

The Default Setting

Women, AI, and
the Future of Work in
UK Manufacturing

Noetic AI
Innovation Policy Lab

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AI policy is a rapidly evolving field; the report reflects frameworks, policies and laws in force as of August 2026.

About this report

Commissioned by Beko UK and Ireland and produced independently by Noetic AI, this report examines how artificial intelligence (AI) may shape women’s career opportunities in UK manufacturing through changes to occupational tasks, AI-mediated employment systems, and workers’ experiences of the technology. It brings together a survey of 890 UK manufacturing professionals on AI use, experience of bias, and its perceived social and economic effects; an analysis combining the International Labour Organization’s occupational AI exposure data with Office for National Statistics employment data; and a review of wider evidence on AI, gender, and work. Its purpose is to support informed discussion and practical action as manufacturers adopt and govern AI.

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About Noetic AI

Noetic AI is an independent AI and emerging technology policy intelligence lab and advisory practice, founded in 2025 by Zoi Roupakia. It works with governments, international organisations, and mission-led institutions on AI policy, innovation systems, industrial transformation, and public sector adoption, translating complex technology questions into evidence, strategy, and practical policy tools.

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Foreword

Teresa Arbuckle

Managing Director of Beko UK and Ireland

Artificial intelligence is changing the world of work rapidly, and manufacturing businesses have much to gain from it. Used well, AI has the potential to support productivity, innovation and more efficient ways of working, empowering people to focus on higher-value activities and do their jobs better. But as we embrace that opportunity, we also need to consider who will be most affected by change and ensure adoption is inclusive and existing inequalities are not reinforced.

Indeed, gender bias in AI has been well documented, which is why Beko commissioned this research: to better understand how responsible use of AI could shape the manufacturing workforce in a fair and inclusive manner. The manufacturing industry has made progress in improving female representation, supported by Government targets to increase female representation to 35% by 2035. However, women still account for less than a third of the workforce. Driving greater representation is something I am passionate about, and at Beko, we have worked hard to build a culture in which women feel included and supported through our Diversity, Equality and Inclusion Committee, Women in Leadership group, and development and training programmes focused on progression and equal opportunity. As the world of work changes, I believe it is vital this progress is carried responsibly into the new systems and technologies we adopt.

This report shows women are disproportionately represented in some of the occupations with the greatest potential exposure to generative AI, particularly administrative and customer-facing roles that often provide important routes into manufacturing businesses. It also finds that women report greater concern about the potential effects of AI bias on pay, job opportunities and wellbeing. Poorer outcomes are not inevitable, but these findings underline why the decisions manufacturing businesses make matter now.

Importantly, this report does not conclude that AI is taking women's jobs in manufacturing. Rather, it highlights AI adoption across manufacturing remains at a relatively early stage creating opportunity for businesses to shape how the technology is introduced, governed and integrated into work. The choices organisations make today will play a significant role in determining whether AI helps widen opportunities and participation in the years ahead.

Across our wider business, we are continuing to strengthen our approach to responsible AI, with strong human oversight and a focus on fairness, transparency and accountability. As AI develops employers have an opportunity to involve women and affected employees in work redesign, support ongoing upskilling and reskilling, test systems for fairness and monitor whether the benefits of AI are being shared equitably. Encouragingly, the research also found common ground among employees with significant majority of both women and men wanting AI systems to be more transparent.

If we get this right, AI can support both the future competitiveness of UK manufacturing and a more inclusive workforce. We need to ensure that AI adoption widens access to skills, fair treatment, participation and progression, building on the progress already made rather than allowing existing inequalities to become the default setting for the next era of industry.

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List of abbreviations

AAAI	Association for the Advancement of Artificial Intelligence
ACM	Association for Computing Machinery
AI	Artificial intelligence
AI RMF	Artificial Intelligence Risk Management Framework
APS	Annual Population Survey
ASHE	Annual Survey of Hours and Earnings
AUROC	Area Under the Receiver Operating Characteristic curve
BIS	Bank for International Settlements
CHI	Conference on Human Factors in Computing Systems
CRM	Customer relationship management
DPIA	Data protection impact assessment
DSIT	Department for Science, Innovation and Technology
EAAMO	ACM Conference on Equity and Access in Algorithms, Mechanisms, and Optimization
ECB	European Central Bank
EMNLP	Conference on Empirical Methods in Natural Language Processing
ERP	Enterprise resource planning
EU	European Union
FAT*	Conference on Fairness, Accountability, and Transparency (now FAccT)
FRVT	Face Recognition Vendor Test
GDPR	General Data Protection Regulation
GenAI	Generative artificial intelligence
GLA	Greater London Authority
GPT	Generative pre-trained transformer
HAI	Human-centred artificial intelligence
HCI	Human–computer interaction
HR	Human resources
ICO	Information Commissioner’s Office
ICSE	International Conference on Software Engineering
IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
ILO	International Labour Organization
ILOSTAT	ILO Department of Statistics

IMF	International Monetary Fund
IRCAI	International Research Centre on Artificial Intelligence
ISCO-08	International Standard Classification of Occupations, 2008 revision
ISEC	Integrated STEM Education Conference
ISIC	International Standard Industrial Classification of All Economic Activities
ISO	International Organization for Standardization
IT	Information technology
JRC	Joint Research Centre (European Commission)
LFS	Labour Force Survey
LLM	Large language model
MTC	Manufacturing Technology Centre
NAACL	North American Chapter of the Association for Computational Linguistics
NBER	National Bureau of Economic Research
NIST	National Institute of Standards and Technology
Nomis	ONS official census and labour market statistics service
OECD	Organisation for Economic Co-operation and Development
ONS	Office for National Statistics
OT	Operational technology
PLC	Programmable logic controller
PNAS	Proceedings of the National Academy of Sciences
SIC 2007	Standard Industrial Classification, 2007 revision
SME	Small and medium-sized enterprise
SOC2020	Standard Occupational Classification, 2020 revision
SOC4	Four-digit Standard Occupational Classification code
STEM	Science, technology, engineering, and mathematics
UK	United Kingdom
UNESCO	United Nations Educational, Scientific and Cultural Organization
US	United States

Executive summary

UK manufacturing is entering the artificial intelligence (AI) transition from an unequal – “default” – starting point. Women accounted for 27.8% of manufacturing employment in 2025, and the median hourly gender pay gap in the sector stood at 14.7%.¹ At the same time, *The UK's Modern Industrial Strategy*, through its *Advanced Manufacturing Sector Plan*, has set a target of raising women's participation in advanced manufacturing to 35% by 2035, while the *AI Opportunities Action Plan* and the AI Champion for Advanced Manufacturing's “Scan–Pilot–Scale” pathway aim to accelerate AI adoption across the sector.² Whether these two ambitions reinforce each other will depend on how AI changes work, how workers are involved, and how its benefits and risks are distributed.

This report examines how the growing use of AI, and generative AI (GenAI) in particular, could reshape women's participation, experience, and progression in UK manufacturing. It considers three connected pathways: changes to the tasks and occupations in which women and men are concentrated; the growing use of AI-mediated systems in recruitment, career development, and workplace decision-making; and differences in how women and men engage with, experience, and perceive AI, including concerns about bias, fairness, and trust.

By bringing together the International Labour Organization's (ILO's) occupational AI exposure data,³ combined with Office for National Statistics (ONS) employment data, an original survey of 890 UK manufacturing professionals conducted by Noetic AI,⁴ and a review of the wider literature on AI, gender, and employment, the report identifies where gendered risks and opportunities may arise as adoption expands. In particular, the report aims to understand what these patterns imply for manufacturers looking to introduce AI in ways that support productivity, workforce participation, and more equitable career opportunities. Adoption is at an early stage – only 2% of manufacturers have AI widely embedded, and 83% of those using AI apply it in back-office functions⁵ – which means the distributional consequences of AI in the sector are still open, and many of the choices that will shape how AI affects work and opportunities in manufacturing are still being made.

What the evidence shows

Women in UK manufacturing are more likely than men to work in occupations exposed to generative AI – 41.1% compared with 23.6%

¹ ONS, Annual Population Survey workplace analysis, January–December 2025, UK manufacturing (SIC 2007 Section C); ONS, Annual Survey of Hours and Earnings, Table 21.12, Manufacturing (SIC C), all employees, median hourly pay excluding overtime, 2025 provisional.

² HM Government (2025). *The UK's Modern Industrial Strategy*. Department for Business and Trade; HM Government (2025). *Advanced Manufacturing Sector Plan*. Department for Business and Trade; Clifford, M. (2025). *AI Opportunities Action Plan*. Department for Science, Innovation and Technology; Dungey, C. (2026). *AI Adoption Plan: Advanced Manufacturing*. Department for Science, Innovation and Technology.

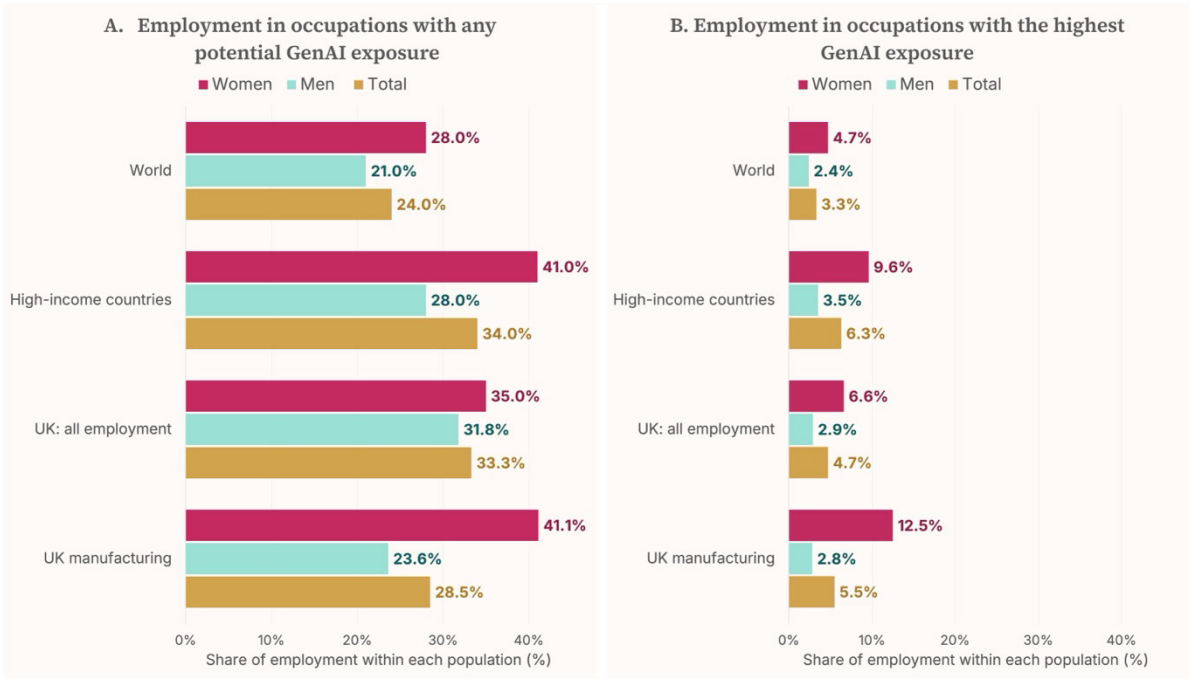
³ Gmyrek, P. et al. (2025). Generative AI and Jobs: A Refined Global Index of Occupational Exposure. *ILO Working Paper*, 140. DOI: 10.54394/HETP0387.

⁴ Roupakia, Z. (2026). *AI Bias in Manufacturing: A UK Workforce Survey*. Noetic AI.

⁵ Make UK (2026). *AI, Skills and the Future of the UK Manufacturing Sector*.

Manufacturing has lower overall GenAI exposure than the economy as a whole, but that average conceals a markedly gendered distribution. An estimated 41.1% of women’s manufacturing employment is in occupations with some exposure to GenAI, compared with 23.6% of men’s. At the highest exposure level, the disparity is sharper in relative terms: 12.5% of women compared with 2.8% of men, a ratio of more than four to one. For women, this is almost twice the UK all-employment share and above the ILO’s high-income benchmark; for men, the manufacturing and UK-wide shares are almost identical (Figure ES.1). Exposure is not a forecast of job loss: it identifies where current tools could perform or assist a substantial share of tasks, and thus where the effects of adoption decisions will be felt first.

FIGURE ES.1: ESTIMATED GENAI EXPOSURE IN UK MANUFACTURING AND WIDER LABOUR MARKET BENCHMARKS, BY GENDER



Note: Each bar uses its own population as the denominator. “Potential GenAI exposure” includes the low, moderate, significant, and highest-exposure categories.

