job postings • Created with Datawrapper

Figure 4.10: No clear pattern in hiring changes for individual occupations (even within exposure groups), but most exposed roles generally facing weaker demand
Change in recruitment activity across occupations by GenAI exposure level
London | Jan-Mar 2026 (3-month period) | SOC 4-digit occupations



Excludes occupations with less than 100 postings for the period Jan-March 2026.
Chart: GLA Economics • Source: Lightcast job postings • Created with Datawrapper

Summation and consistency with wider evidence

Taken together, **the emerging AI adoption evidence broadly aligns with the exposure analysis and task-based impact framework**, suggesting that the early labour market effects of AI are generally concentrated in the most exposed occupations and industries. While the adoption evidence suggests that AI is already beginning to translate into real-world impacts – through a mix of job change, new job creation and, so far, more limited signs of displacement – current use still appears to reflect only a fraction of its broader technical potential, as shown by recent work from Anthropic. [75] They find that **real-world workplace usage remains substantially narrower than theoretical capability**, with many technically feasible tasks not yet widely embedded into professional workflows. In practice, this means that near-term labour market effects are likely to depend not just on what AI can do, but on where those capabilities are actually being adopted and embedded at scale. It is worth emphasising, however, that this represents a preliminary picture of GenAI's impacts, and that the work presented here provides a solid foundation on which to continue supplementing the research into this area.

[75] Labor market impacts of AI: A new measure and early evidence (Anthropic, 2026)

Chapter 5: Conclusion and potential implications for policymakers

5.1: Conclusions

This report brings together three strands of evidence: (i) task-based theory on how new technologies affect labour demand; (ii) occupational exposure analysis for London; and (iii) emerging evidence on AI adoption and labour market change. Together, these strands provide useful context for understanding how GenAI is most likely to affect work, where impacts may emerge over time, and why outcomes may differ across occupations.

London's potential exposure to GenAI is relatively high, reflecting the capital's concentration of professional and knowledge-intensive work. Nearly half of London's workforce are in roles where a share of tasks could be affected by GenAI's contemporary capabilities. Exposure is highest in information-processing and clerical roles, and therefore in sectors such as finance, ICT and professional services where these occupations are most prevalent. As set out in Chapter 2, exposure is not a forecast of job losses, but an indication of where job content is most likely to change. In many cases, this also signals where there is scope for productivity gains – for example, by automating routine tasks, speeding up workflows and improving the quality or consistency of outputs – alongside potential disruption in the most exposed roles. The ILO-based exposure measure is also time-sensitive, given the pace of change in AI capabilities. Even so, these advances are more likely to affect the scale, depth and pace of change than the broad pattern of exposure, which remains concentrated in cognitive, information-processing and language-intensive work. Therefore, the findings should not be construed as a definitive assessment of job loss or augmentation potential, rather merely an indication using one common methodology.

Early evidence on AI adoption from workers and businesses is broadly consistent with this exposure profile and the task-based channels of impact described earlier in the report. The data suggests that employers are increasingly using GenAI to support workers and automate parts of jobs – such as drafting, summarising, analysis and routine processing – rather than replacing whole roles at this stage. This aligns with the expectation that, at least initially, GenAI is more likely to be complementary, driving task reallocation and augmentation in many occupations, with displacement risk more concentrated in a narrower set of routine roles. Overall, early evidence points to several dynamics occurring in parallel: (i) changing task content within existing jobs, (ii) the emergence of new AI-related specialist roles, and (iii) early signs of softer labour demand in some highly exposed routine administrative occupations.

Rapidly accelerating improvements in AI model capability and relatively low barriers to experimentation mean these early signals could become steadily more pronounced as GenAI adoption spreads. If diffusion is faster and broader than in some previous technological waves, labour market adjustment may occur over shorter timescales and among cognitive roles previously less susceptible to automation impacts. However, the direction and scale of employment effects will ultimately depend on factors such as how widely and intensely firms adopt the technology, levels of trust around AI use, and how effectively workers can adapt to these changes.

Finally, the impacts of AI are likely to be unevenly distributed across London's workforce. Because exposure is concentrated in particular occupations and sectors, impacts will also differ across demographic and income groups, reflecting existing patterns of occupational segregation. This raises the possibility of widening inequality if disruption is concentrated in certain lower-paid routine roles while productivity gains accrue more strongly to higher-paid professional work. Younger workers may be particularly affected where entry-level tasks are more exposed and traditional career progression routes change, although they may also be among the most adaptable to a changing and increasingly digitalised labour market.

5.2: Potential considerations for policymakers

A key implication arising from this research is the importance of strengthening digital and AI-related skills across the workforce. International evidence indicates that new technologies are more likely to complement workers where they have the skills to use them productively, apply judgement, and manage risks.[76] Where skills gaps persist, adoption may be slower, competitiveness threatened, and the benefits of technological change may be less widely shared.

Employers will be central to delivering this in practice, as many of the most effective skill gains come through workplace training, job redesign and day-to-day use. Public policy can support and enable employer-led action by ensuring the wider skills and employment system provides strong foundations and reaches those least likely to access training. Policy interventions will also need to respond quickly as AI capabilities and employer needs evolve.

Looking ahead, the evidence suggests a number of potential priorities for London that, while not exhaustive, policymakers may wish to consider:

1. **Ensuring access to basic AI and digital literacy across the workforce.** While uptake will increase through employer adoption and individual use, international evidence and surveys of Londoners suggest this will be uneven.[77,78] Even in roles where AI is expected to complement work, workers without AI-related skills or experience can face weaker employment prospects. This reinforces the case for embedding broad-based AI training across education pathways, equipping workers with the confidence to use AI applications, alongside a practical understanding of data protection and rules for safe use.[79,80] Provision should also ensure that no group misses out on training opportunities, with targeted support to those who have historically had lower engagement with learning so as to avoid reinforcing existing inequalities, or creating new ones.
2. **Recognising and developing complementary 'human' skills**. In addition to AI-specific expertise, the literature highlights the growing importance of skills such as problem-solving and critical thinking for effective AI use. These skills help reduce the risk of overreliance on plausible-sounding AI outputs by enabling users to test and challenge AI-generated content, identify errors or bias, and decide when human checks are needed.[81] Applied consistently, these skills can build public trust in AI use across the economy – an issue frequently cited as a major barrier to adoption. Alongside this, creative and communication skills can help workers use GenAI more effectively, thereby supporting further productivity gains.
3. **Developing specialist AI and digital capabilities.** Alongside general AI literacy, London needs a strong pipeline of workers with specialist skills to develop, deploy and maintain AI systems safely and effectively (for example in AI data engineering, model risk management, cyber security and responsible AI governance). These capabilities – which are expected to continue growing in demand – will enable effective adoption at scale and help organisations manage quality and compliance risks.[82]

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[76] Gen-AI: Artificial Intelligence and the Future of Work | IMF (Cazzaniga, et al., 2024)
[77] Skill needs and policies in the age of artificial intelligence: OECD Employment Outlook (2023)
[78] Separate surveys of Londoners (Ipsos and YouGov) find that AI use at work varies by demographic group, occupation and industry, and that confidence in using GenAI tools differs accordingly.
[79] AI Skills for Life and Work: Rapid Evidence Review (UK GOV, 2026)
[80] IMF presses governments to step up support for workers displaced by AI (Financial Times, 2026)
[81] Building an AI-ready public workforce (OECD, 2026)
[82] AI Skills for Life and Work: Labour market and skills projections (UK Gov, 2026)

4. **Targeting support towards highly exposed roles and progression pathways.** Workers in routine administrative roles – and some professional occupations – may face the most direct task disruption as a result of AI adoption. Some will transition relatively easily because they have desirable transferable skills, but others may find it harder to move into less exposed work, particularly where neighbouring roles are affected in similar ways.[83] Targeted upskilling, careers guidance and progression support will help those most at risk move into higher-value tasks or alternative roles.

5. **Supporting employer readiness and workplace change.** Given the pace of improvement in AI capabilities, training will need to be continuous and embedded in day-to-day work to translate use into real performance gains. However, many employers – especially SMEs who struggle most to adopt AI – will require support to effectively integrate AI. This may include guidance on how to redesign roles and workflows, strengthen data and digital foundations, and put clear governance in place so productivity improvements are realised in practice.[84] Evidence suggests these supports and guidance on AI use cases are most effective when targeted and sector specific.[85]

These policy priorities matter because London's exposure to GenAI is high, adoption is rising, and early evidence suggests multiple – potentially profound – labour market effects are emerging in parallel. This is reflected in employer behaviour, with AI-related skills requirements broadening across a wide range of roles (Chapter 4). This reinforces the importance of a skills offer that builds both broad AI literacy and complementary "human" skills, develops AI-specialist capacity, and supports firms to embed AI safely and effectively. Provision also needs to be inclusive, so groups with lower engagement in training are not left behind, and so workers in the most exposed roles have clear routes to retrain and progress.

Box 5.1: UK Government AI upskilling initiative[86]

In recognition of the importance of workforce skills, the UK Government has launched a programme to provide *free AI training for up to 10 million workers by 2030* in collaboration with industry. This initiative aims to equip a large share of the working population with core AI skills, reducing barriers to adoption and helping ensure that workers can benefit from emerging technologies. For London, this creates an opportunity to align local provision with national offers – and to ensure uptake among high-exposure occupations and under-served groups.