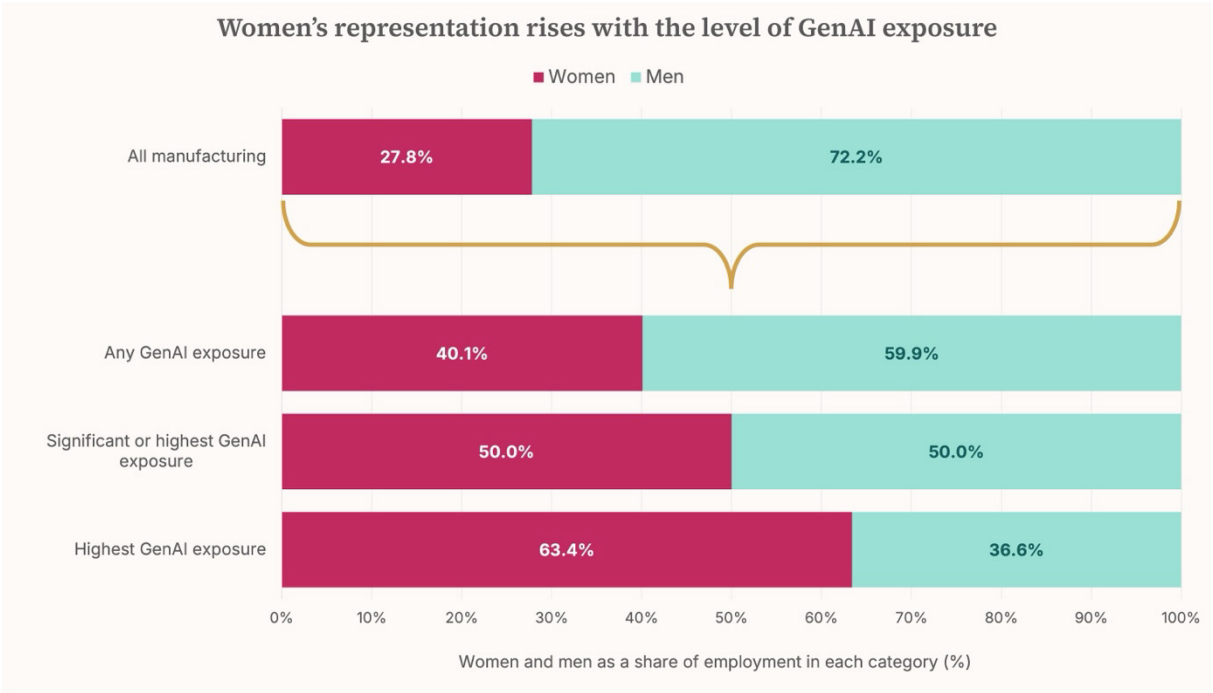
Source: World, high-income countries, and UK all employment: Gmyrek, P. et al. (2025). Generative AI and Jobs: A Refined Global Index of Occupational Exposure, *ILO Working Paper*, 140; UK manufacturing: Author’s analysis of ONS Annual Population Survey four-digit SOC2020 occupation by four-digit SIC 2007 industry data, April 2025–March 2026, scaled within SOC major groups to ONS Annual Population Survey workplace analysis T10c via Nomis, January–December 2025; ONS SOC2020 coding index (December 2025); and ILO exposure classifications from Gmyrek, P. et al. (2025). Generative AI and Jobs: A Refined Global Index of Occupational Exposure, *ILO Working Paper*, 140, Annex Table A1.

Women represent 27.8% of the manufacturing workforce but 63.4% of those in the most exposed jobs – where manufacturers are adopting AI first

The exposure gap is a product of occupational segregation. Administrative and secretarial work combines the highest concentration of exposure with one of the highest shares of women: around two-thirds of these jobs are held by women, and more than 85% of them sit in the two highest-exposure categories. Skilled trades and process, plant, and machine operative groups contain no occupations in those categories and are predominantly male. As a result, women’s share rises from 27.8% of manufacturing employment overall to 40.1% of exposed employment, 50.0% of employment

in occupations with significant or highest exposure, and 63.4% at the highest level (Figure ES.2). Current AI adoption in manufacturing is also concentrated in back-office functions⁶ such as HR, finance, and administration. The measures are not identical – the exposure analysis refers specifically to GenAI, while the adoption evidence covers AI more broadly – but together they indicate that some of the functions in which women are most strongly represented are also among those likely to experience AI-related change relatively early.

FIGURE ES.2: WOMEN'S SHARE OF UK MANUFACTURING EMPLOYMENT, BY LEVEL OF GENAI EXPOSURE



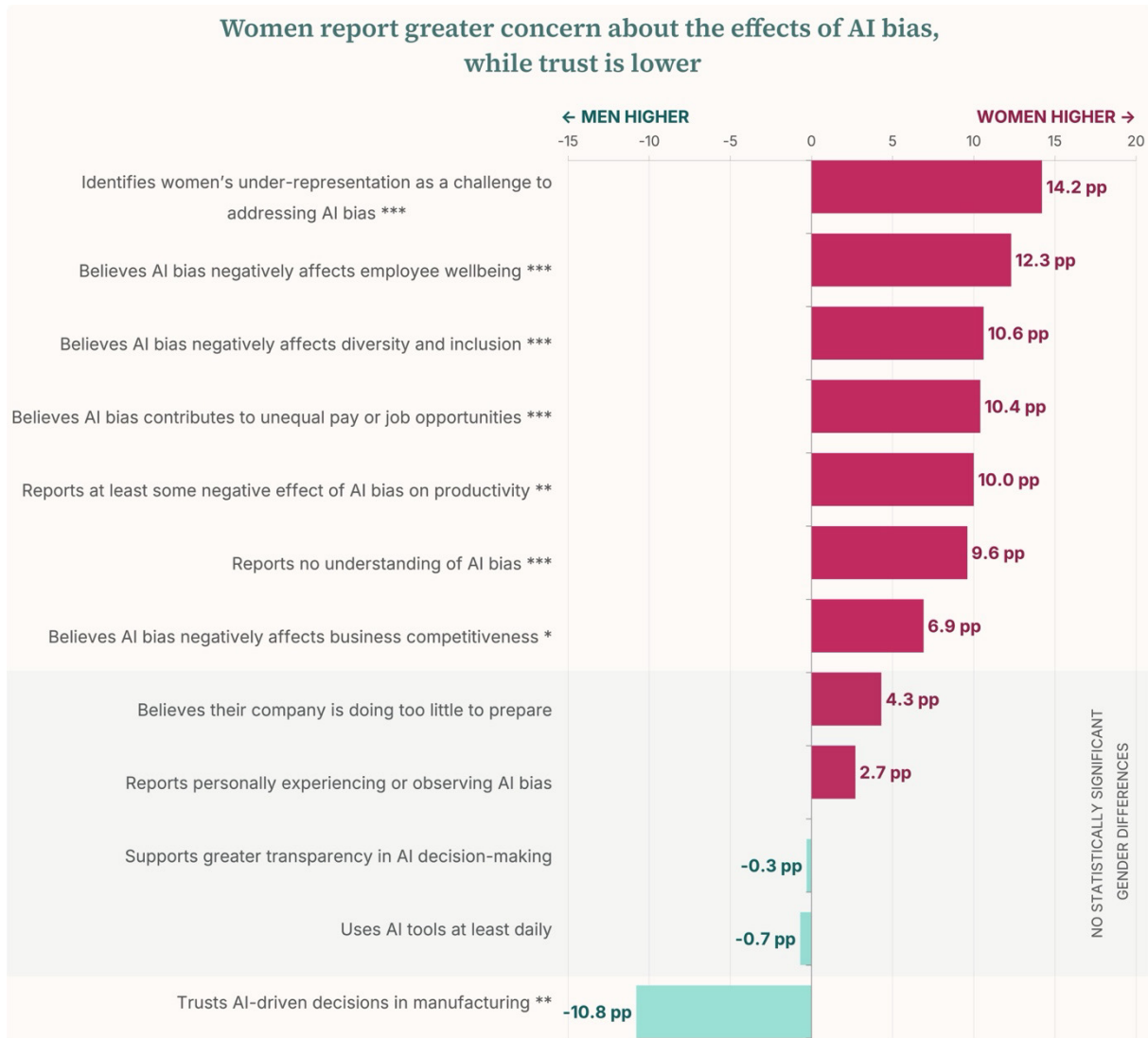
Note: “Any GenAI exposure” includes occupations classified by the ILO as having low, moderate, significant, or highest GenAI exposure. Women and men total 100% within each row. The first row shows the baseline composition of UK manufacturing employment; the three rows below progressively restrict the population to GenAI-exposed occupations.

Source: Author’s analysis of ONS Annual Population Survey four-digit SOC2020 occupation by four-digit SIC 2007 industry data, April 2025–March 2026, scaled within SOC major groups to ONS Annual Population Survey workplace analysis T10c via Nomis, January–December 2025, UK manufacturing (SIC 2007 Section C), by SOC2020 major group and sex; ONS SOC2020 coding index (December 2025); and ILO exposure classifications from Gmyrek, P. et al. (2025). Generative AI and Jobs: A Refined Global Index of Occupational Exposure, *ILO Working Paper*, 140, Annex Table A1.

⁶ Make UK (2026). *AI, Skills and the Future of the UK Manufacturing Sector*.

Women and men use AI at similar rates and encounter AI bias at similar frequencies, but women have approximately twice the odds of reporting concern about its effects on pay and job opportunities, diversity and inclusion, and wellbeing

FIGURE ES.3: SELECTED GENDER DIFFERENCES IN PERCEPTIONS OF AI BIAS ACROSS KEY INDICATORS



Note: Based on up to 886 respondents (550 men and 336 women). Bars show the percentage point difference between women and men in the proportion selecting the specified response or combined response categories. Positive values indicate a higher proportion among women; negative values indicate a higher proportion among men. The representation item was part of a multiple-response question. Statistical significance is based on chi-square tests with Yates' correction: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Items without stars show no statistically significant gender difference. For methodology, see Appendix B.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

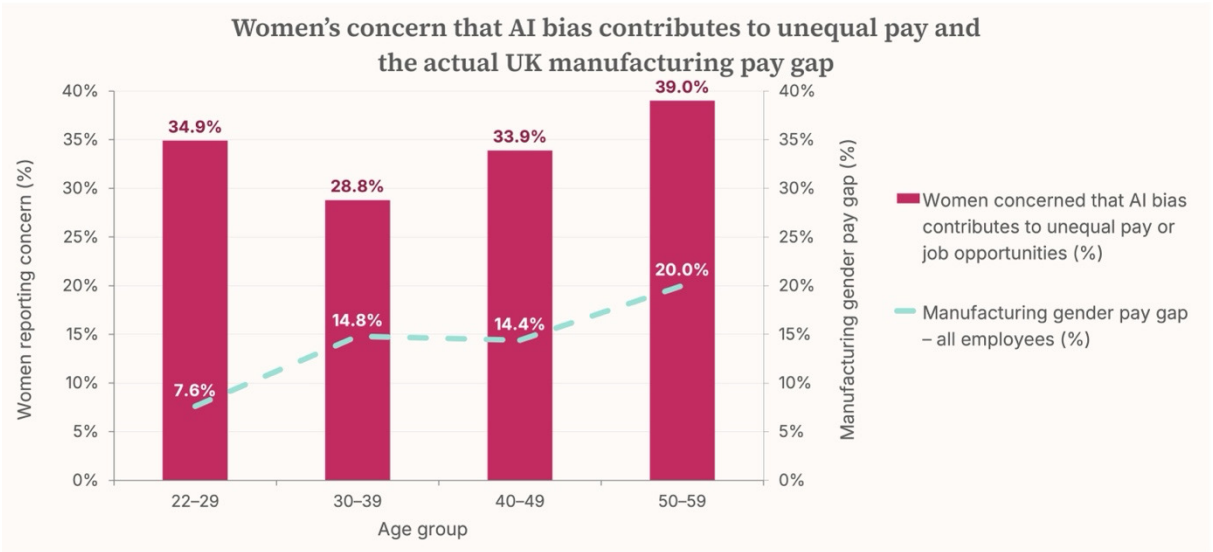
Women and men report similar levels of AI use and self-reported expertise, and similar experience of AI bias: 24.7% of women and 22.0% of men have personally experienced or observed it. The divide appears when respondents consider its effects. Women are more likely to believe AI bias negatively

affects employee wellbeing (41.1% vs 28.7%), pay or job opportunities (33.3% vs 22.9%), and diversity and inclusion (27.7% vs 17.1%). Each gap is 10 percentage points or more. The differences persist after accounting for occupational role, company size, age, and AI use and expertise, and extend to economic effects: around 55% of women, compared with 45% of men, see at least some negative effect of AI bias on productivity, and 27.1% of women, compared with 20.2% of men, on competitiveness (Figure ES.3).

Concern about AI-related pay inequality is already high among the youngest women in the workforce

Women aged 22–29 report levels of concern about AI contributing to unequal pay that come close to those of women in their 50s, despite facing a sector-wide manufacturing gender pay gap of 7.6% compared with 20.0% for women aged 50–59, a difference of more than 12 percentage points (Figure ES.4).⁷ Concern is running ahead of the pay gap currently seen for younger age groups, suggesting that expectations about fairness are present early in careers. For a sector aiming to reach 35% women by 2035, how those expectations are met may shape retention as much as recruitment.

FIGURE ES.4: WOMEN’S CONCERN ABOUT AI-BIAS-RELATED PAY INEQUALITY AND THE MANUFACTURING GENDER PAY GAP, BY AGE GROUP



Note: Based on 302 women respondents aged 22–59 with valid age data. The left axis (bars) shows the percentage of women who responded “Probably yes” and “Definitely yes” to the question, “Do you believe AI bias contributes to unequal pay or job opportunities in UK manufacturing?” The 18–21 and 60+ age groups are excluded because of the small sample sizes. Differences in concern between age groups are not statistically significant. The right axis (line) shows the median manufacturing gender pay gap. For methodology, see Appendix B.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI; ONS (2025). Annual Survey of Hours and Earnings, Table 21.12, Manufacturing (SIC C), 2025 provisional.