5.3: Future monitoring of labour market developments

Given the uncertainty around longer-term employment and wider labour market effects, ongoing measurement and analysis will be essential in order to evaluate the shifting impacts of AI. While task-based exposure scores provide an early indication of where impacts are *most likely* to occur given current technical capabilities, the adoption and labour market indicators discussed in Chapter 4 can help show where impacts are *starting* to occur in reality. Policymakers should therefore assume a greater labour market observatory role in this area and consider:

[83] Research suggests that many of the most exposed administrative roles (level 4) have the lowest adaptive capacity to transition to alternative, lesser exposed employment. As a result, if these roles were to experience AI-related job losses, affected workers would likely face greater risks of longer-term unemployment, lower re-employment rates, and larger relative earnings losses than other groups. By contrast, highly exposed professional roles often draw on broader and more transferable skills, which may make adjustment easier even where job content changes. Measuring US workers' capacity to adapt to AI-driven job displacement | Brookings (2026)
[84] AI adoption by small and medium-sized enterprises (OECD, 2025)
[85] SME Digital Adoption Taskforce: final report (DBT,2025).
[86] Free AI training for all - UK Government (2025)

- **Tracking adoption and intensity of use** in high-exposure sectors and occupations, including whether AI is moving from pilots and experimentation into core business processes.
- **Monitoring employment and pay outcomes** by occupation and sector using official statistics, to identify any emerging shifts in headcount, hours or wages that may be associated with AI.
- **Tracking changing labour demand and job content change** in highly exposed roles using vacancies and hiring data, alongside evidence on changing task mixes, job redesign and job quality.
- **Assessing whether AI-related productivity gains are emerging, and where,** by linking adoption and depth of integration to productivity indicators across sectors and occupations.
- **Tracking changing skills demand and training uptake,** including how AI-related requirements are appearing in job adverts and whether workers are receiving training and moving into new tasks or roles.
- **Evaluating which AI-related training approaches improve outcomes,** focusing on measurable impacts such as productivity, pay, and re-employment.

This report serves as a foundational evidence base on what is increasingly becoming a pivotal topic of consideration for businesses and policymakers alike. The analysis presented here, while rigorous, is preliminary given the nature and evolution of GenAI's capabilities.

Nonetheless, it represents a stepping stone towards monitoring and expanding analysis on this topic to better inform the priorities and strategies to be adopted by the Mayor's Taskforce. Such expanded analysis could involve incorporating new methodologies, experiences from other jurisdictions, and scenario analysis to triangulate AI impacts with wider economic and social conditions.

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Appendices

Appendix 1: Acronyms

Term	Description
AI	Artificial Intelligence
AIOE	Artificial Intelligence Occupational Exposure
APS	Annual Population Survey
ASHE	Annual Survey of Hours and Earnings
BICS	Business Insights and Conditions Survey
DBT	UK Department for Business and Trade
DfE	UK Department for Education
DSIT	UK Department of Science, Innovation and Technology
GenAI	Generative Artificial Intelligence
GPT	Generative Pre-trained Transformer
ILO	International Labour Organization
IMF	International Monetary Fund
IP	Intellectual Property
ISCO	International Standard Classification of Occupations (2008 iteration)
LLMs	Large Language Models
ML	Machine Learning
N.E.C.	Not Elsewhere Classified
NHS	UK National Health Service
OECD	Organisation for Economic Co-operation and Development
ONS	Office for National Statistics
SIC	UK Standard Industrial Classification
SOC 2010	UK Standard Occupational Classification (2010 iteration)
SOC 2020	UK Standard Occupational Classification (2020 iteration)

Appendix 2: Technical overview of ILO occupational exposure methodology

Given the significant labour market implications of GenAI, several innovative approaches have emerged in recent years that seek to identify which jobs might be most affected by its capabilities.

Broadly, studies fall into three families:

(i) **task-susceptibility** methods evaluate how well GenAI can handle specific job tasks, and then aggregate these up to the occupation level,

(ii) **capability-proximity** methods assess the overlap between AI applications and human abilities, and then aggregate these up to the occupational level,

(iii) **usage/productivity** methods analyse how LLM models are actually being used by different occupations and what they do to task performance / productivity.

While similar in their endeavour to relate current GenAI capabilities to work activities, the variation in methodologies does result in some nuanced differences in occupational exposure estimates. **Across the literature however, there is strong consensus that occupational exposure scores should be interpreted only as signals of technical potential for GenAI to disrupt, rather than a forecast of employment change**. **To date, there is limited direct validating evidence linking AI exposure scores to observed changes in employment or wage outcomes**. Indeed, most measures are sign-agnostic as to whether GenAI is more likely to automate or augment a role, but even where methods do provide directional guidance realised outcomes still depend on a wide range of adoption factors, discussed in Chapter 1.

Furthermore, the speed at which GenAI tools and capabilities are being enhanced means that studies of this nature can become easily outdated. As such explicit versioning (exposure at a certain point in time to a specific model of GenAI) becomes a critical consideration and is likely to change as systems continue to improve. Accordingly, it is important that occupational exposure scores be interpreted cautiously and considered alongside evidence of adoption, demand conditions and other labour market data sources.

Despite these general limitations – including the inherent uncertainty around AI labour market effects – all three approaches present a strong analytical basis for modelling potential occupational impacts, and indeed, are often complementary to one another. However, informed by literature preference for task-based analytical lenses, its inclusion of granular occupational exposure scores along with automation/augmentation directional nuance, and being amongst the most up-to-date task frameworks calibrated to current GenAI-specific capabilities (early-2025), the primary analysis included this paper is anchored in the ILO's task-susceptibility exposure framework. A summary of the framework, along with its strengths and limitations, is set out below.

Overview of International Labour Organization (ILO) GenAI exposure methodology (2025)

- **Task-led foundation:** Researchers at the ILO (Gmyrek et al., 2023; 2025) have developed a new GenAI occupational exposure index derived from task level data. It draws upon Poland's 6-digit occupational system (which is aligned with the ISCO-08 taxonomy) and includes almost 30,000 specific tasks. This deep granularity provides a rich base for assessing the automation potential of specific tasks before rolling up to occupations.

- **Human judgements (workers and experts):** To ground their analysis, the authors first collect worker judgements on the potential to automate tasks with GenAI. To do so, they conduct a representative worker survey of about 1,640 respondents that yields roughly 52,560 task judgements across the broad ISCO occupational groups. Next, international experts conduct a review of a large subset of these judgements to validate and adjust scores. This results in a robust (Delphi-style) human-judgement knowledge set of task exposures that blends both front-line worker and expert perspectives. Throughout, assessment of automation potential prioritises workplace realities and task-execution over purely technological capability claims.

- **Scaling judgements with AI assistants:** The team then use two LLM-based predictors (AI assistants), trained on this verified knowledge base of task-level exposure, to score the full ~30,000 ISCO-08 task set consistently. The worker/expert process and LLM predictor combined thereby yield task-level automation scores grounded in examples and justifications. Relative to their 2023 iteration, the 2025 release recalibrates several clerical and administrative tasks downward to reflect ongoing human oversight and current tool limits, while raising exposure for some professional and technical roles in line with advances in multimodal and more agentic systems.

- **Task aggregation to occupations:** The authors then aggregate these tasks up into the 430+ ISCO-08unit group occupations. Unlike some other methodologies, a limitation of this approach is that task scores are aggregated to ISCO 4-digit occupations with equal weights, since the ISCO-08 taxonomy does not provide indication of relative task importance to each role. For each occupation, the ILO computes the mean (μ) and dispersion (σ) of its task scores. The mean captures the overall level of GenAI exposure while the dispersion signals how consistently tasks within the occupation are exposed (i.e., concentrated vs patchy exposure).

- **Exposure levels with directional nuance**: These scores are then grouped into different 'exposure levels' that reflect both degree and consistency of exposure to GenAI. Higher, more uniform exposure implies a stronger tilt toward automation-prone task mixes (Levels 3 and 4), while lower or more variable exposure suggests a more augmentation-oriented profile (Levels 1, 2 and below). The logic here is that when task dispersion/variation is high, it is understood that non-automatable tasks act as bottlenecks that keep humans in the loop. In such cases, exposure is more consistent with augmentation than with uniform automation.