⁷ ONS, Annual Survey of Hours and Earnings, 2025 provisional, median hourly pay excluding overtime, Manufacturing (SIC C), by age group.

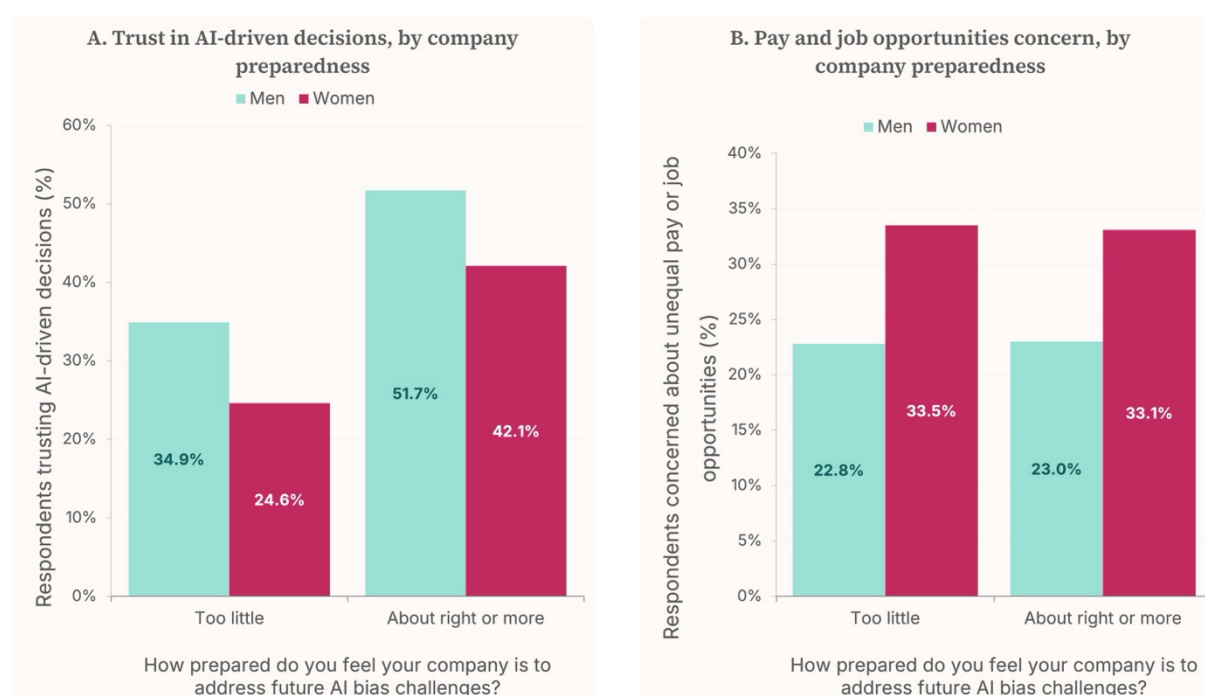
Women are less likely to trust AI-driven decisions – 32.1% compared with 42.9% of men – and the gap is widest mid-career

Women are less likely than men to trust AI-driven decisions in manufacturing (32.1% compared with 42.9%) and more likely to report no understanding of AI bias (24.1% compared with 14.5%). Both differences weaken once AI use and expertise are considered, suggesting that differences in engagement with AI may explain part of the gap in confidence and understanding. Trust is similar among the youngest respondents but the gender gap is widest among those aged 40–49. Women and men otherwise hold similar views on transparency, regulation, and whether their organisation is doing enough to prepare for AI bias challenges.

Organisational preparedness is associated with greater trust in AI-driven decisions, but not with lower fairness concern about pay and job opportunities

Perceived organisational preparedness is positively associated with trust in AI-driven decisions but not with lower concern about pay and job opportunities. Trust rises for both women and men, from around a quarter of women and a third of men among those who think their company is doing too little to prepare, to over 40% and 50% respectively among those who think it is doing enough. If preparedness reassured respondents about fairness, concern about pay and job opportunities might be expected to fall as trust rises. It does not: concern remains at around one-third among women and just under a quarter among men in both groups. Roughly half of women and men believe their company is doing too little. Greater perceived preparedness is therefore associated with greater confidence in AI, but concerns about fairness appear to require a different set of responses; the two need to proceed together (Figure ES.5).

FIGURE ES.5: TRUST IN AI-DRIVEN DECISIONS AND CONCERNS ABOUT PAY AND JOB OPPORTUNITIES, BY GENDER AND PERCEIVED COMPANY PREPAREDNESS



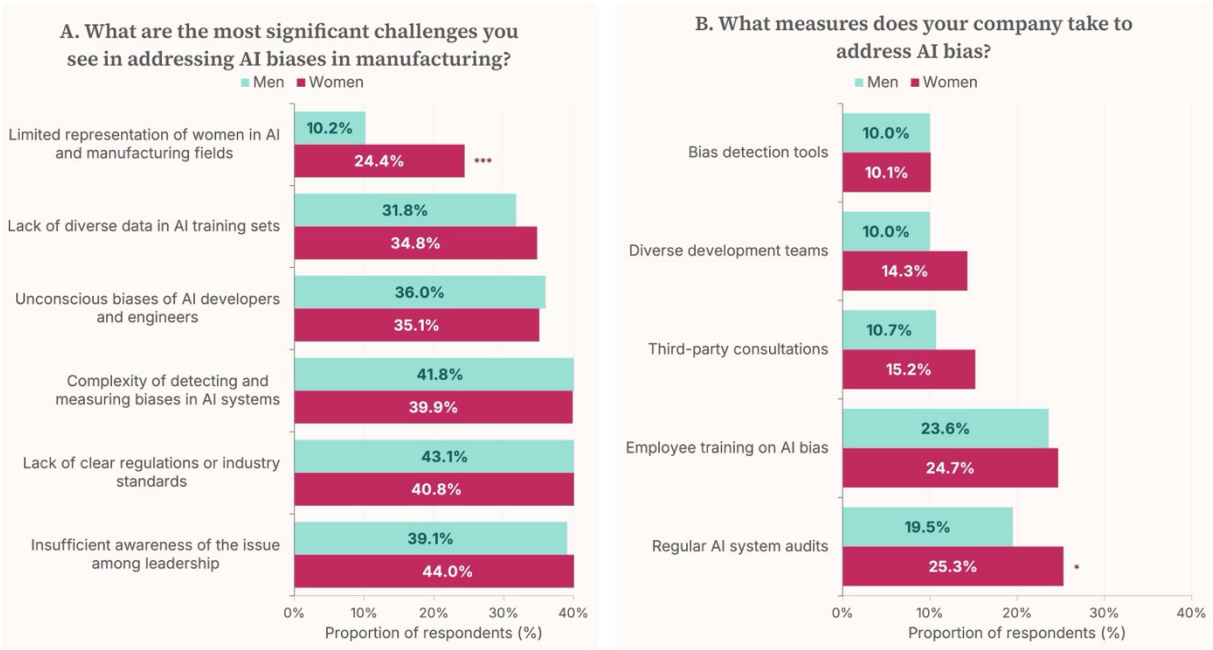
Note: Based on 886 respondents (550 men, 336 women). Panel A: respondents answering "Probably yes" or "Definitely yes" to "Do you trust AI-driven decisions in manufacturing?". Panel B: respondents answering "Probably yes" or "Definitely yes" to "Do you think AI bias contributes to unequal pay or job opportunities?". "Too little" combines "Far too little" and "Slightly too little". "About right or more" combines "Neither too much nor too little," "Slightly too much", and "Far too much". Preparedness is positively associated with trust ($r = 0.27$, *** $p < 0.001$) but not with concern about pay and job opportunities ($r = 0.02$, not significant). Subgroup sizes: Too little: 289 men, 191 women; About right or more: 261 men, 145 women. For methodology, see Appendix B.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

Women are more than twice as likely as men to see their own under-representation as a barrier to tackling AI bias, and most workers do not know what their employer is doing about it

Women and men identify broadly similar barriers to addressing AI bias, including unclear regulation, difficulty detecting bias, and insufficient leadership awareness. One difference stands out: 24.4% of women, compared with 10.2% of men, identify the limited representation of women in AI and manufacturing roles as a significant barrier. At the same time, 58% of respondents are unaware of any measures their company is taking to address AI bias. Where measures are reported, employee training is the most common (24%), followed by regular AI system audits (22%). Despite these differences, there is a strong consensus on transparency: around 87% of both women and men believe AI systems should be more transparent (Figure ES.6).

FIGURE ES.6: CHALLENGES AND MEASURES IN ADDRESSING AI BIAS, BY GENDER



Note: Based on 886 respondents (550 men, 336 women). Respondents could select more than one response; percentages therefore do not total 100%. "None that I am aware of" and "Other" responses are not shown. Panel A: gender difference is statistically significant for limited representation of women (*** $p < 0.001$). Panel B: gender difference is statistically significant for regular AI systems audits (* $p < 0.05$). All other items: no significant gender difference. For methodology, see Appendix B.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

Hiring is where AI bias is most often observed, and where the wider evidence is strongest

Hiring and recruitment is the area where survey respondents most frequently report observing AI bias, and women are more likely than men to identify flawed hiring decisions (28.3% compared with 20.5%), increased hiring costs (10.7% compared with 4.0%), and loss of talent through recruitment or promotion decisions (16.7% compared with 11.5%) as potential consequences. The wider evidence suggests something similar: a large-scale audit of open-source large language models (LLMs) found most models favoured men in callback decisions, particularly for higher-wage roles; and another found the female version of an identical candidate was rated more highly but recommended to receive a lower salary.⁸ In the UK, the Information Commissioner's Office's (ICO) 2024 audits of recruitment tools produced 296 recommendations to providers on fairness, transparency, and protected-characteristic data, and its 2026 Recruitment Rewired review calls for meaningful human involvement and fairness monitoring.⁹ Bias is not uniform across tools, which makes context-specific testing more useful to employers than any single published audit.

AI can shape women's careers at several stages; the effects are not uniformly negative, and the long-term evidence is thin

AI can influence who sees and applies for vacancies, how candidates are screened, and – after entry – how tasks, feedback, and opportunities are allocated.¹⁰ Studies in Denmark and the United States also find women less likely than men to use GenAI at work, including within similar occupations.¹¹ The evidence is not uniformly negative: some studies find productivity gains and improved relative outcomes for women, while training and worker consultation are associated with more favourable

⁸ Chaturvedi, S. and Chaturvedi, R. (2025). Who Gets the Callback? Generative AI and Gender Bias. arXiv:2504.21400; Gerszberg, N. et al. (2026). Quantifying Gender Bias in Large Language Models: When ChatGPT Becomes a Hiring Manager. arXiv:2604.00011; Nghiem, H. et al. (2024). You Gotta be a Doctor, Lin: An Investigation of Name-Based Bias of Large Language Models in Employment Recommendations. EMNLP 2024.

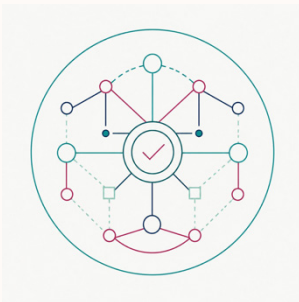
⁹ Information Commissioner's Office (2024). AI Tools in Recruitment: Audit Outcomes Report; Information Commissioner's Office (2026). Recruitment rewired: an update on the ICO's work on the fair and responsible use of automation in recruitment. <https://ico.org.uk/about-the-ico/what-we-do/recruitment-rewired/>.

¹⁰ Lambrecht, A. and Tucker, C. (2019). Algorithmic Bias? An Empirical Study of Apparent Gender-Based Discrimination in the Display of STEM Career Ads. *Management Science*, 65(7). DOI: 10.1287/mnsc.2018.3093; Imana, B. et al. (2021). Auditing for Discrimination in Algorithms Delivering Job Ads. *Proceedings of The Web Conference 2021*, 3767–3778. DOI: 10.1145/3442381.3450077; He, J. and Kang, S. (2025). Debiasing job ads by replacing masculine language increases gender diversity of applicant pools. *PNAS*, 122 (7). DOI: 10.1073/pnas.2409854122; Milanez, A. et al. (2025). Algorithmic management in the workplace: New evidence from an OECD employer survey. *OECD Artificial Intelligence Papers*, No. 31. DOI: 10.1787/287c13c4-en; Parziale, A. et al. (2026). Once Upon a Team: Investigating Bias in LLM-Driven Software Team Composition and Task Allocation. *ICSE-SEIS 2026: Proceedings of the IEEE/ACM 48th International Conference on Software Engineering*, 77–88. DOI: 10.1145/3786581.3786930.

¹¹ Humlum, A. and Vestergaard, E. (2025). The unequal adoption of ChatGPT exacerbates existing inequalities among workers. *PNAS*, 122(1). DOI: 10.1073/pnas.2414972121; Bick, A. et al. (2025). The Rapid Adoption of Generative AI. *NBER Working Paper*, 32966. DOI: 10.3386/w32966; Aldasoro, I. et al. (2024). The gen AI gender gap. *BIS Working Papers*, No. 1197. Bank for International Settlements.

experiences of AI adoption.¹² What remains largely unknown is whether access to AI tools, training, and AI-enabled work affects women's progression, pay, and retention over time, and almost none of this evidence is specific to UK manufacturing. Exposure identifies where work may change; it does not determine whether those changes widen or narrow opportunity.

Resetting the default: five areas of action for inclusive AI adoption in UK manufacturing



1. Know where AI is shaping work and workforce decisions – and govern it accordingly

FOR ORGANISATIONS

- ☐ Keep an organisation-wide view of significant AI uses affecting workers or applicants, including supplier-embedded features: purpose, tasks, groups affected, and accountable owner.
- ☐ Assess likely changes to job content, workload, autonomy, skills, and progression while adoption choices and workflows can still be changed.
- ☐ Use role redesign to widen opportunity and access to higher-value work; plan transition support where change is substantial.

FOR POLICYMAKERS

- ☐ Integrate work design, skills, and responsible AI governance into publicly supported adoption programmes.
- ☐ Provide proportionate tools and sector guidance for SMEs to assess task change, redesign work, and connect adoption with existing skills, careers, and workforce development provision.

¹² Lane, M. et al. (2023). The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers. *OECD Social, Employment and Migration Working Papers*, No. 288. DOI: 10.1787/ea0a0fe1-en; Gu, W. et al. (2025). Algorithmic Supervisor and Employee Performance. *Production and Operations Management*, 34(10). DOI: 10.1177/10591478251331095; Portell-Fonolla, S. et al. (2026). Artificial intelligence applications supporting women's career development: a scoping review. *International Journal for Educational and Vocational Guidance*. DOI: 10.1007/s10775-026-09807-0.



2. Direct training and skills support to where AI is changing work

FOR ORGANISATIONS

- ❑ Extend role-specific AI learning to administrative, clerical, customer-facing, and professional roles, not just technical specialists.
- ❑ Provide protected learning time, opportunities to practise, and access to suitable tools.
- ❑ Match support to the scale of change: upskilling within roles; reskilling, career guidance, and mobility where change is substantial.

FOR POLICYMAKERS

- ❑ Build on national programmes with manufacturing-specific, modular and work-based learning for non-technical roles experiencing task change.
- ❑ Help employers identify changing skill needs early enough for training and transition planning to precede role change.



3. Test AI systems for fair treatment before and after deployment

FOR ORGANISATIONS

- ❑ Apply stronger assurance where AI materially influences recruitment, pay, performance, progression or access to work.
- ❑ Impact-assess, test in context, monitor after deployment, and seek supplier evidence for higher-impact uses.
- ❑ Preserve meaningful human judgement, transparency, and routes to review, and define in advance who can pause or withdraw a system.

FOR POLICYMAKERS

- ❑ Translate employment, equality, data protection, and responsible AI requirements into practical manufacturing guidance.
- ❑ Build on ICO and DSIT guidance to develop manufacturing-specific procurement questions, templates, and worked examples for smaller firms.
- ❑ Align guidance so firms work from one coherent set of expectations.



4. Involve women and affected workers in AI adoption and work redesign

FOR ORGANISATIONS

- ❑ Involve women and affected workers in procurement, deployment, workflow change, and role redesign while choices remain open.
- ❑ Use consultation to understand workforce effects, not just technical risk: consider workload, autonomy, skills, and progression.
- ❑ Ensure women are represented in AI projects, testing, and oversight, and can access newly created responsibilities and internal progression routes.

FOR POLICYMAKERS

- ❑ Embed worker voice and social dialogue in publicly supported AI adoption and transition programmes.
- ❑ Use skills and careers policy to strengthen women's pathways into digital, technical, professional, and leadership roles.



5. Track whether the benefits and opportunities from AI are being shared fairly

FOR ORGANISATIONS

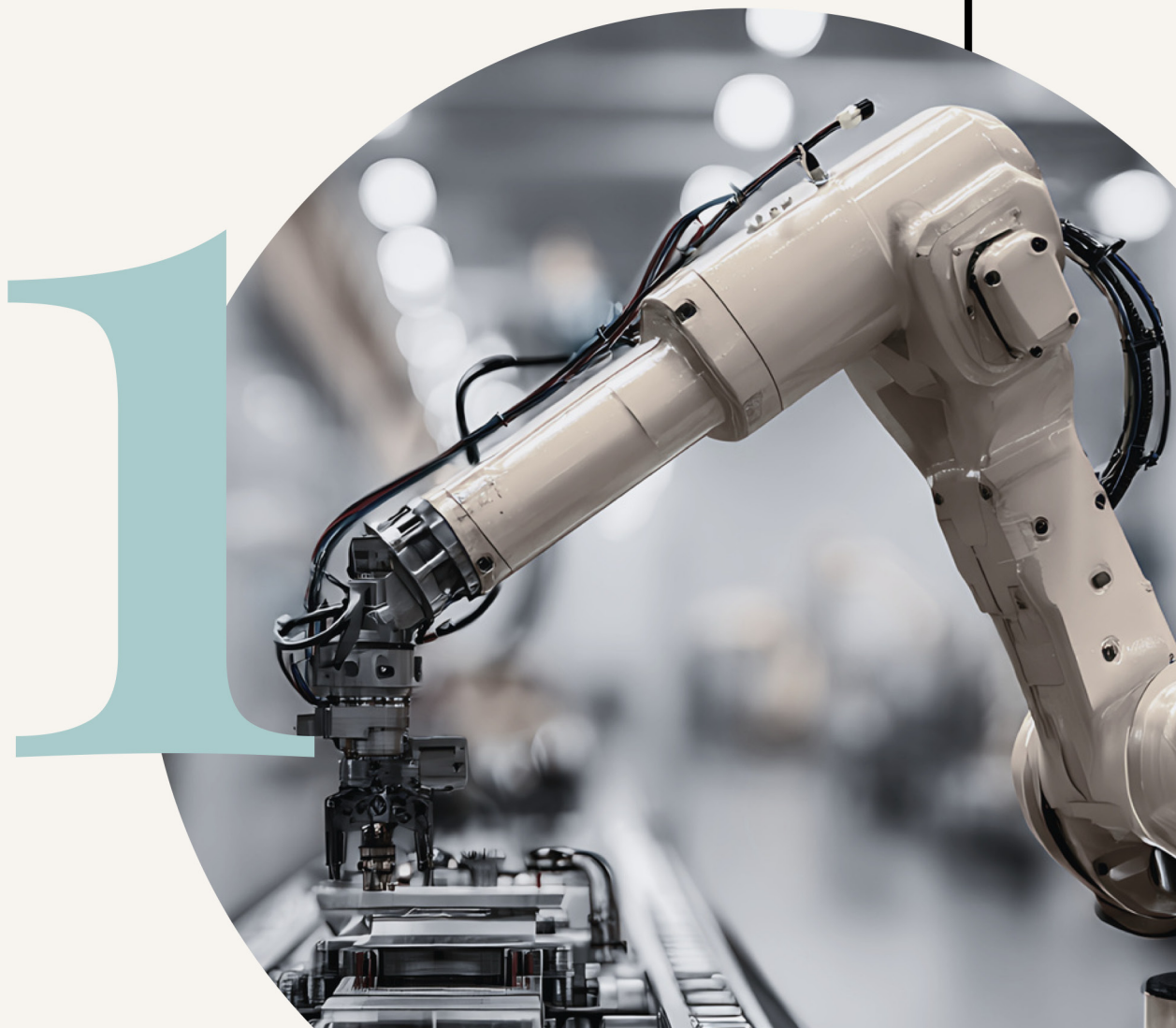
- ❑ Monitor access to tools, employer-supported training, AI projects, and new responsibilities alongside adoption and productivity.
- ❑ Where AI materially affects work, examine recruitment, task allocation, performance, progression, pay, wellbeing, and retention by gender and occupation.
- ❑ Treat persistent disparities as a trigger for review, and keep entry and progression routes under review as administrative and professional roles change.

FOR POLICYMAKERS

- ❑ Improve sector evidence on adoption, training access, and transitions by gender, occupation, and business function.
- ❑ Support longitudinal research on progression, pay, and retention, and evaluate whether public programmes reach workers in exposed occupations.

Introduction

What this report examines, and
the evidence it draws on



1 Introduction

This report examines how the growing use of artificial intelligence (AI), and generative AI (GenAI) in particular, could reshape women's participation, experience, and progression in UK manufacturing. It considers three connected pathways through which these effects may emerge: changes to the tasks and occupations in which women and men are concentrated; the increasing use of AI-mediated systems in recruitment, career development, and workplace decision-making; and differences in how workers engage with, experience, and perceive AI, including concerns about bias, fairness, and trust.

By bringing together an analysis of the International Labour Organization's (ILO's) occupational AI exposure data,¹³ combined with Office for National Statistics (ONS) employment data, an original survey of 890 UK manufacturing professionals conducted by Noetic AI,¹⁴ and a review of the wider literature on AI, gender, and employment, the report identifies where gendered risks and opportunities may arise as adoption expands. In particular, the report aims to understand what these patterns imply for manufacturers looking to introduce AI in ways that support productivity, workforce participation, and more equitable career opportunities.

The pace of technological change is unusual by recent standards. GenAI is moving from experimental applications into core business processes. Across OECD countries, firm-level AI adoption more than doubled between 2023 and 2025, rising from 8.7% to 20.2% of firms, with 31% of SMEs now reporting using GenAI tools.¹⁵ The Stanford University *Artificial Intelligence Index Report* documents how successive model generations have delivered step-changes in language, reasoning, and analytical capability, compressing what were multi-year research horizons into months.¹⁶

At the same time, *The UK's Modern Industrial Strategy*, published in June 2025, sets an explicit workforce target through its *Advanced Manufacturing Sector Plan*: increasing women's participation in advanced manufacturing to 35% by 2035, the "35 by 35" ambition developed with the Women in Manufacturing UK initiative.¹⁷ The *AI Opportunities Action Plan*, published in early 2025, set a parallel ambition to accelerate AI adoption across the economy.¹⁸ In June 2026 the AI Champion for Advanced Manufacturing proposed a "Scan-Pilot-Scale" pathway for industrial AI adoption, underpinned by workforce skills and inclusive implementation.¹⁹ Whether or not the drive to scale AI and the ambition to widen women's participation reinforce each other will depend partly on how AI changes work, how workers are involved, and how its benefits and risks are distributed.

Although AI adoption in UK manufacturing remains in its early stages, the work functions where AI is landing first are the functions where women in manufacturing are concentrated and where current

¹³ Gmyrek, P. et al. (2025). *Generative AI and Jobs: A Refined Global Index of Occupational Exposure*. ILO Working Paper, 140. DOI: 10.54394/HETP0387.

¹⁴ Roupakia, Z. (2026). *AI Bias in Manufacturing: A UK Workforce Survey*. Noetic AI.

¹⁵ OECD (2026). *AI Use by Individuals Surges Across the OECD as Adoption by Firms Continues to Expand*. News announcement, January 2026; OECD (2025). *Generative AI and the SME Workforce: New Survey Evidence*. DOI: 10.1787/2d08b99d-en.

¹⁶ Stanford HAI (2025). *Artificial Intelligence Index Report 2025*. Stanford University.

¹⁷ HM Government (2025). *The UK's Modern Industrial Strategy*. Department for Business and Trade; HM Government (2025). *Advanced Manufacturing Sector Plan*. Department for Business and Trade; Women in Manufacturing UK Initiative (n.d.). About us: our target. <https://engage-events.ifm.eng.cam.ac.uk/WiMUK#/aboutus>.

¹⁸ Clifford, M. (2025). *AI Opportunities Action Plan*. Department for Science, Innovation and Technology.

¹⁹ Dungey, C. (2026). *AI Adoption Plan: Advanced Manufacturing*. Department for Science, Innovation and Technology.

GenAI tools could perform or assist a substantial share of tasks (although exposure does not predict job loss, instead identifying where task change is technically possible).²⁰ A Make UK survey published in June 2026 found that only 2% of manufacturers have AI widely embedded across their operations, with fewer than 40% using it in some areas, nearly one in five not using it at all, and over half citing skills shortages as the primary barrier.²¹ Where AI is being used, it is concentrated in back-office functions: 83% of manufacturers use it in areas such as HR, finance, and administration, compared with 11% in production, 7% in supply chain, and 6% in quality control. The Made Smarter practical toolkit confirms this pattern: most SME manufacturers begin their AI journey with IT-based business support systems, such as planning, scheduling, reporting, and customer communication, before progressing to operational technology (OT) applications on the production line.²² Adoption is therefore early enough that its distributional consequences are still open, and many of the choices that will shape how AI affects work and opportunity in manufacturing are still being made.

In addition, research and regulatory audits show that applicant tracking, CV screening, skills matching, assessment, and workforce management can reproduce gender and racial bias through data, model design, proxy variables, and the way tools are used in practice.²³ The evidence varies across technologies and settings, but it is established enough to make fairness a material issue for employers adopting AI in decisions about people.²⁴ This matters for the gender analysis presented here because UK manufacturing enters this period of technological change with longstanding gender imbalances in participation, occupational distribution, and progression. The sector's 35 by 35 ambition reflects the importance of widening the talent pool, while recent work on women in manufacturing continues to document under-representation in technical and senior roles. AI adoption will therefore unfold within an existing labour market structure, and its effects will be shaped partly by that baseline starting point (see Box 1).²⁵

²⁰ International Labour Organization (2026). *Gen AI, occupational segregation and gender equality in the world of work*. ILO Research Brief. DOI: 10.54394/00033798.