Table A2.1: **GenAI Exposure levels: Definitions and interpretation**[87]

GenAI Exposure level	Interpretation	Example occupations
Exposed: Level 4 *(High task exposure, Low task exposure variability)*	High and consistent exposure to GenAI across tasks within the occupation. Most current tasks in these jobs have a **high potential of automation**, with little variability in task-level exposure.	Administrative / clerical roles, Bookkeepers, Brokers
Exposed: Level 3 *(Significant task exposure, high task exposure variability)*	Above-moderate occupational exposure. Even though some key tasks remain less exposed, the overall potential of automation of the current tasks with GenAI is growing in these occupations.	Economists, Software developers, Accountants
Exposed: Level 2 *(Moderate task exposure, high task exposure variability)*	Moderate occupational AI exposure, with high task-level variability. These occupations include a mix of some tasks that are exposed to GenAI and others not at risk, making the impact uneven.	Management consultants, Marketing professionals, IT system designers
Exposed: Level 1 *(Low task exposure, high task exposure variability)*	Low overall GenAI exposure at the occupational level, but high variability across tasks. Some tasks within these occupations have an elevated automation potential, even if the occupation as a whole remains strongly reliant on tasks that have a low potential of automation.	Sales assistants, Laboratory technicians, Legal associate professionals
Limited Exposure All other occupations *(Low task exposure, low-mod task exp. variability)*	Occupations with minimal-low GenAI occupational exposure, where most tasks remain relatively unaffected. Low-moderate task exposure variability, also makes these occupations **less likely to be impacted by AI automation, although not immune**.	Carpenters, Care workers, Primary school teachers

Box A2.1: Overview of alternative approaches to estimating AI occupational exposure

A) Proximity between AI capability and human abilities

A prominent alternative strand of the exposure literature builds on Felten et al.'s (2021; 2023) seminal work assessing the proximity of AI's technical capability to perform human abilities, rather than specific tasks. They link 10 concrete AI applications (e.g., language modelling, image generation) to 52 O*NET human abilities (e.g., oral comprehension, inductive reasoning), via crowd-rated relatedness and then weight these by each occupation's ability "importance" and "level" to produce AI Occupational Exposure (AIOE) scores. These scores are relative, sign-agnostic indicators of technical proximity rather than judgements predicting whether tasks will be automated or augmented (it ranks jobs within a series rather than giving absolute probabilities). The UK Department for Education (DfE, 2023) applies this methodology to SOC, reusing the AI application-ability relatedness and O*NET weights to generate UK occupation and sector profiles (including an LLM-specific exposure). Similar to Felten, it is relative and does not take a stance on whether AI is likely to 'assist or replace' specific occupations.

Williamson et al. (2024) at the Irish Government Economic and Evaluation Service (IGEES) extends the Felten exposure approach by pairing it with a complementarity index developed by the IMF (Pizzinelli et al. 2023). This complementarity index seeks to capture features of jobs – including human interaction,

[87] The ILO's original exposure methodology included 6 exposure gradients: levels 1-4, 'minimal exposure' and 'no exposure'. Owing in part to the rapid development of GenAI, inherent subjectivity of exposure grading, and emerging use cases among the supposedly least exposed occupations, these latter two groups were combined into a new 'limited exposure' category.

responsibility, autonomy, physical/varied conditions, and tool use – that make AI more likely to assist workers rather than substitute for them. Occupations are then arranged into four quadrants (high/low exposure × high/low complementarity) for policy triage.

B) Time-saving potential with LLM and real-world usage

A related strand of work estimates exposure at the level of tasks, focusing on where GenAI could materially change how work is done. Eloundou et al. (2023) define exposure as the share of an occupation's O*NET tasks that could be completed significantly faster, at similar quality, with LLMs or LLM-enabled tools, based on expert judgements. This is largely sign-agnostic: high exposure may imply faster completion with an assistant, partial automation of sub-tasks, or fuller automation depending on context. Henseke et al. (2025) apply a similar approach in the UK, rating the time-saving potential of LLMs across tasks and anchoring these ratings using worker-reported task importance from the Skills and Employment Survey, producing a Generative AI Susceptibility Index (GAISI) that captures within-occupation variation. Complementing these susceptibility measures, an emerging body of evidence uses real-world platform data to observe how GenAI is actually being used. Anthropic's Economic Index (2026), for example, maps large volumes of Claude interactions to O*NET tasks and occupations. It finds use is concentrated in cognitive tasks (such as writing, analysis and coding) rather than physical or managerial work, and that interactions to date skew more toward augmentation than full automation.

Table A2.2: Overview comparison of AI occupational exposure methodologies[88]

Methodology	Examples	Approach overview	Key strengths	Key limitations / cautions	How findings align
(i) Task-susceptibility (occupation task exposure) – *chosen approach*	Gmyrek et al. (ILO, 2023; 2025)	**Task-technology overlap**: measures how much typical job tasks within an occupation could be automated under GenAI's current capabilities. **Consistency** of GenAI exposure across tasks gives an indication of broad automation vs mixed augmentation.	• GenAI-specific and more recently developed (early-2025) • Task-based measure (aligned with literature.) • Granular and internationally adaptable • Strong for distributional analysis • Includes potential direction of change • Uses worker / expert judgements on exposure	• Masks within-occupation variation (e.g., seniority) • Depends on LLM modelling and worker/expert judgement of AI capabilities • Does not incorporate adoption or realised outcomes • ISCO–SOC mapping adds some noise • Unweighted task importance within roles	Both approaches broadly agree that exposure is highest in language- and information-heavy work – especially administrative / clerical and many ICT and professional roles. Capability-proximity measures often imply a larger exposed workforce because they map AI capabilities to broad human abilities, while the ILO task-based approach is typically more conservative by accounting for task-level bottlenecks, oversight needs and mixed exposure within roles. Tentative directional guidance is also generally aligned across roles in favour of augmentation.
(ii) Capability proximity (AI applications aligned to human abilities; sometimes with complementarity)	Felten et al. (2021; 2023) Pizzinelli et al. (IMF, 2023; 2024) Williamson et al. (IGEES, 2024) Department for Education (2023)	**Ability alignment**: measures how closely AI applications map to O*NET human abilities, weighted by each occupation's ability importance / level. When paired with **complementarity indicator**, offers a steer on whether AI is more likely to assist vs. substitute.	• Strong conceptual link to skills / abilities framework • Granular and widely adapted across countries • Complementarity layer adds interpretive value for direction of outcomes • Strong for distributional analysis	• Assumption-heavy; sensitive to mapping choices • Masks within-occupation variation (e.g., seniority) • May miss workplace constraints / bottlenecks • Does not incorporate adoption or realised outcomes • Originally developed pre-GenAI for broader AI capability taxonomies • O*NET–SOC mapping adds some noise	

[88] Usage-based exposure methodologies are discussed separately above (Box A2.1) but are not included in this table as associated research does not currently provide comprehensive occupational exposure measures adaptable to the UK setting.

Appendix 3: Adapting ILO exposure methodology to UK data

To apply the ILO GenAI exposure estimates (built on ISCO-08) to UK employment data (recorded in SOC 2020), a two-step crosswalk was used to align the different occupational taxonomies. In practice, the join proceeds from SOC 2020 to ISCO-08 (to attach the exposure), and then results are reported back at the SOC 2020 unit-group (4-digit) level.

Conversion steps

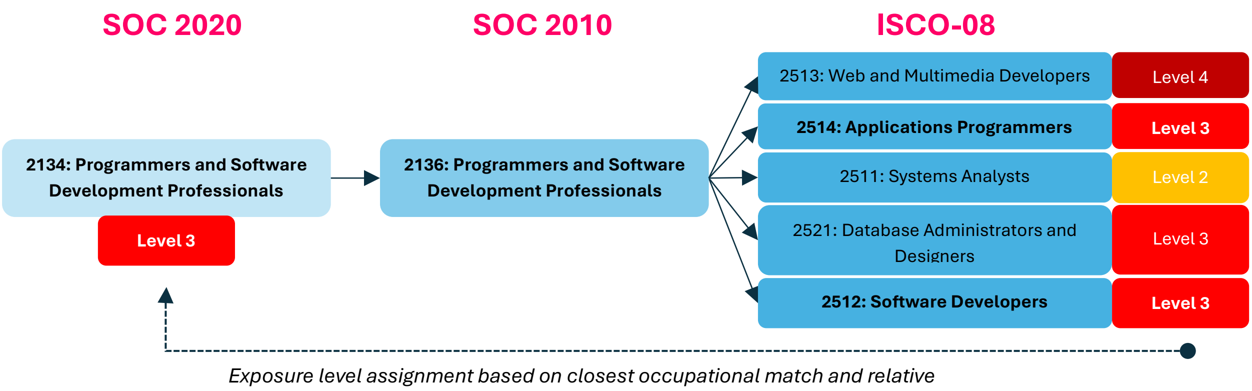
i. **SOC 2020 → SOC 2010.** SOC 2020 4-digit occupational unit groups were mapped to SOC 2010 using the ONS proportional relationship tables.
ii. **SOC 2010 → ISCO-08.** SOC 2010 4-digit unit groups were then mapped to ISCO-08 4-digit unit groups using the ONS mapping / proportional conversion tables. [89]
iii. **Join and return.** ILO exposure scores (at ISCO-08 unit-group level) were merged onto the linked ISCO codes, and the results were returned to SOC 2020 for further analysis with UK data.

Allocation rules and practical constraints

- **Many-to-many links.** Because ISCO and SOC differ in scope, timing and granularity – and because SOC 2020 does not always map one-to-one to SOC 2010 – crosswalks are frequently many-to-many rather than clean one-to-one matches. Where an occupation maps to multiple codes in the other taxonomy, the corresponding exposure is generally allocated depending on proportional concentration, using the published crosswalk shares, as well as employment weights where available. Very small linked occupational shares may be excluded or pooled (subject to sensitivity checks) where they likely reflect peripheral tasks more closely associated with another role.

- **Levels, not precise exposure scores.** Owing to these many-to-many links and taxonomy differences, it is not possible to accurately translate exact ISCO task-level exposure scores and dispersion values into SOC 2020. However, the ILO's occupational exposure levels can be assigned, as related ISCO codes generally share similar task profiles and therefore, fall within the same exposure level – or bucket. See Figure A3.1 as an example.

Figure A3.1: Example of gradient assignment process with one-to-many match



Note: Of the five ISCO-08 occupation codes that relate to the UK SOC occupation 'Programmers and Software Development Professionals', ISCO's 'Software Developers' and 'Applications Programmers' had the highest concentrations in that occupation. Therefore, their exposure level scores (3) were the primary determinants in assigning an exposure score to the SOC2020 occupation.