²¹ Make UK (2026). *AI, Skills and the Future of the UK Manufacturing Sector*.

²² Made Smarter (2026). *AI Adoption in Manufacturing: A Practical Toolkit*. Note: The toolkit distinguishes between IT AI (business systems: ERP, CRM, copilots) and OT AI (production systems: machines, sensors, PLCs) and notes that most SMEs start with IT AI because it is lower-cost, faster to trial, and easier to reverse.

²³ Dastin, J. (2018). Amazon scraps secret AI recruiting tool that showed bias against women. Reuters; Wilson, K. and Caliskan, A. (2024). Gender, Race, and Intersectional Bias in Resume Screening via Language Model Retrieval.

Proceedings of the Seventh AAAI/ACM Conference on AI, Ethics, and Society, 7(1), 1578–1590. DOI:

10.1609/aies.v7i1.31748; Raghavan, M. et al. (2020). Mitigating Bias in Algorithmic Hiring. *Proceedings of FAT* 2020*.

²⁴ Bengio, Y. et al. (2025). *International AI Safety Report: The International Scientific Report on the Safety of Advanced AI*. Department for Science, Innovation and Technology; NIST (2023). *Artificial Intelligence Risk Management Framework (AI RMF 1.0)*. DOI: 10.6028/NIST.AI.100-1.

²⁵ Castañeda-Navarrete, J., Roupakia, Z., Döme, V. and Anzolin, G. (2024). *Women in UK Manufacturing 2024: Addressing Labour Shortages and Bridging the Gender Gap*. IfM Engage, University of Cambridge.

Box 1: The default setting

UK manufacturing has started the AI adoption transition from an unequal baseline. In 2025, UK manufacturing employed approximately 2.6 million people, of whom an estimated 724,700 (27.8%) were women. They accounted for 27.3% of managers, directors and senior officials, while the median hourly gender pay gap in manufacturing was 14.7%. These measures are not outcomes of AI, but they provide important context for judging how changes in tasks, access, and progression are distributed.

Sources: ONS, Annual Population Survey workplace analysis, January–December 2025, UK manufacturing (SIC 2007 Section C); ONS, Annual Survey of Hours and Earnings, Table 21.12, Manufacturing (SIC C), all employees, median hourly pay excluding overtime, 2025 provisional.

The rest of this report is structured in four key sections: Section 2 maps occupational AI exposure and the gendered distribution of potential task changes; Section 3 presents the survey findings on AI use, experiences of bias, trust, and perceived effects; Section 4 reviews evidence on how AI may shape access to work and opportunities after entry; and Section 5 concludes with recommendations for organisations and policymakers.

Occupational exposure to generative AI

Where GenAI exposure falls across UK manufacturing and why it is higher for women

2



2 Occupational exposure to generative AI

Generative AI (GenAI) is likely to reach manufacturing through a different set of tasks than earlier waves of industrial automation. The current tools are strongest in language, information-processing, and data-based work, while many physical and manual activities remain less directly exposed. In a sector that combines production, engineering, technical, administrative, and commercial roles, the occupational distribution of employment is therefore central to understanding where GenAI may reshape work.

This section examines how occupational exposure to GenAI is distributed across UK manufacturing, focusing on differences between women and men. It draws on the International Labour Organization's (ILO's) 2025 index of occupational exposure to GenAI and combines it with UK employment data to examine broad occupational patterns and a more detailed estimate for the sector (see Boxes 2 and 3).

Exposure should not be read as a forecast of job loss. The ILO index measures the technical potential for current GenAI tools to perform or assist tasks within an occupation. Whether that potential leads to automation, augmentation, changes in job design, or productivity gains depends on how firms adopt the technology, how work is reorganised, and how the transition is managed. After setting out the ILO framework, the analysis compares UK manufacturing with wider UK and international evidence, examines where the most highly exposed occupations are concentrated, and uses more detailed UK occupational data to estimate how manufacturing employment is distributed across exposure categories.

2.1 How the International Labour Organization classifies occupational exposure

The ILO index scores tasks within each occupation for their potential to be performed or assisted by current GenAI tools, then groups occupations into four exposure gradients according to the level and consistency of those scores. Occupations that do not meet the threshold for any gradient are classed as minimally exposed. Table 1 summarises the classification used in this report.

TABLE 1: ILO CLASSIFICATION OF OCCUPATIONAL EXPOSURE TO GENAI

GenAI exposure gradient	What it means	Examples
Gradient 4: highest GenAI exposure	Most tasks can be performed or substantially assisted by current GenAI tools, with little variation across tasks. These occupations face the greatest potential for task automation.	Bookkeeping and payroll clerks, data entry clerks, general office clerks, financial analysts
Gradient 3: significant GenAI exposure	A substantial share of tasks can be assisted by current GenAI tools, although some remain less exposed. Work in these occupations could change considerably.	Software developers, accountants, secretaries and receptionists, customer service clerks

Gradient 2: moderate GenAI exposure	The occupation contains a mix of exposed and unexposed tasks, so effects are likely to vary within the role.	Electronics engineers, commercial sales representatives, graphic designers, management consultants
Gradient 1: low GenAI exposure	Overall exposure is limited, although particular tasks may still have meaningful automation or augmentation potential.	Cashiers, shop sales assistants, car and van drivers
Minimal GenAI exposure	Core tasks are predominantly physical, manual, interpersonal or hands-on, and current GenAI tools have limited capability to perform them.	Welders, machinists, machine operators, electricians, warehouse labourers, production managers

Note: In the analysis that follows, “exposed occupations” refers to occupations classified within any of the ILO’s four exposure categories. “Higher exposure” refers specifically to the significant and highest gradients.

Source: Gmyrek, P. et al. (2025). Generative AI and Jobs: A Refined Global Index of Occupational Exposure. *ILO Working Paper*, 140.

Box 2: What the AI exposure index is

The ILO’s 2025 index (*Working Paper*, 140) draws on 52,558 human assessments of 2,861 occupational tasks, mapped to the ISCO-08 classification of 436 occupational groups. It publishes scores from 0 to 1 for 427 four-digit ISCO-08 occupations. Around one in four workers globally is in an exposed occupation; 3.3% of global employment is in Gradient 4. In high-income countries, 9.6% of female employment is in Gradient 4, compared with 3.5% of male employment. Exposure does not equal displacement: the ILO identifies transformation of jobs as the more likely outcome.

The exposure gap describes occupational structure, not job loss. It shows that women in UK manufacturing are more concentrated in roles whose tasks overlap with current GenAI capabilities. For manufacturers, this helps identify where role redesign, training, and workforce consultation may be most important as adoption develops.

Source: Gmyrek, P. et al. (2025). Generative AI and Jobs: A Refined Global Index of Occupational Exposure. *ILO Working Paper*, 140.

2.2 A wider gender exposure gap within manufacturing

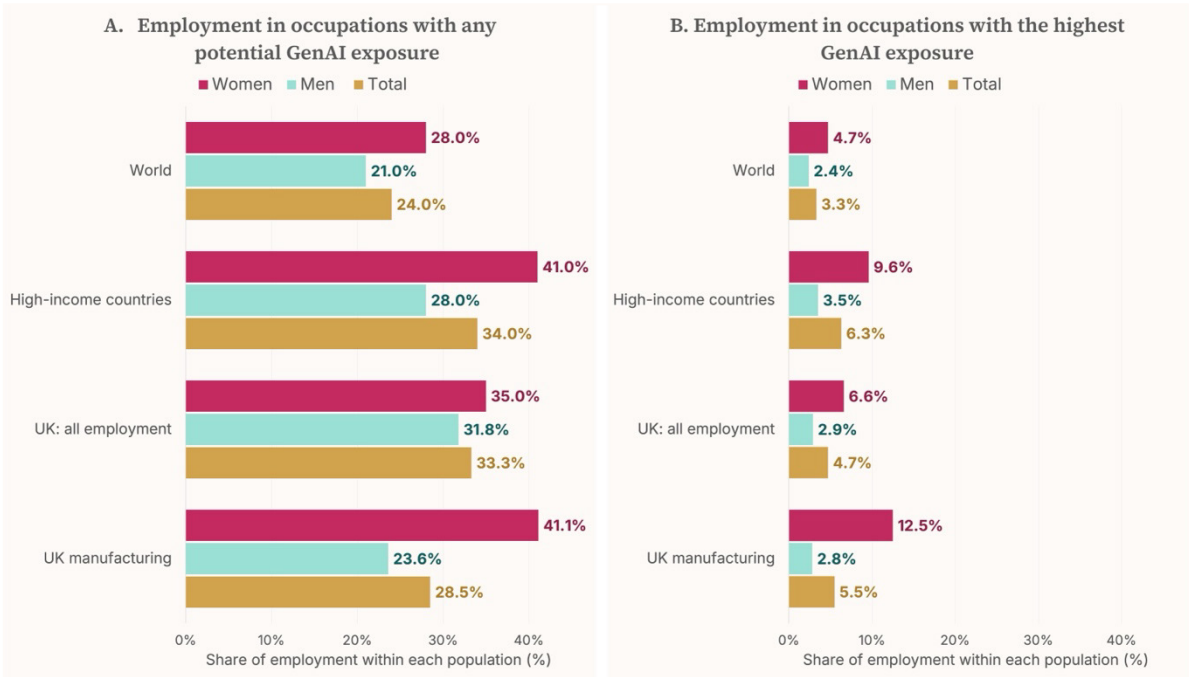
Although UK manufacturing has lower overall GenAI exposure than the economy as a whole, the distribution within the sector is markedly gendered. An estimated 41.1% of women working in UK manufacturing are in occupations exposed to GenAI, compared with 23.6% of men. At the highest exposure level, the corresponding shares are 12.5% and 2.8%.

Figure 1 places the UK manufacturing estimates alongside wider UK and international benchmarks. Across UK employment as a whole, 33.3% of employment is in occupations with potential GenAI exposure. The corresponding share in manufacturing is lower, at 28.5%. This sector average, however, conceals a much wider difference by sex. In manufacturing, an estimated 41.1% of women’s

employment is exposed to GenAI compared with 23.6% of men's, a gap of 17.5 percentage points. Across UK employment, the equivalent shares are 35.0% and 31.8%, a gap of 3.2 percentage points.

The difference is particularly pronounced at the highest exposure level. An estimated 12.5% of women's manufacturing employment is in the highest-exposure occupations, compared with 2.8% of men's. For women, this is almost twice the UK all-employment share of 6.6% and above the 9.6% high-income benchmark; for men, the manufacturing and UK-wide shares are almost identical, at 2.8% and 2.9%. The direction of the difference is consistent with wider ILO²⁶ and OECD²⁷ evidence showing greater GenAI exposure among women in many high-income labour markets, reviewed in Section 4.

FIGURE 1: ESTIMATED GENAI EXPOSURE IN UK MANUFACTURING AND WIDER LABOUR MARKET BENCHMARKS, BY GENDER



Note: Each bar uses its own population as the denominator. "Potential GenAI exposure" includes the low, moderate, significant, and highest-exposure categories.

Source: World, high-income countries, and UK all employment: Gmyrek, P. et al. (2025). Generative AI and Jobs: A Refined Global Index of Occupational Exposure, *ILO Working Paper*, 140; UK manufacturing: Author's analysis of ONS Annual Population Survey four-digit SOC2020 occupation by four-digit SIC 2007 industry data, April 2025–March 2026, scaled within SOC major groups to ONS Annual Population Survey workplace analysis T10c via Nomis, January–December 2025; ONS SOC2020 coding index (December 2025); and ILO exposure classifications from Gmyrek, P. et al. (2025), Annex Table A1.

Men, nevertheless, account for 72.2% of UK manufacturing employment. Exposure shares and workforce composition answer different questions: the former show how concentrated exposure is within women's and men's employment, while the latter shows who makes up the potentially affected

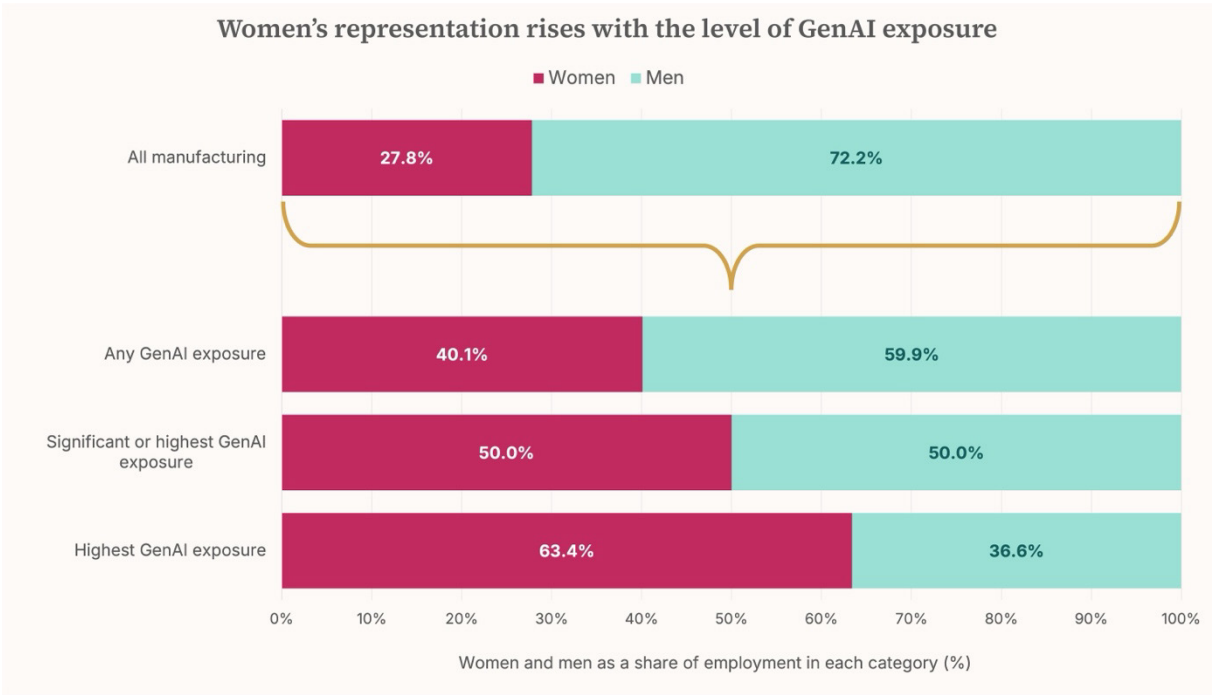
²⁶ Gmyrek, P. et al. (2025). Generative AI and Jobs: A Refined Global Index of Occupational Exposure. *ILO Working Paper*, 140. DOI: 10.54394/HETP0387.

²⁷ OECD (2024). *Job Creation and Local Economic Development 2024: The Geography of Generative AI*. DOI: 10.1787/83325127-en.

workforce. Figure 2 looks at the same distribution from the opposite direction. Women remain a minority of the sector overall but become the majority at the highest exposure level. The exposure gap therefore has two dimensions: women have higher exposure rates within their own employment, and their share of the workforce rises as exposure becomes more intensive.

Women account for 27.8% of UK manufacturing employment, but an estimated 40.1% of exposed employment, 50.0% of employment in occupations with significant or highest exposure, and 63.4% of employment in the highest-exposure occupations.

FIGURE 2: WOMEN’S SHARE OF UK MANUFACTURING EMPLOYMENT, BY LEVEL OF GENAI EXPOSURE



Note: “Any GenAI exposure” includes occupations classified by the ILO as having low, moderate, significant, or highest GenAI exposure. Women and men total 100% within each row. The first row shows the baseline composition of UK manufacturing employment; the three rows below progressively restrict the population to GenAI-exposed occupations.

Source: Author’s analysis of ONS Annual Population Survey four-digit SOC2020 occupation by four-digit SIC 2007 industry data, April 2025–March 2026, scaled within SOC major groups to ONS Annual Population Survey workplace analysis T10c via Nomis, January–December 2025, UK manufacturing (SIC 2007 Section C), by SOC2020 major group and sex; ONS SOC2020 coding index (December 2025); and ILO exposure classifications from Gmyrek, P. et al. (2025). Generative AI and Jobs: A Refined Global Index of Occupational Exposure. *ILO Working Paper*, 140, Annex Table A1.

Box 3: Policy context: managing AI adoption in manufacturing

Manufacturing employs nearly 500 million workers globally. In April 2026 the ILO convened a Technical Meeting on AI in Manufacturing (Geneva, 13–17 April 2026), bringing together government, employer, and worker representatives from 54 countries. They adopted the ILO's first tripartite conclusions on AI in manufacturing, which link productivity objectives with skills development, protection of fundamental rights at work, occupational safety and health, and social dialogue. Exposure identifies where the technical potential for change is concentrated, but outcomes depend on how technologies are introduced, governed, and integrated into work. The adopted conclusions will be submitted to the 358th Session of the ILO Governing Body in November 2026.

Source: ILO (2026). Conclusions and Recommendations, Technical Meeting on AI in the Manufacturing Industry.

2.3 Where higher generative AI exposure is concentrated

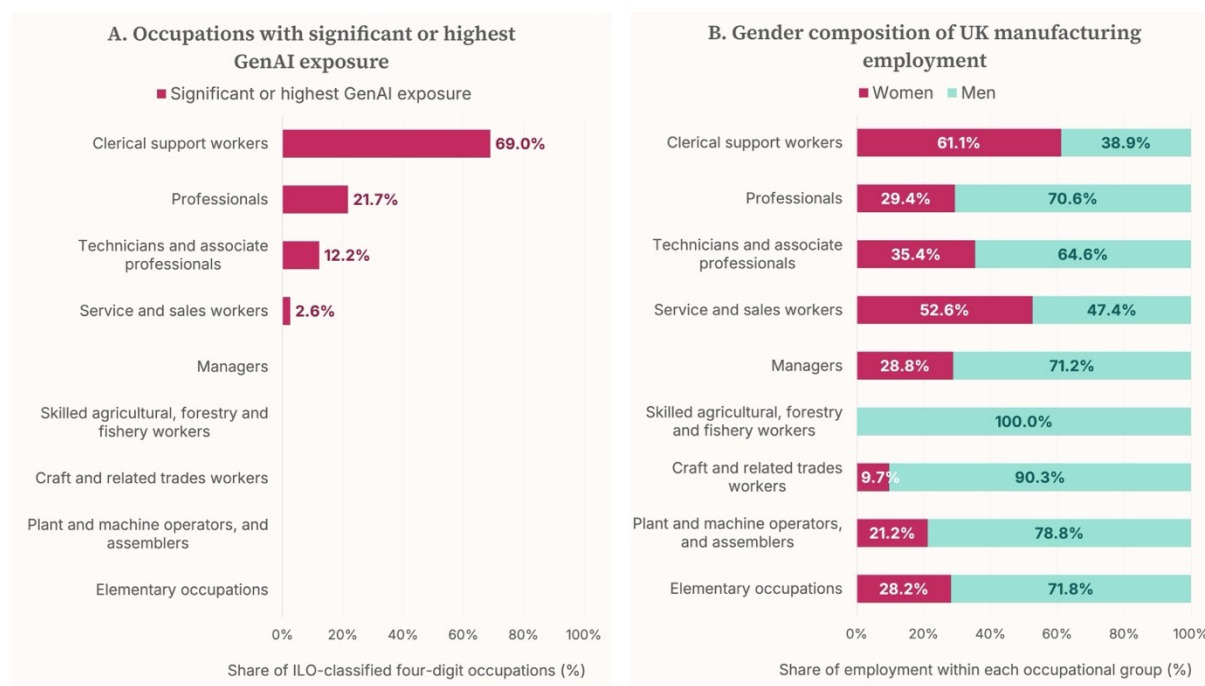
Significant and highest GenAI exposure is concentrated in clerical and selected professional and technical occupations. Clerical support is the clearest case: 69.0% of ILO-classified clerical occupations fall within the two highest-exposure categories, and women account for around 61% of reported clerical support employment in UK manufacturing. By contrast, craft and related trades and plant and machine operator groups contain no occupations in the two highest categories and are around 90% and 79% male, respectively.

Across the 427 four-digit ISCO-08 occupations used in this analysis, 13 are classified in the highest-exposure gradient and a further 38 in the significant gradient.²⁸ These 51 occupations are concentrated in a small number of broad occupational groups and are entirely absent from others, as Figure 3 illustrates. Clerical support accounts for the largest concentration: 69.0% of its four-digit occupations are in the two highest-exposure categories. These include data entry, bookkeeping and payroll, general office, and personnel clerks. Women hold 61.1% of clerical support jobs in UK manufacturing.

Professional occupations contain another 20 higher-exposure occupations, but they represent a much smaller share of the group, at around 21.7%. The exposed subset includes financial analysts, software developers, database administrators, accountants, economists, and marketing professionals; most engineering and science occupations are not in the two highest categories. Women hold 29.4% of professional jobs in manufacturing. Technicians and associate professionals account for 10 higher-exposure occupations, while service and sales account for one.

²⁸ Occupational groups follow the ILO's ISCO-08 classification. The groups referred to in this section are: clerical support workers (Major Group 4: office clerks, secretaries, bookkeeping, payroll, and personnel clerks); professionals (Major Group 2: engineers, scientists, accountants, software developers); managers (Major Group 1); craft and related trades (Major Group 7: machinists, welders, electricians); plant and machine operators (Major Group 8); and elementary occupations (Major Group 9). Section 2.4 uses the ONS SOC2020 classification, which groups occupations differently but covers the same workforce.

FIGURE 3: HIGHER-EXPOSURE OCCUPATIONS AND THE GENDER COMPOSITION OF UK MANUFACTURING EMPLOYMENT



Note: Panel A shows the share of four-digit occupations covered by the ILO exposure index that fall within the significant or highest GenAI exposure categories; it is based on occupation counts, not employment. Panel B shows the gender composition of UK manufacturing employment within each broad ISCO-08 major group.

Source: Panel A: Gmyrek, P. et al. (2025). *Generative AI and Jobs: A Refined Global Index of Occupational Exposure*. *ILO Working Paper*, 140. Annex Table A1. Panel B: ILOSTAT, *Employment by sex, occupation and economic activity, UK Labour Force Survey 2025*; manufacturing defined as ISIC Rev.4 divisions 10-33. Skilled agricultural, forestry and fishery workers (Major Group 6) appear in the ILOSTAT data, with a small number of workers recorded under manufacturing. They are retained for consistency with the source data.

By contrast, craft and related trades, plant and machine operators, elementary occupations, and managers contain no occupations in the significant or highest categories. These are also groups in which men predominate. The concentration of high exposure in clerical and selected professional work, rather than across manufacturing as a whole, is therefore central to the gender pattern.

The ILO's March 2026 research brief establishes that female-dominated occupations are almost twice as likely to be exposed to GenAI as male-dominated ones: 29% versus 16%. At the two higher exposure levels, 16% of female-dominated occupations fall into Gradients 3 and 4, compared with 3% of male-dominated occupations. The female-dominated occupations in these categories are concentrated primarily in business administration and clerical support, and women are more exposed than men in 88% of the 84 countries in the sample.²⁹ These findings are corroborated by other analyses. Del Rio-Chanona and colleagues find that in high-income countries, 8.5% of female

²⁹ International Labour Organization (2026). *Gen AI, occupational segregation and gender equality in the world of work*. ILO Research Brief. DOI: 10.54394/00033798. Figures 5 and 6.

employment falls in the highest exposure gradient compared with 3.9% of male employment.³⁰ The OECD's exposure work also finds greater exposure among women and in more digitally intensive labour markets.³¹

2.4 How generative AI exposure maps onto UK manufacturing

Employment-weighted estimates show the same pattern from a UK manufacturing perspective: administrative and secretarial work combines the highest concentration of GenAI exposure with one of the highest shares of women, while production, process, and skilled-trade groups remain predominantly male and much less exposed.

Figure 4 translates the ILO classification into the UK occupational structure using SOC2020 employment data. Unlike Figure 3, which counts occupations, it shows how manufacturing employment is distributed across exposure categories within each major group.

Administrative and secretarial work stands apart: 71.3% of employment in the group is estimated to be in the highest-exposure gradient and a further 15.4% in the significant-exposure gradient. The group employs approximately 177,000 people in UK manufacturing, of whom 120,200 (67.9%) are women. Sales and customer service work also has a sizeable share of employment in the significant-exposure gradient. It employs a further 69,800 people, with women accounting for 50.3%. Together, these two groups – where higher GenAI exposure is most concentrated – employ around 155,300 women, equivalent to one in five women working in manufacturing.

By comparison, the sector's largest occupational groups are professional occupations (498,800), skilled trades (487,900), and process, plant, and machine operative occupations (423,800). Skilled trades and process, plant, and machine operative occupations are predominantly male and contain no occupations in the highest or significant-exposure gradients. Professional and associate professional occupations (498,800 and 360,700 respectively) are also male-majority, but around half of their employment is in exposed occupations, mostly at moderate levels, and together they employ a further 261,300 women.

The employment-weighted picture helps reconcile two observations that can otherwise appear contradictory. Manufacturing is a relatively low-exposure sector in aggregate, yet women within manufacturing face much higher exposure than men. The sector average is pulled down by large male-dominated occupational groups with little direct GenAI exposure, while women's employment is more concentrated in the smaller set of administrative and support roles where exposure is highest.