[89] The ISCO-UK SOC conversions were developed for an ONS research project, and do not constitute official guidance on classification conversion. Moreover, the truncated tables available are one directional: ISCO-08 → UK SOC 2010. The ONS therefore, advise user caution in application.

- **Triangulation sense check.** In some cases, however, imperfect matches or discrepancies in terms of occupational exposure gradients necessitate personal judgement on assignment of exposure classification. In such cases additional review steps are conducted including a review of SOC task descriptions and cross-checking exposure levels against other UK-SOC adapted capability-proximity measures (e.g. DfE (2023) and Williamson et al. (2024)).

- **Mixed-content SOCs.** Some SOC 2020 unit groups bundle specialisms that ISCO separates (including "not elsewhere classified, n.e.c." groups). Where mapped ISCO codes span different exposure levels, the SOC is often marked as mixed-content and its level therefore should be treated as indicative.

- **Country context and task weighting.** In the ILO method, tasks are aggregated to occupations with equal task weights (task-importance shares are unavailable in ISCO). UK worker time-use may differ and susceptibility to emerging technologies, so results should be read alongside UK-specific evidence where relevant.

- **GenAI versioning.** The ILO use early-2025 GenAI capabilities as the basis for its exposure estimates. However, future releases may revise certain ISCO exposure levels as GenAI continues to evolve, which would have implications for SOC mapping. It is important to note also that this exposure methodology relates only to generative AI technologies, and so does not take account for any potential labour market implications arising from other AI or automation technologies.

Therefore, given these caveats, despite careful application of ONS crosswalks, some **measurement noise / inaccuracy is unavoidable** due to fundamental taxonomy differences and evolving technology. However, despite these differences, the exposure estimates for London and the UK in this report are **broadly consistent with the ILO's own international results** and distributional patterns, suggesting that the ISCO–SOC mapping performs reasonably well for this analysis.

Estimating the scale of GenAI exposure groups in terms of employment

To apply the ILO exposure framework to the UK, and London, context this analysis combines the task-based exposure classifications with UK occupational employment microdata. Occupational employment estimates at SOC 4-digit level are drawn from the Office for National Statistics (ONS) Annual Population Survey (APS), using a three-year pooled dataset covering 2022–2024 accessed via the Secure Research Service. Pooling across three years increases sample size and improves the robustness of estimates, particularly when analysing detailed occupations and sub-groups.

All analysis is based on respondents' location of work (rather than residence), and includes employment reported in both first and second jobs where relevant. Survey weights are applied to ensure results are representative of the working population. Specifically, the analysis uses the 2022 APS individual weights, which reflect how many people each survey respondent represents based on their characteristics. To reduce the influence of extreme values, weights are winsorised at the 99.5th percentile.

As the APS is a household survey, employment estimates derived from it may differ from other published labour market statistics that use alternative data sources or methods. Differences can arise due to coverage, location classification, weighting approaches, and definitions (for example, whether measures are based on people in employment or counts of jobs). These considerations should be borne in mind when comparing figures across sources.

Appendix 4: GenAI exposure level analysis, by worker characteristic

The charts below show how the workforce is distributed across GenAI exposure levels for different worker characteristics. They complement the analysis in Chapter 4 by highlighting which groups are more represented in higher- and lower-exposure occupations, and therefore where GenAI-related job change may be felt most.

Figure A4.1: Younger and older workers are overrepresented among the most exposed occupations, level 4

Share of workers in each GenAI exposure level by age group
London | 2022-2024 employment estimates

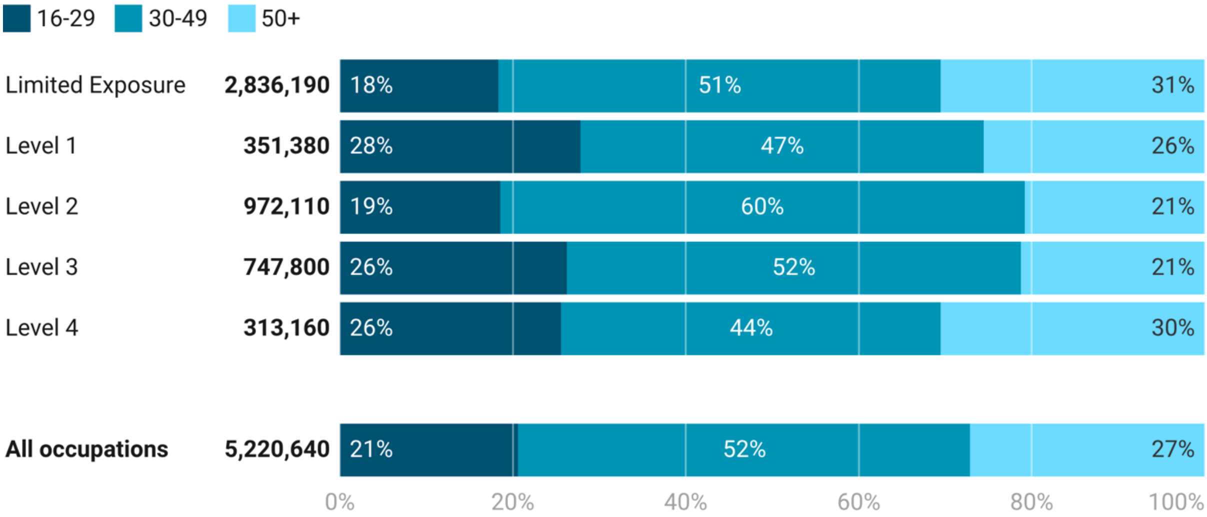


Chart: GLA Economics adaptation of ILO (2025) approach • Source: ONS Annual Population Survey - Pooled Annual (2022-2024) • Created with Datawrapper

Figure A4.2: Women are overrepresented in the most GenAI exposed admin occupations

Share of workers in each GenAI exposure level by sex
London | 2022-2024 employment estimates

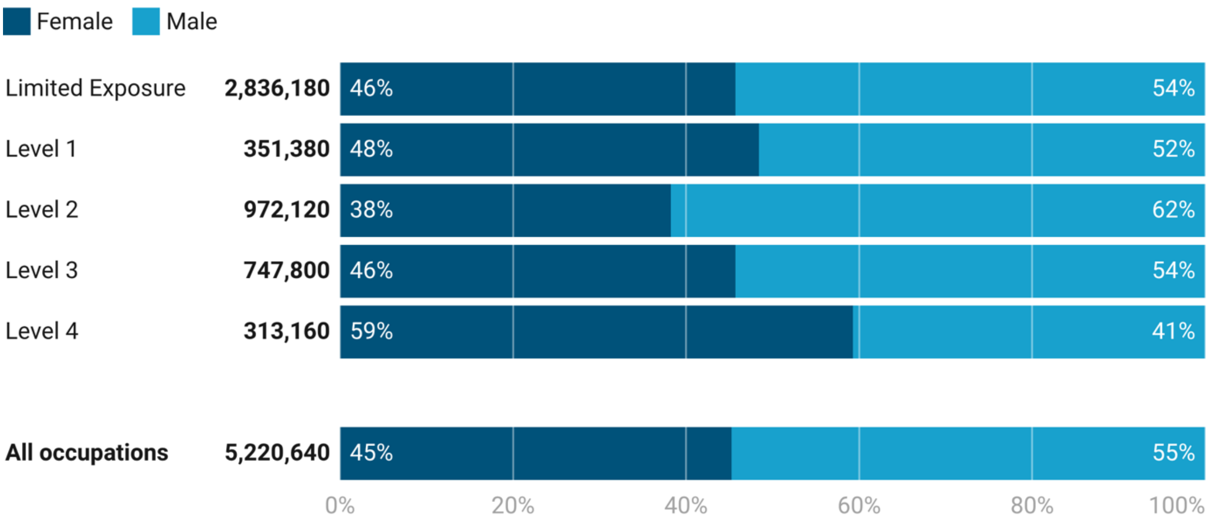


Chart: GLA Economics adaptation of ILO (2025) approach • Source: ONS Annual Population Survey - Pooled Annual (2022-2024) • Created with Datawrapper

Figure A4.3: Asian workers are overrepresented in the highest exposure groups
Share of workers in each GenAI exposure level by ethnicity
London | 2022-2024 employment estimates

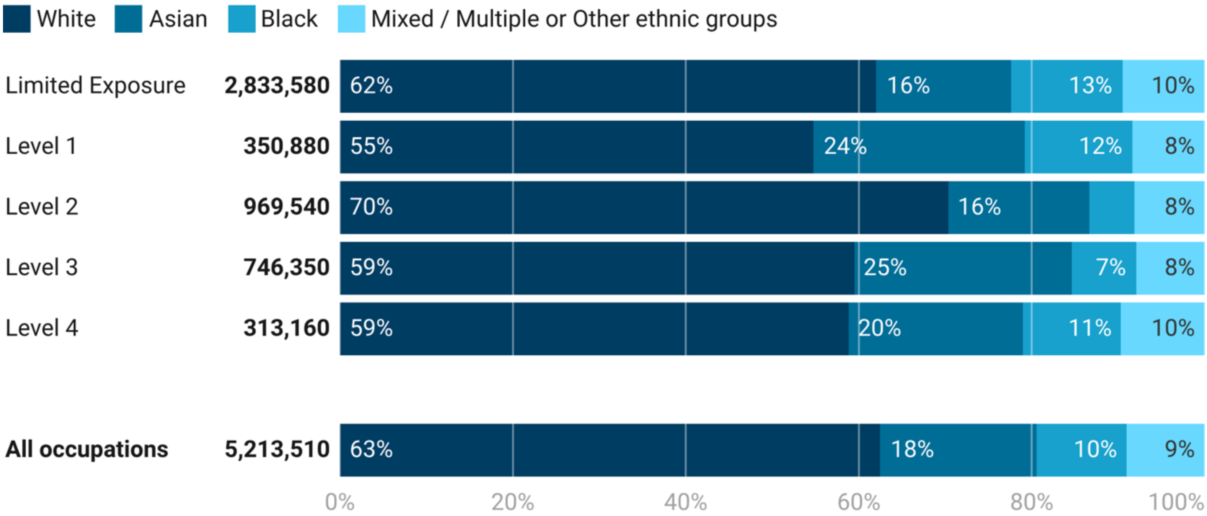
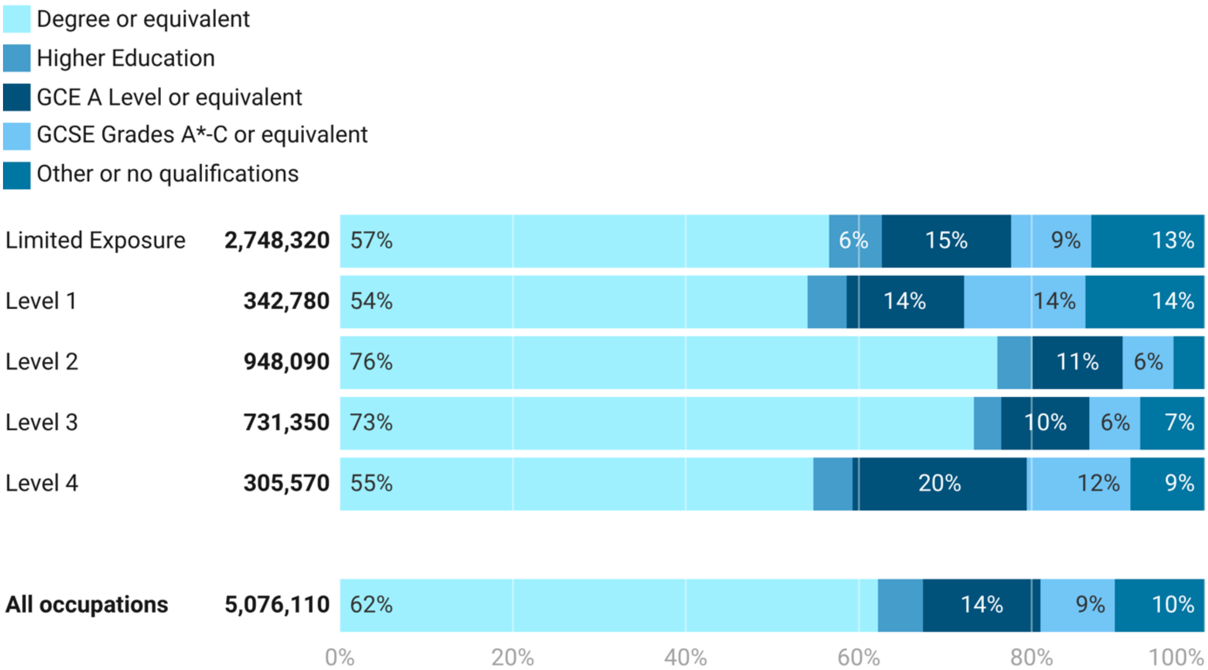


Chart: GLA Economics adaptation of ILO (2025) approach • Source: ONS Annual Population Survey - Pooled Annual (2022-2024) • Created with Datawrapper

Figure A4.4: The most and least exposed groups share a similar educational level profile
Share of workers in each GenAI exposure level by highest level of educational attainment
London | 2022-2024 employment estimates

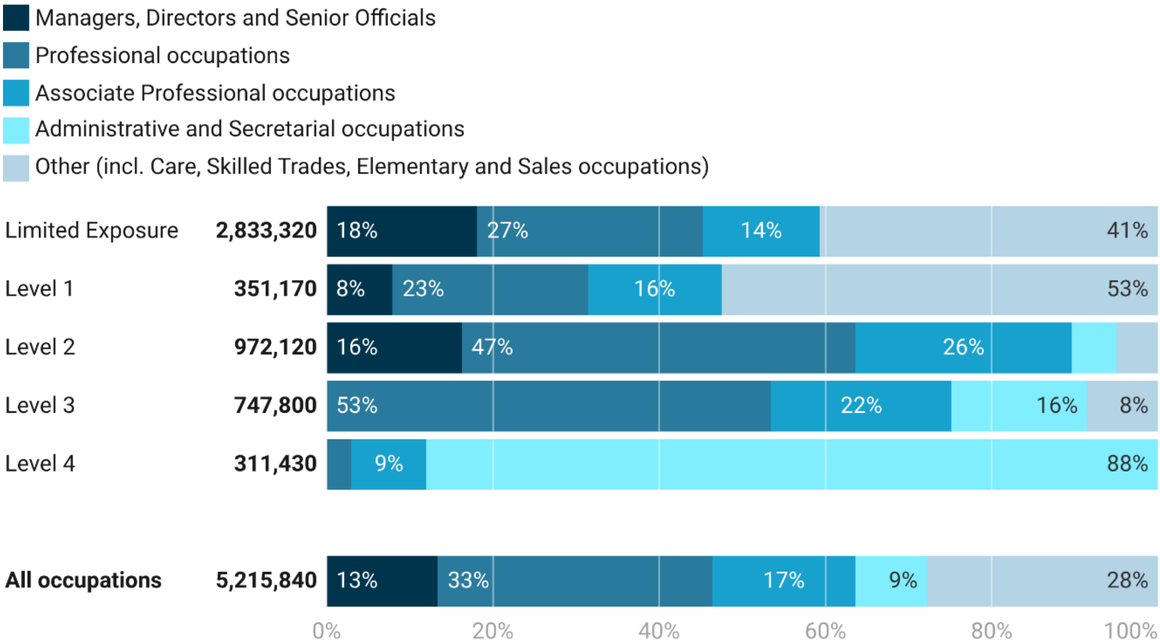


Note: Total values (bold) may not sum to the London total as a result of statistical suppression of some small values within groups, or no response recorded.

Chart: GLA Economics adaptation of ILO (2025) approach • Source: ONS Annual Population Survey - Pooled Annual (2022-2024) • Created with Datawrapper

Figure A4.5: Admin roles dominate the most exposed group

Share of workers in each GenAI exposure level by occupation of employment
London | 2022-2024 employment estimates | SOC 1-digit

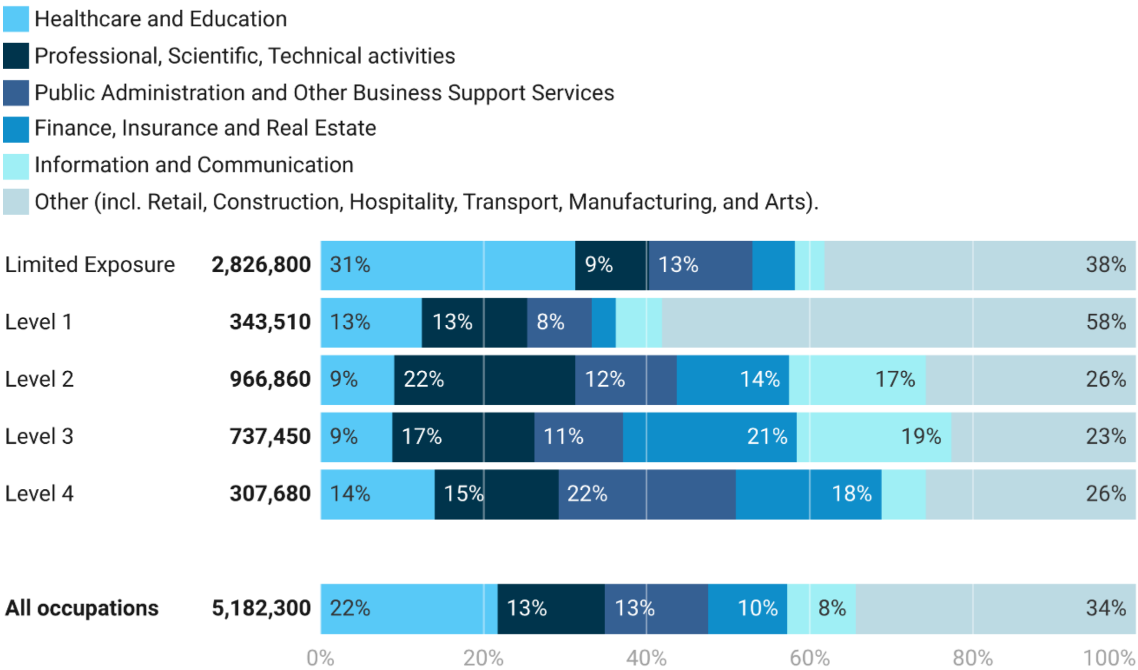


Note: Total values (bold) may not sum to the London total as a result of statistical suppression of some small values within groups, or no response recorded.