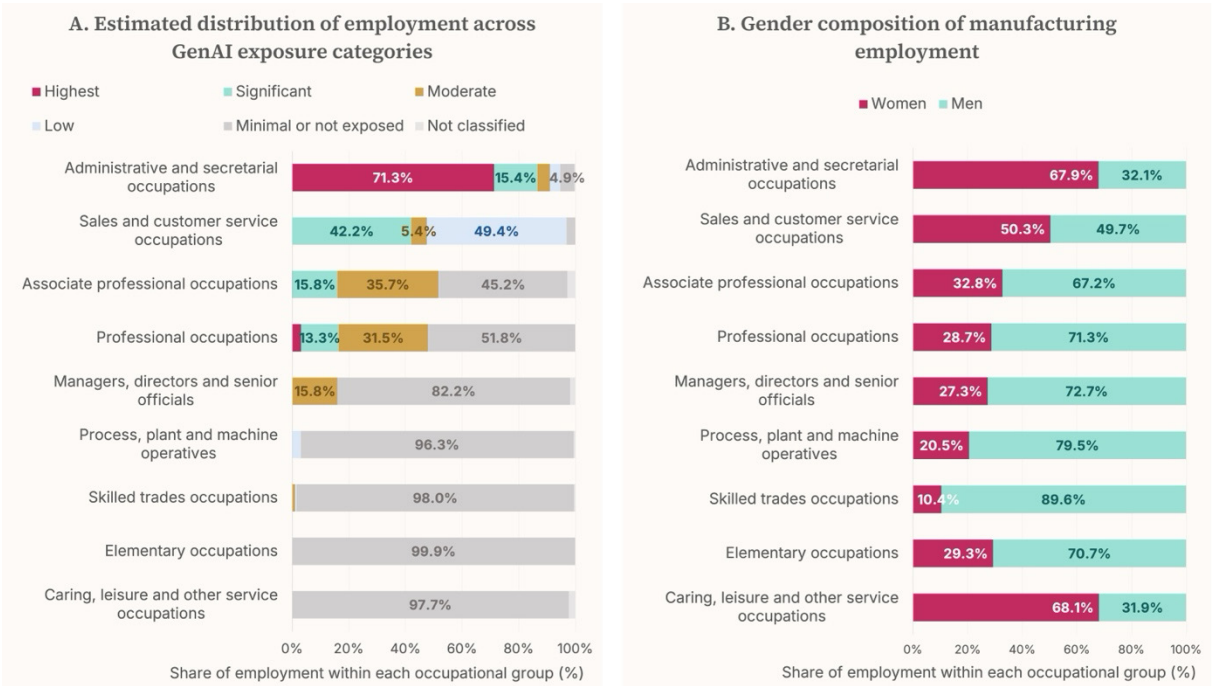
These estimates describe technical potential, not deployment. But the Make UK survey data adds more evidence: 83% of manufacturers using AI apply it in areas such as HR, finance, and administration – the functions where women are concentrated – with only 11% in production, 7% in supply chain, and

³⁰ Del Rio-Chanona, R. M. et al. (2025). AI and Jobs: A Review of Theory, Estimates, and Evidence. DOI: 10.48550/arXiv.2509.15265; International Labour Organization (2026). *AI in Manufacturing: Challenges and Opportunities for Promoting Decent Work, Productivity and a Just Transition*. DOI: 10.54394/00033213.

³¹ OECD (2024). *Job Creation and Local Economic Development 2024: The Geography of Generative AI*. DOI: 10.1787/83325127-en

6% in quality control.³² The Made Smarter toolkit describes a similar sequence: many manufacturers begin with IT-based AI in business support functions before moving towards operational technology applications in production. This sequencing matters: GenAI does not arrive on the shop floor first; it often arrives in administrative, HR, and finance work, where women are more strongly represented.³³ Figure 4 shows how that deployment pattern overlaps with the occupational distribution of exposure.

FIGURE 4: ESTIMATED GENAI EXPOSURE AND GENDER COMPOSITION ACROSS UK MANUFACTURING OCCUPATIONAL GROUPS



Note: Panel A is employment-weighted. “Minimal exposure” and “Not exposed” are combined for visual presentation; occupations without an ILO exposure classification are shown separately as “Not classified”. Panel B shows women and men as shares of employment within each SOC2020 major occupational group.

Source: Panel A: Author’s analysis of ONS Annual Population Survey four-digit SOC2020 occupation by four-digit SIC 2007 industry data, April 2025–March 2026, scaled within SOC major groups to ONS Annual Population Survey workplace analysis T10c via Nomis, January–December 2025; SOC2020 occupations linked to ISCO-08 using the ONS SOC2020 coding index (December 2025); and ILO exposure classifications from Gmyrek, P. et al. (2025). Generative AI and Jobs: A Refined Global Index of Occupational Exposure. *ILO Working Paper*, 140, Annex Table A1. Panel B: ONS Annual Population Survey workplace analysis T10c via Nomis, January–December 2025, UK manufacturing (SIC 2007 Section C), SOC2020 major group by sex.

³² Make UK (2026). *AI, Skills and the Future of the UK Manufacturing Sector*.
³³ Made Smarter (2026). *AI Adoption in Manufacturing: A Practical Toolkit*.

2.5 From exposure to outcomes

Exposure is a starting point rather than an outcome. ILO analysis and the April 2026 tripartite conclusions both emphasise that transformation is more likely than elimination.³⁴ European evidence also shows that higher AI exposure can coexist with rising female employment shares.³⁵ What matters is how firms redesign work, invest in skills, and distribute productivity gains.

For UK manufacturing, this matters because the roles most exposed are disproportionately held by women, sitting within a sector where the median hourly gender pay gap was 14.7% in 2025. If retraining and role redesign reach these occupations, AI may enhance rather than erode them; if they do not, women could bear a larger share of the adjustment costs.³⁶

One plausible route of transformation is through task reorganisation in administrative and secretarial work, which sits at the top of the ILO exposure scale.³⁷ If firms use GenAI primarily to reduce costs, these roles may shrink through attrition, consolidation, or redesign around fewer workers. Make UK data shows that current AI use is already concentrated in HR, finance, and administration.³⁸ Women make up around 68% of employment in the relevant administrative and secretarial group,³⁹ which makes the distribution of transition support a practical workforce issue.

The capacity to manage this transition cannot be taken for granted. The Employer Skills Survey 2024 found that 51% of manufacturing employers had provided training in the previous 12 months, down from 54% in 2022, placing manufacturing among the sectors least likely to provide training. At the same time, Skills England's 2026 assessment of advanced manufacturing identifies notably higher proficiency requirements than the UK average in digital literacy, numeracy, and problem-solving and decision-making. Its analysis of AI-related skills also points to demand spanning technical, non-technical, and responsible and ethical capabilities as adoption moves from pilots towards wider system integration. As GenAI begins to reshape administrative and business support work, there are questions about whether training is available, and whether it reaches the occupations in which exposure is concentrated and supports workers as roles are redesigned.⁴⁰

The implications may extend beyond the jobs themselves. For some workers, administrative and support roles may also provide entry points into manufacturing organisations and experience that supports later progression. GLA Economics reaches a similar conclusion for London's labour market,

³⁴ ILO (2026). Conclusions and Recommendations, Technical Meeting on AI in the Manufacturing Industry; Gmyrek, P. et al. (2025). Generative AI and Jobs: A Refined Global Index of Occupational Exposure. *ILO Working Paper*, 140. DOI: 10.54394/HETP0387.

³⁵ Albanesi, S., et al. (2025). *AI and Women's Employment in Europe*. ECB Working Paper No. 3077. European Central Bank.

³⁶ ONS (2025). Annual Survey of Hours and Earnings, Table 21.12, Manufacturing (SIC C), all employees, median hourly pay excluding overtime, 2025 provisional.

³⁷ Gmyrek, P. et al. (2025). Generative AI and Jobs: A Refined Global Index of Occupational Exposure. *ILO Working Paper*, 140. DOI: 10.54394/HETP0387.

³⁸ Make UK (2026). *AI, Skills and the Future of the UK Manufacturing Sector*.

³⁹ Author's analysis. ILO (2025) exposure scores; ONS APS April 2025–March 2026.

⁴⁰ Department for Education and Skills England (2025). Employer Skills Survey 2024. Official Statistics; Skills England (2026). Sector Skills Needs Assessment – Advanced Manufacturing. Updated 4 August 2026.

arguing that where automation reduces these entry-level roles, progression routes weaken and the supply of workers into mid- and senior-level positions falls over time.⁴¹

A recent US analysis shows that exposure alone does not determine vulnerability. Manning and colleagues combine AI exposure scores with a measure of workers' capacity to manage a job transition.⁴² Most of the highly exposed workers are in professional roles with strong adaptive capacity. The concentrated risk sits among a smaller group of clerical and administrative workers who are both highly exposed and poorly positioned to transition, 86% of whom are women. Neither finding is specific to UK manufacturing, but together they identify a risk worth monitoring as firms redesign support functions.

At the same time, the evidence is not uniformly negative. Where AI augments workers, experimental and field studies point to gains in productivity and, in some settings, narrower performance gaps between workers. OECD evidence suggests less experienced workers can benefit disproportionately from GenAI assistance.⁴³ Albanesi and colleagues find rising female employment shares in AI-exposed occupations across 16 European countries.⁴⁴ Whether women in manufacturing capture those gains will depend on access to tools, training, redesigned work, and higher-value tasks.

The route from exposure to outcome also runs through systems that are increasingly AI-mediated. Recruitment platforms, screening tools, and talent management systems can reproduce gender and racial bias under some conditions, although the wider evidence is mixed and context-dependent.⁴⁵ The *International AI Safety Report* treats bias and discrimination as a core governance risk.⁴⁶ Occupational exposure tells manufacturers where tasks may change; it does not tell them whether the systems governing access, progression, and adaptation are operating fairly. Sections 3 and 4 examine that question from two different angles: workers' perceptions, and the wider evidence on employment systems.

⁴¹ Dwan-O'Reilly, J. (2026). London's workforce exposure to generative artificial intelligence. *GLA Economics Working Paper*, 103. Greater London Authority. The GLA analysis adapts the same ILO (2025) exposure framework used here to the London labour market.

⁴² Manning, S., et al. (2026). *Measuring US Workers' Capacity to Adapt to AI-Driven Job Displacement*. Brookings Institution.

⁴³ Calvino, F. et al. (2025). The Effects of Generative AI on Productivity, Innovation and Entrepreneurship. *OECD Artificial Intelligence Papers*, No. 39.

⁴⁴ Albanesi, S., et al. (2025). *AI and Women's Employment in Europe*. ECB Working Paper No. 3077. European Central Bank.

⁴⁵ Wilson, K. and Caliskan, A. (2024). Gender, Race, and Intersectional Bias in Resume Screening via Language Model Retrieval. *Proceedings of the Seventh AAAI/ACM Conference on AI, Ethics, and Society*, 7(1), 1578–1590. DOI: 10.1609/aaies.v7i1.31748; Raghavan, M. et al. (2020). Mitigating Bias in Algorithmic Hiring. *Proceedings of FAT* 2020*; Dastin, J. (2018). Amazon scraps secret AI recruiting tool that showed bias against women. Reuters.

⁴⁶ Bengio, Y. et al. (2025). *International AI Safety Report: The International Scientific Report on the Safety of Advanced AI*. Department for Science, Innovation and Technology.

AI bias and its perceived impacts in UK manufacturing

How women and men
understand AI bias, perceive its
social and economic effects, and
trust AI-supported decisions



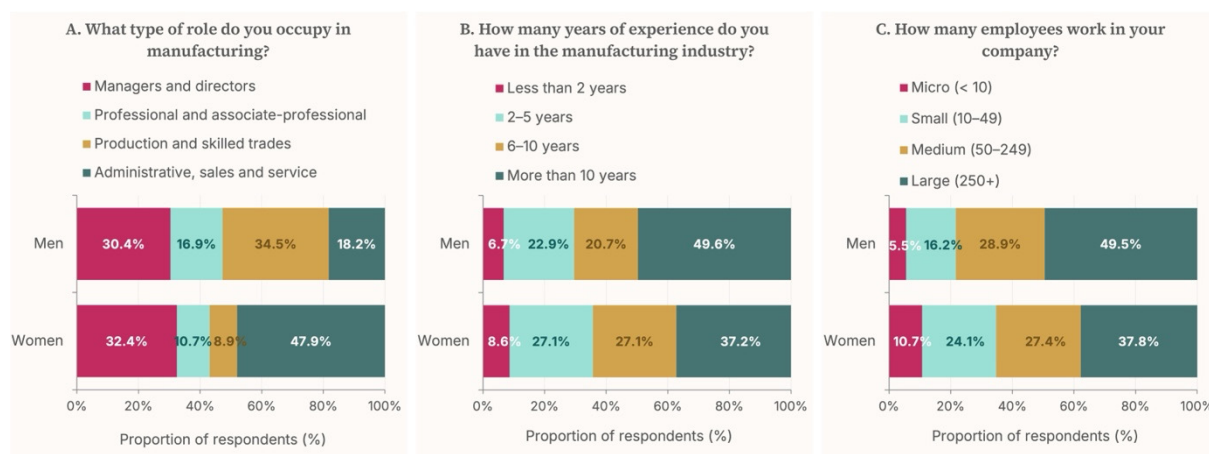
3 AI bias and its perceived impacts in UK manufacturing

Artificial intelligence is being introduced across manufacturing activities, from production and quality assurance to recruitment, workforce management, and administrative decision-making. Its adoption creates opportunities for firms and their employees but also raises questions about whether AI systems operate consistently and fairly across different settings and groups. Understanding how manufacturing professionals use these technologies, recognise potential bias, and assess its consequences is therefore important for responsible adoption (see Box 4).

Box 4: What is AI bias?

AI bias refers to systematic patterns in the data, design, operation, or outputs of an AI system that produce distorted or unequal results. It can take both technical and social forms. Technical bias arises when a system performs less accurately under particular conditions, for example when an AI-supported quality-control system is less reliable for certain products, materials, or operating environments. And social bias occurs when a system produces or reinforces unequal outcomes for people or groups, for example when an AI-supported recruitment system disadvantages applicants with particular demographic characteristics. The two forms can overlap, as limitations in data or system design may produce or amplify unequal social outcomes.