Chart: GLA Economics adaptation of ILO (2025) approach • Source: ONS Annual Population Survey - Pooled Annual (2022-2024) • Created with Datawrapper

Figure A4.6: Finance, ICT and public admin employ disproportionate shares of exposed

Share of workers in each GenAI exposure level by industry of employment
London | 2022-2024 employment estimates



Note: Total values (bold) may not sum to the London total as a result of statistical suppression of some small values within groups, or no response recorded.

Chart: GLA Economics adaptation of ILO (2025) approach • Source: ONS Annual Population Survey - Pooled Annual (2022-2024) • Created with Datawrapper

Figure A4.7: London's relative specialisation in professional activities shown in its share of exposed roles, particularly level 3

Share of workers in each GenAI exposure level by region of employment

London | 2022-2024 employment estimates | Grouped ITL1 regions

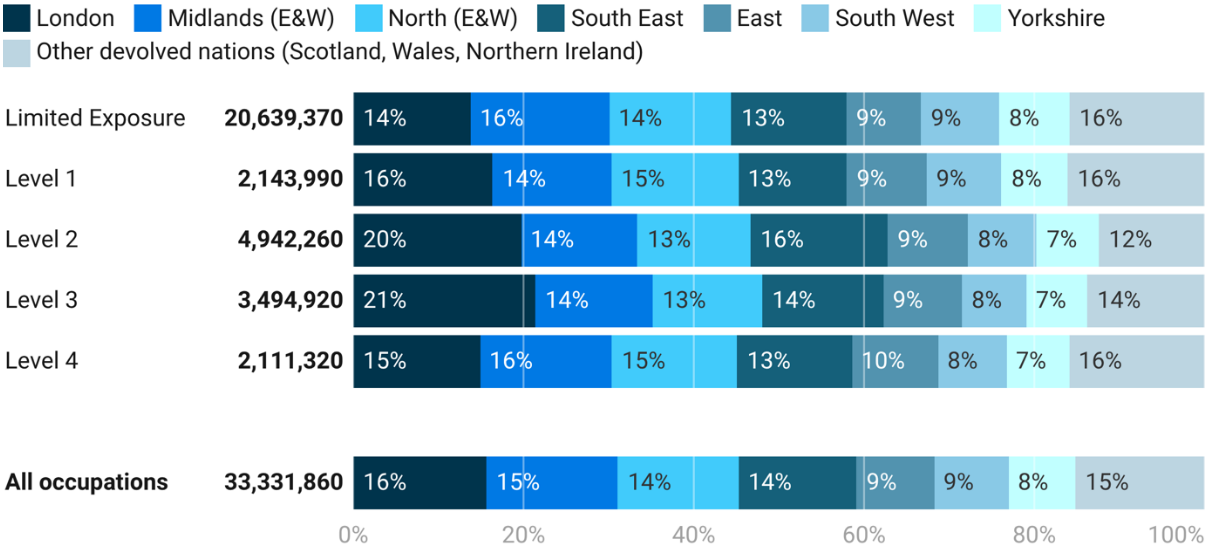


Chart: GLA Economics adaptation of ILO (2025) approach • Source: ONS Annual Population Survey - Pooled Annual (2022-2024) • Created with Datawrapper

Figure A4.8: London's central business district accounts for the majority of workers at all levels of exposure, although other regions have disproportionate shares in level 4

Share of workers in each GenAI exposure level by sub-regional partnership (SRP) areas

London | 2022-2024 employment estimates

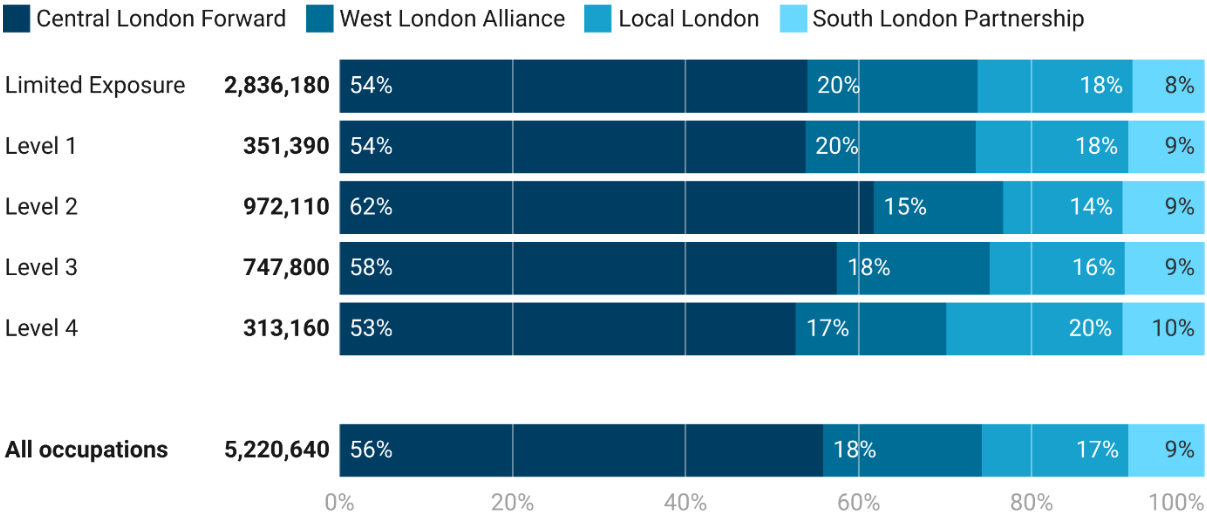


Chart: GLA Economics adaptation of ILO (2025) approach • Source: ONS Annual Population Survey - Pooled Annual (2022-2024) • Created with Datawrapper

Appendix 5: UK SOC 2020 GenAI exposure levels

Exposure levels for UK SOC 2020 4-digit unit groups are derived by cross-walking from the ILO's ISCO-08 4-digit estimates (Gmyrek et al., 2025). As the two taxonomies differ in scope and granularity, mappings are not always one-to-one, as set out in Appendix 3. While care has been taken to assign levels transparently and consistently, some measurement noise is inevitable in specific occupational areas.

In total, 120 of the 412 SOC 2020 occupations were identified as being potentially exposed to the capabilities of GenAI, of which 16 are Level 4, 34 are Level 3, 47 are Level 2 and 23 are Level 1. The full SOC tables and associated exposure levels are set out in the table below.

Table A5.1: Estimated GenAI exposure levels for all UK SOC 4-digit occupations

SOC 2020 (4-digit code)	**SOC 2020 occupation name**	**GenAI Exposure** *(Cross-walked from ILO 2025)*
2141	Web design professionals	Level 4
3531	Brokers	Level 4
4111	National government administrative occupations	Level 4
4112	Local government administrative occupations	Level 4
4113	Officers of non-governmental organisations	Level 4
4121	Credit controllers	Level 4
4122	Book-keepers, payroll managers and wages clerks	Level 4
4124	Finance officers	Level 4
4129	Financial administrative occupations n.e.c.	Level 4
4132	Pensions and insurance clerks and assistants	Level 4
4136	Human resources administrative occupations	Level 4
4151	Sales administrators	Level 4
4152	Data entry administrators	Level 4
4159	Other administrative occupations n.e.c.	Level 4
4217	Typists and related keyboard occupations	Level 4
7113	Telephone salespersons	Level 4
2131	IT project managers	Level 3
2132	IT managers	Level 3
2134	Programmers and software development professionals	Level 3
2137	IT network professionals	Level 3
2421	Chartered and certified accountants	Level 3
2422	Finance and investment analysts and advisers	Level 3
2423	Taxation experts	Level 3
2433	Actuaries, economists and statisticians	Level 3
2471	Librarians	Level 3
2491	Newspaper and periodical editors	Level 3
2492	Newspaper and periodical journalists and reporters	Level 3
3133	Database administrators and web content technicians	Level 3
3412	Authors, writers and translators	Level 3
3532	Insurance underwriters	Level 3
3533	Financial and accounting technicians	Level 3
3542	Importers and exporters	Level 3
3544	Data analysts	Level 3
3552	Business sales executives	Level 3
3554	Marketing associate professionals	Level 3
4123	Bank and post-office clerks	Level 3
4131	Records clerks and assistants	Level 3
4134	Transport and distribution clerks and assistants	Level 3
4211	Medical secretaries	Level 3

4212	Legal secretaries	Level 3
4213	School secretaries	Level 3
4214	Company secretaries and administrators	Level 3
4215	Personal assistants and other secretaries	Level 3
4216	Receptionists	Level 3
6212	Travel agents	Level 3
7211	Call and contact centre occupations	Level 3
7212	Telephonists	Level 3
7213	Communication operators	Level 3
7214	Market research interviewers	Level 3
7219	Customer service occupations n.e.c.	Level 3
1132	Marketing, sales and advertising directors	Level 2
1137	Information technology directors	Level 2
1150	Managers and directors in retail and wholesale	Level 2
1231	Health care practice managers	Level 2
2112	Biological scientists	Level 2
2115	Social and humanities scientists	Level 2
2119	Natural and social science professionals n.e.c.	Level 2
2124	Electronics engineers	Level 2
2133	IT business analysts, architects and systems designers	Level 2
2135	Cyber security professionals	Level 2
2136	IT quality and testing professionals	Level 2
2139	Information technology professionals n.e.c.	Level 2
2142	Graphic and multimedia designers	Level 2
2162	Other researchers, unspecified discipline	Level 2
2431	Management consultants and business analysts	Level 2
2432	Marketing and commercial managers	Level 2
2439	Business, research and administrative professionals n.e.c.	Level 2
2440	Business and financial project management professionals	Level 2
2454	Chartered surveyors	Level 2
2472	Archivists and curators	Level 2
2482	Quality assurance and regulatory professionals	Level 2
2493	Public relations professionals	Level 2
2494	Advertising accounts managers and creative directors	Level 2
3131	IT operations technicians	Level 2
3132	IT user support technicians	Level 2
3534	Financial accounts managers	Level 2
3541	Estimators, valuers and assessors	Level 2
3543	Project support officers	Level 2
3549	Business associate professionals n.e.c.	Level 2
3556	Sales accounts and business development managers	Level 2
3557	Events managers and organisers	Level 2
3571	Human resources and industrial relations officers	Level 2
3572	Careers advisers and vocational guidance specialists	Level 2
3573	Information technology trainers	Level 2
3574	Other vocational and industrial trainers	Level 2
4135	Library clerks and assistants	Level 2
4141	Office managers	Level 2
4142	Office supervisors	Level 2
4143	Customer service managers	Level 2
7121	Collector salespersons and credit agents	Level 2
7122	Debt, rent and other cash collectors	Level 2
7123	Roundspersons and van salespersons	Level 2
7129	Sales related occupations n.e.c.	Level 2
7131	Shopkeepers and owners - retail and wholesale	Level 2
7220	Customer service supervisors	Level 2
9211	Postal workers, mail sorters and messengers	Level 2

9219	Elementary administration occupations n.e.c.	Level 2
1221	Hotel and accommodation managers and proprietors	Level 1
1225	Travel agency managers and proprietors	Level 1
1255	Managers and directors in the creative industries	Level 1
2113	Biochemists and biomedical scientists	Level 1
2114	Physical scientists	Level 1
2224	Psychotherapists and cognitive behaviour therapists	Level 1
2225	Clinical psychologists	Level 1
2226	Other psychologists	Level 1
2323	Education advisers and school inspectors	Level 1
2419	Legal professionals n.e.c.	Level 1
2434	Business and related research professionals	Level 1
3111	Laboratory technicians	Level 1
3417	Photographers, audio-visual and broadcasting equipment operators	Level 1
3520	Legal associate professionals	Level 1
3553	Merchandisers	Level 1
5421	Pre-press technicians	Level 1
6250	Bed and breakfast and guest house owners and proprietors	Level 1
7111	Sales and retail assistants	Level 1
7112	Retail cashiers and check-out operators	Level 1
7114	Pharmacy and optical dispensing assistants	Level 1
7115	Vehicle and parts salespersons and advisers	Level 1
7125	Visual merchandisers and related occupations	Level 1
8213	Taxi and cab drivers and chauffeurs	Level 1
1111	Chief executives and senior officials	Limited Exposure
1121	Production managers and directors in manufacturing	Limited Exposure
1122	Production managers and directors in construction	Limited Exposure
1123	Production managers and directors in mining and energy	Limited Exposure
1131	Financial managers and directors	Limited Exposure
1133	Public relations and communications directors	Limited Exposure
1134	Purchasing managers and directors	Limited Exposure
1135	Charitable organisation managers and directors	Limited Exposure
1136	Human resource managers and directors	Limited Exposure
1139	Functional managers and directors n.e.c.	Limited Exposure
1140	Directors in logistics, warehousing and transport	Limited Exposure
1163	Senior officers in fire, ambulance, prison and related services	Limited Exposure
1171	Health services and public health managers and directors	Limited Exposure
1172	Social services managers and directors	Limited Exposure
1211	Managers and proprietors in agriculture and horticulture	Limited Exposure
1212	Managers and proprietors in forestry, fishing and related services	Limited Exposure
1222	Restaurant and catering establishment managers and proprietors	Limited Exposure
1223	Publicans and managers of licensed premises	Limited Exposure
1224	Leisure and sports managers	Limited Exposure
1232	Residential, day and domiciliary care managers and proprietors	Limited Exposure
1233	Early education and childcare services proprietors	Limited Exposure
1241	Managers in transport and distribution	Limited Exposure
1242	Managers in storage and warehousing	Limited Exposure
1243	Managers in logistics	Limited Exposure
1251	Property, housing and estate managers	Limited Exposure
1252	Garage managers and proprietors	Limited Exposure
1253	Hairdressing and beauty salon managers and proprietors	Limited Exposure
1254	Waste disposal and environmental services managers	Limited Exposure
1256	Betting shop and gambling establishment managers	Limited Exposure
1257	Hire services managers and proprietors	Limited Exposure
1258	Directors in consultancy services	Limited Exposure
1259	Managers and proprietors in other services n.e.c.	Limited Exposure
2111	Chemical scientists	Limited Exposure

2125	Production and process engineers	Limited Exposure
2126	Aerospace engineers	Limited Exposure
2151	Conservation professionals	Limited Exposure
2152	Environment professionals	Limited Exposure
2161	Research and development (R&D) managers	Limited Exposure
2221	Physiotherapists	Limited Exposure
2237	Other nursing professionals	Limited Exposure
2251	Pharmacists	Limited Exposure
2311	Higher education teaching professionals	Limited Exposure
2312	Further education teaching professionals	Limited Exposure
2317	Teachers of English as a foreign language	Limited Exposure
2319	Teaching professionals n.e.c.	Limited Exposure
2321	Head teachers and principals	Limited Exposure
2322	Education managers	Limited Exposure
2324	Early education and childcare services managers	Limited Exposure
2329	Other educational professionals n.e.c	Limited Exposure
2412	Solicitors and lawyers	Limited Exposure
2435	Professional/Chartered company secretaries	Limited Exposure
2451	Architects	Limited Exposure
2455	Construction project managers and related professionals	Limited Exposure
2481	Quality control and planning engineers	Limited Exposure
3112	Electrical and electronics technicians	Limited Exposure
3120	CAD, drawing and architectural technicians	Limited Exposure
3212	Pharmaceutical technicians	Limited Exposure
3219	Health associate professionals n.e.c.	Limited Exposure
3221	Youth and community workers	Limited Exposure
3223	Housing officers	Limited Exposure
3229	Welfare and housing associate professionals n.e.c.	Limited Exposure
3231	Higher level teaching assistants	Limited Exposure
3319	Protective service associate professionals n.e.c.	Limited Exposure
3413	Actors, entertainers and presenters	Limited Exposure
3416	Arts officers, producers and directors	Limited Exposure
3421	Interior designers	Limited Exposure
3422	Clothing, fashion and accessories designers	Limited Exposure
3429	Design occupations n.e.c.	Limited Exposure
3432	Sports coaches, instructors and officials	Limited Exposure
3551	Buyers and procurement officers	Limited Exposure
3555	Estate agents and auctioneers	Limited Exposure
3560	Public services associate professionals	Limited Exposure
4133	Stock control clerks and assistants	Limited Exposure
5113	Gardeners and landscape gardeners	Limited Exposure
5242	Telecoms and related network installers and repairers	Limited Exposure
5243	TV, video and audio servicers and repairers	Limited Exposure
5244	Computer system and equipment installers and servicers	Limited Exposure
5250	Skilled metal, electrical and electronic trades supervisors	Limited Exposure
5436	Catering and bar managers	Limited Exposure
6131	Nursing auxiliaries and assistants	Limited Exposure
6134	Houseparents and residential wardens	Limited Exposure
6135	Care workers and home carers	Limited Exposure
6136	Senior care workers	Limited Exposure
6214	Rail travel assistants	Limited Exposure
6219	Leisure and travel service occupations n.e.c.	Limited Exposure
6232	Caretakers	Limited Exposure
6312	Parking and civil enforcement occupations	Limited Exposure
7124	Market and street traders and assistants	Limited Exposure
7132	Sales supervisors - retail and wholesale	Limited Exposure
8131	Paper and wood machine operatives	Limited Exposure

8141	Assemblers (electrical and electronic products)	Limited Exposure
8142	Assemblers (vehicles and metal goods)	Limited Exposure
8143	Routine inspectors and testers	Limited Exposure
8144	Weighers, graders and sorters	Limited Exposure
8149	Assemblers and routine operatives n.e.c.	Limited Exposure
8211	Large goods vehicle drivers	Limited Exposure
8214	Delivery drivers and couriers	Limited Exposure
9233	Exam invigilators	Limited Exposure
9264	Waiters and waitresses	Limited Exposure
1112	Elected officers and representatives	Limited Exposure
1161	Officers in armed forces	Limited Exposure
1162	Senior police officers	Limited Exposure
2121	Civil engineers	Limited Exposure
2122	Mechanical engineers	Limited Exposure
2123	Electrical engineers	Limited Exposure
2127	Engineering project managers and project engineers	Limited Exposure
2129	Engineering professionals n.e.c.	Limited Exposure
2211	Generalist medical practitioners	Limited Exposure
2212	Specialist medical practitioners	Limited Exposure
2222	Occupational therapists	Limited Exposure
2223	Speech and language therapists	Limited Exposure
2229	Therapy professionals n.e.c.	Limited Exposure
2231	Midwifery nurses	Limited Exposure
2232	Community nurses	Limited Exposure
2233	Specialist nurses	Limited Exposure
2234	Nurse practitioners	Limited Exposure
2235	Mental health nurses	Limited Exposure
2236	Children's nurses	Limited Exposure
2240	Veterinarians	Limited Exposure
2252	Optometrists	Limited Exposure
2253	Dental practitioners	Limited Exposure
2254	Medical radiographers	Limited Exposure
2255	Paramedics	Limited Exposure
2256	Podiatrists	Limited Exposure
2259	Other health professionals n.e.c.	Limited Exposure
2313	Secondary education teaching professionals	Limited Exposure
2314	Primary education teaching professionals	Limited Exposure
2315	Nursery education teaching professionals	Limited Exposure
2316	Special needs education teaching professionals	Limited Exposure
2411	Barristers and judges	Limited Exposure
2452	Chartered architectural technologists, and planning officers	Limited Exposure
2453	Quantity surveyors	Limited Exposure
2461	Social workers	Limited Exposure
2462	Probation officers	Limited Exposure
2463	Clergy	Limited Exposure
2464	Youth work professionals	Limited Exposure
2469	Welfare professionals n.e.c.	Limited Exposure
2483	Environmental health professionals	Limited Exposure
3113	Engineering technicians	Limited Exposure
3114	Building and civil engineering technicians	Limited Exposure
3115	Quality assurance technicians	Limited Exposure
3116	Planning, process and production technicians	Limited Exposure
3119	Science, engineering and production technicians n.e.c.	Limited Exposure
3211	Dispensing opticians	Limited Exposure
3213	Medical and dental technicians	Limited Exposure
3214	Complementary health associate professionals	Limited Exposure
3222	Child and early years officers	Limited Exposure

3224	Counsellors	Limited Exposure
3232	Early education and childcare practitioners	Limited Exposure
3240	Veterinary nurses	Limited Exposure
3311	Non-commissioned officers and other ranks	Limited Exposure
3312	Police officers (sergeant and below)	Limited Exposure
3313	Fire service officers (watch manager and below)	Limited Exposure
3314	Prison service officers (below principal officer)	Limited Exposure
3411	Artists	Limited Exposure
3414	Dancers and choreographers	Limited Exposure
3415	Musicians	Limited Exposure
3431	Sports players	Limited Exposure
3433	Fitness and wellbeing instructors	Limited Exposure
3511	Aircraft pilots and air traffic controllers	Limited Exposure
3512	Ship and hovercraft officers	Limited Exposure
3581	Inspectors of standards and regulations	Limited Exposure
3582	Health and safety managers and officers	Limited Exposure
5111	Farmers	Limited Exposure
5112	Horticultural trades	Limited Exposure
5114	Groundsmen and greenkeepers	Limited Exposure
5119	Agricultural and fishing trades n.e.c.	Limited Exposure
5211	Sheet metal workers	Limited Exposure
5212	Metal plate workers, smiths, moulders and related occupations	Limited Exposure
5213	Welding trades	Limited Exposure
5214	Pipe fitters	Limited Exposure
5221	Metal machining setters and setter-operators	Limited Exposure
5222	Tool makers, tool fitters and markers-out	Limited Exposure
5223	Metal working production and maintenance fitters	Limited Exposure
5224	Precision instrument makers and repairers	Limited Exposure
5225	Air-conditioning and refrigeration installers and repairers	Limited Exposure
5231	Vehicle technicians, mechanics and electricians	Limited Exposure
5232	Vehicle body builders and repairers	Limited Exposure
5233	Vehicle paint technicians	Limited Exposure
5234	Aircraft maintenance and related trades	Limited Exposure
5235	Boat and ship builders and repairers	Limited Exposure
5236	Rail and rolling stock builders and repairers	Limited Exposure
5241	Electricians and electrical fitters	Limited Exposure
5245	Security system installers and repairers	Limited Exposure
5246	Electrical service and maintenance mechanics and repairers	Limited Exposure
5249	Electrical and electronic trades n.e.c.	Limited Exposure
5311	Steel erectors	Limited Exposure
5312	Stonemasons and related trades	Limited Exposure
5313	Bricklayers	Limited Exposure
5314	Roofers, roof tilers and slaters	Limited Exposure
5315	Plumbers & heating and ventilating installers and repairers	Limited Exposure
5316	Carpenters and joiners	Limited Exposure
5317	Glaziers, window fabricators and fitters	Limited Exposure
5319	Construction and building trades n.e.c.	Limited Exposure
5321	Plasterers	Limited Exposure
5322	Floorers and wall tilers	Limited Exposure
5323	Painters and decorators	Limited Exposure
5330	Construction and building trades supervisors	Limited Exposure
5411	Upholsterers	Limited Exposure
5412	Footwear and leather working trades	Limited Exposure
5413	Tailors and dressmakers	Limited Exposure
5419	Textiles, garments and related trades n.e.c.	Limited Exposure
5422	Printers	Limited Exposure
5423	Print finishing and binding workers	Limited Exposure

5431	Butchers	Limited Exposure
5432	Bakers and flour confectioners	Limited Exposure
5433	Fishmongers and poultry dressers	Limited Exposure
5434	Chefs	Limited Exposure
5435	Cooks	Limited Exposure
5441	Glass and ceramics makers, decorators and finishers	Limited Exposure
5442	Furniture makers and other craft woodworkers	Limited Exposure
5443	Florists	Limited Exposure
5449	Other skilled trades n.e.c.	Limited Exposure
6111	Early education and childcare assistants	Limited Exposure
6112	Teaching assistants	Limited Exposure
6113	Educational support assistants	Limited Exposure
6114	Childminders	Limited Exposure
6116	Nannies and au pairs	Limited Exposure
6117	Playworkers	Limited Exposure
6121	Pest control officers	Limited Exposure
6129	Animal care services occupations n.e.c.	Limited Exposure
6132	Ambulance staff (excluding paramedics)	Limited Exposure
6133	Dental nurses	Limited Exposure
6137	Care escorts	Limited Exposure
6138	Undertakers, mortuary and crematorium assistants	Limited Exposure
6211	Sports and leisure assistants	Limited Exposure
6213	Air travel assistants	Limited Exposure
6221	Hairdressers and barbers	Limited Exposure
6222	Beauticians and related occupations	Limited Exposure
6231	Housekeepers and related occupations	Limited Exposure
6240	Cleaning and housekeeping managers and supervisors	Limited Exposure
6311	Police community support officers	Limited Exposure
8111	Food, drink and tobacco process operatives	Limited Exposure
8112	Textile process operatives	Limited Exposure
8113	Chemical and related process operatives	Limited Exposure
8114	Plastics process operatives	Limited Exposure
8115	Metal making and treating process operatives	Limited Exposure
8119	Process operatives n.e.c.	Limited Exposure
8120	Metal working machine operatives	Limited Exposure
8132	Mining and quarry workers and related operatives	Limited Exposure
8133	Energy plant operatives	Limited Exposure
8134	Water and sewerage plant operatives	Limited Exposure
8135	Printing machine assistants	Limited Exposure
8139	Plant and machine operatives n.e.c.	Limited Exposure
8145	Tyre, exhaust and windscreen fitters	Limited Exposure
8146	Sewing machinists	Limited Exposure
8151	Scaffolders, stagers and riggers	Limited Exposure
8152	Road construction operatives	Limited Exposure
8153	Rail construction and maintenance operatives	Limited Exposure
8159	Construction operatives n.e.c.	Limited Exposure
8160	Production, factory and assembly supervisors	Limited Exposure
8212	Bus and coach drivers	Limited Exposure
8215	Driving instructors	Limited Exposure
8219	Road transport drivers n.e.c.	Limited Exposure
8221	Crane drivers	Limited Exposure
8222	Fork-lift truck drivers	Limited Exposure
8229	Mobile machine drivers and operatives n.e.c.	Limited Exposure
8231	Train and tram drivers	Limited Exposure
8232	Marine and waterways transport operatives	Limited Exposure
8233	Air transport operatives	Limited Exposure
8234	Rail transport operatives	Limited Exposure

8239	Other drivers and transport operatives n.e.c.	Limited Exposure
9111	Farm workers	Limited Exposure
9112	Forestry and related workers	Limited Exposure
9119	Fishing and other elementary agriculture occupations n.e.c.	Limited Exposure
9121	Groundworkers	Limited Exposure
9129	Elementary construction occupations n.e.c.	Limited Exposure
9131	Industrial cleaning process occupations	Limited Exposure
9132	Packers, bottlers, canners and fillers	Limited Exposure
9139	Elementary process plant occupations n.e.c.	Limited Exposure
9221	Window cleaners	Limited Exposure
9222	Street cleaners	Limited Exposure
9223	Cleaners and domestics	Limited Exposure
9224	Launderers, dry cleaners and pressers	Limited Exposure
9225	Refuse and salvage occupations	Limited Exposure
9226	Vehicle valets and cleaners	Limited Exposure
9229	Elementary cleaning occupations n.e.c.	Limited Exposure
9231	Security guards and related occupations	Limited Exposure
9232	School midday and crossing patrol occupations	Limited Exposure
9241	Shelf fillers	Limited Exposure
9249	Elementary sales occupations n.e.c.	Limited Exposure
9251	Elementary storage supervisors	Limited Exposure
9252	Warehouse operatives	Limited Exposure
9253	Delivery operatives	Limited Exposure
9259	Elementary storage occupations n.e.c.	Limited Exposure
9261	Bar and catering supervisors	Limited Exposure
9262	Hospital porters	Limited Exposure
9263	Kitchen and catering assistants	Limited Exposure
9265	Bar staff	Limited Exposure
9266	Coffee shop workers	Limited Exposure
9267	Leisure and theme park attendants	Limited Exposure
9269	Other elementary services occupations n.e.c.	Limited Exposure

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