FIGURE 5: PROFILE OF SURVEY RESPONDENTS, BY GENDER



Note: Based on 886 respondents (550 men and 336 women). Occupational roles were consolidated from the original survey categories. Percentages may not total 100% because of rounding.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

Section 3 draws on AI Bias in Manufacturing: A UK Workforce Survey, an online survey of 890 UK manufacturing professionals conducted between January and September 2025.⁴⁷ It examines AI use and adoption, understanding and experience of AI bias, its perceived social and economic effects, trust in AI-supported decisions, organisational preparedness, and responses to bias.

As this section focuses on differences between women and men, the descriptive analysis draws on up to 886 respondents: 336 women and 550 men. Three respondents who identified as non-binary and one who preferred not to state their gender were not included in these comparisons, as the numbers were too small to support any analysis. Figure 5 shows the profile of survey respondents, and full details of the sample, measures, and analytical approach are provided in Appendix B.

The section begins by describing the respondents and their engagement with AI. It then examines experience and perceptions of bias, its perceived social and economic effects, and trust and organisational responses. As the survey is based on a non-random online sample and self-reported perceptions, the findings describe patterns within the survey population rather than nationally representative estimates or direct measurements of bias in UK manufacturing.

3.1 AI engagement and understanding

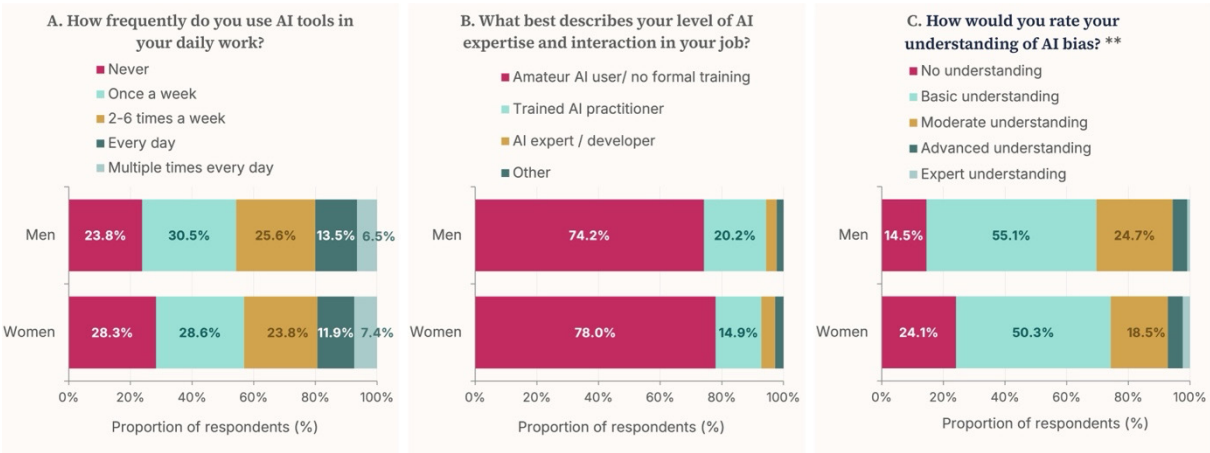
Women and men reported similar levels of AI use and self-reported expertise, but they apply AI in different areas of manufacturing. Women are also more likely to report a lack of understanding of AI bias, although this difference decreases after accounting for AI use and expertise.

AI engagement was broadly similar among the women and men surveyed. Almost three-quarters used AI tools at least weekly, including around one in five who used them every day or several times a day. Most respondents described themselves as amateur users without formal AI training: 78.0% of women and 74.2% of men. And fewer than 5% identified as AI experts or developers. There was no statistically significant gender difference in frequency of AI use or self-reported expertise (Figure 6, Panels A and B), and that broad similarity provides a useful context for the rest of the section. The gender differences that emerge later cannot simply be attributed to women having much less day-to-day contact with AI.

A clearer difference appears in respondents' understanding of AI bias. Almost one-quarter of women (24.1%) said they have no understanding of AI bias, compared with 14.5% of men (Figure 6, Panel C). The difference remains statistically significant after accounting for age, occupational role, and company size, but is smaller and no longer statistically significant when AI-use frequency and self-reported expertise are included in the model. This suggests that AI use and expertise account for part of the observed difference, although the survey could not establish the underlying causal mechanism.

⁴⁷ Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

FIGURE 6: AI USE, EXPERTISE, AND UNDERSTANDING OF AI BIAS, BY GENDER



Note: Based on 886 respondents (550 men, 336 women). Panels A and B: no statistically significant gender difference. Panel C: statistically significant gender difference (** $p < 0.01$). Values less than 5% are not displayed. For methodology, see Appendix B.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

Similar levels of self-reported expertise in this sample should not be confused with equal representation in specialist AI roles. Wider UK labour market evidence continues to show substantial under-representation of women in formal AI employment. The Department for Science, Innovation and Technology’s AI Labour Market Survey 2025, for example, found that women accounted for 20% of AI roles across surveyed UK organisations in 2025, down from 24% in 2020.⁴⁸

The understanding gap exists within a broader context of reduced training provision in the sector, as discussed in Section 2.5. The Employer Skills Survey 2024 found that 51% of manufacturing employers provided any form of training, down from 54% in 2022, placing manufacturing among the three sectors least likely to provide training, alongside primary sector and utilities, and construction.⁴⁹ This does not show that reduced training provision caused the gender difference in understanding, but it underlines the importance of ensuring that AI capability-building reaches the wider manufacturing workforce as adoption expands.

Women and men also differ in where they use AI. Among respondents who selected at least one application, women were more likely to report using AI in customer service and support (48% compared with 28% of men) and in HR and recruitment (19% compared with 10% of men). And men were more likely to report its use in manufacturing processes (35% compared with 23% of women) and predictive maintenance (16% compared with 9%). Each of these differences is statistically significant (Figure 7).

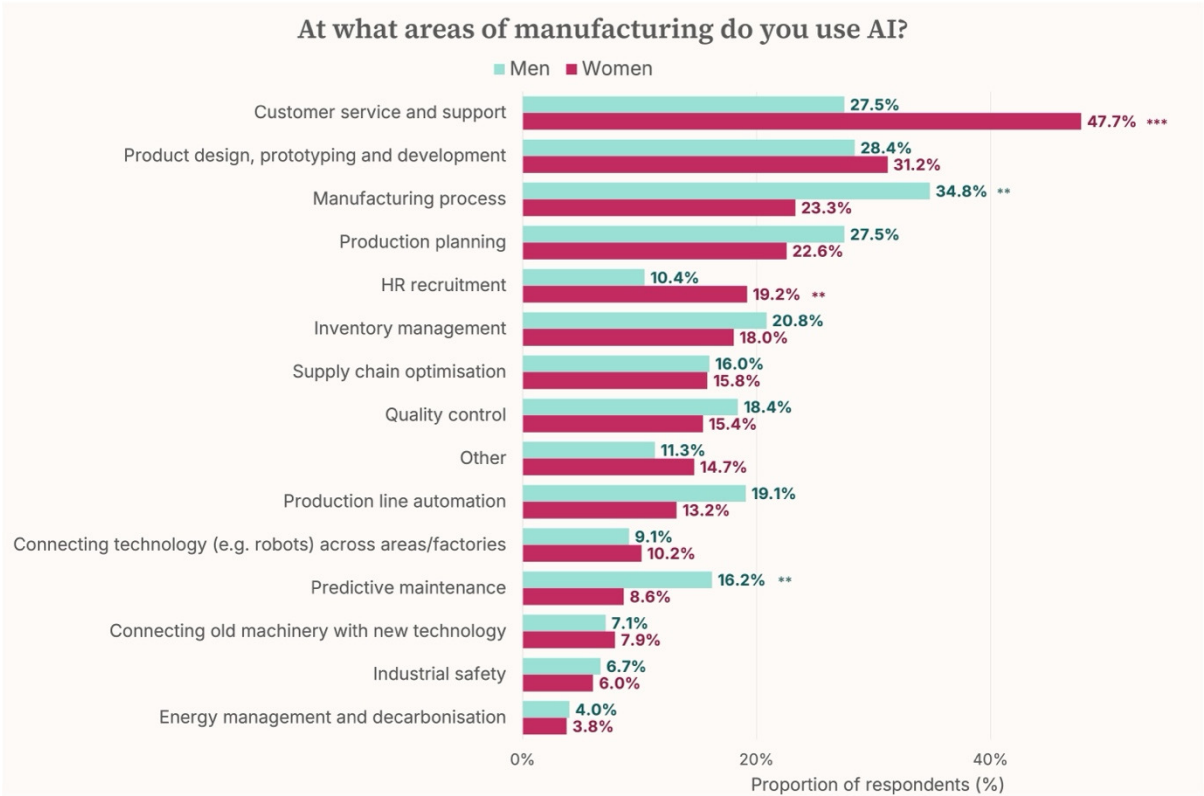
This pattern is consistent with the occupational structure described in Section 2. Women are more concentrated in administrative and service-facing roles, while men are more strongly represented in production and skilled trades. By contrast, reported use of particular technologies – including GenAI, computer vision, and natural language processing – is broadly similar among women and men. The

⁴⁸ Department for Science, Innovation and Technology (2026). *AI Labour Market Survey 2025 report: executive summary*.

⁴⁹ Department for Education and Skills England (2025). *Employer Skills Survey 2024*. Official Statistics.

gender difference appears to lie less in the technologies themselves than in the organisational functions and tasks to which they are applied.

FIGURE 7: AI APPLICATION AREAS IN MANUFACTURING, BY GENDER



Note: Based on 717 respondents who selected at least one application (451 men, 266 women). Gender differences are statistically significant for customer service and support (*** $p < 0.001$), manufacturing process (** $p < 0.01$), HR recruitment (** $p < 0.01$), and predictive maintenance (** $p < 0.01$). Differences for other application areas are not statistically significant. For methodology, see Appendix B.

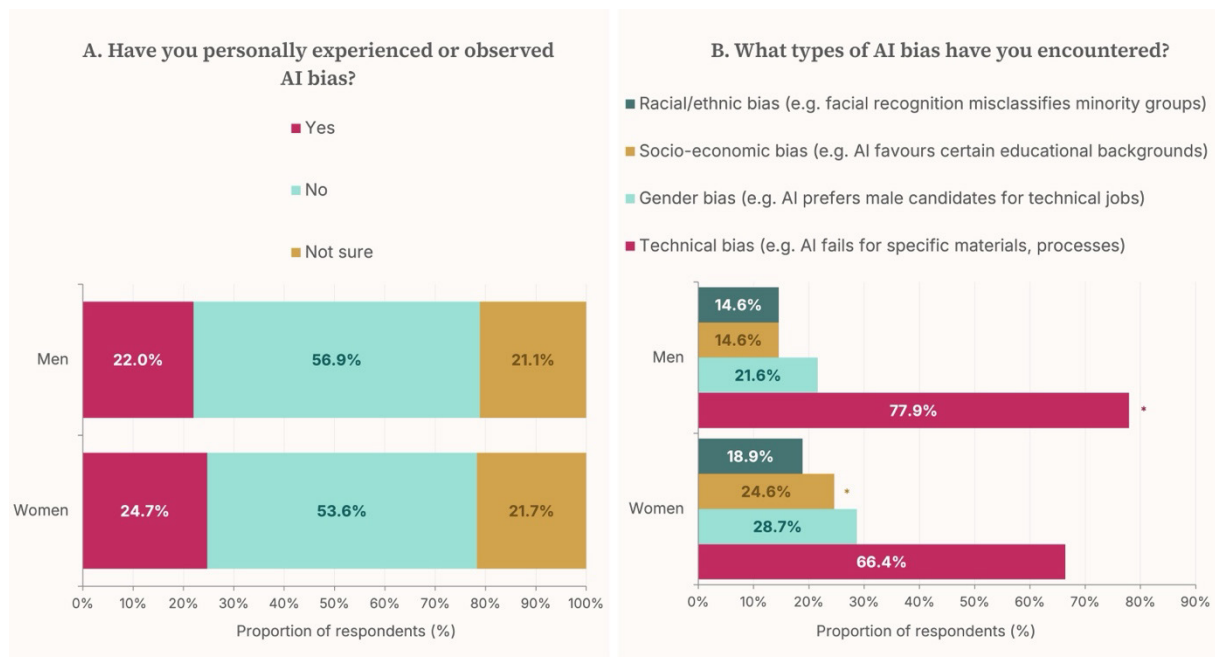
Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

3.2 Awareness and experience of AI bias

Women and men reported similar overall levels of experience with AI bias, and they encounter social and technical forms at similar frequencies. Differences emerge in the types of bias identified: women are more likely to report socio-economic bias, while men are more likely to report technical bias.

The overall incidence of reported AI bias is similar for women and men. Around one-quarter of women (24.7%) and 22.0% of men said they have personally experienced or observed AI bias, while a further 21% of each group were unsure (Figure 8, Panel A). The difference is not statistically significant; and there is no significant gender difference in how frequently respondents reported encountering social or technical forms of bias (Figure 9).

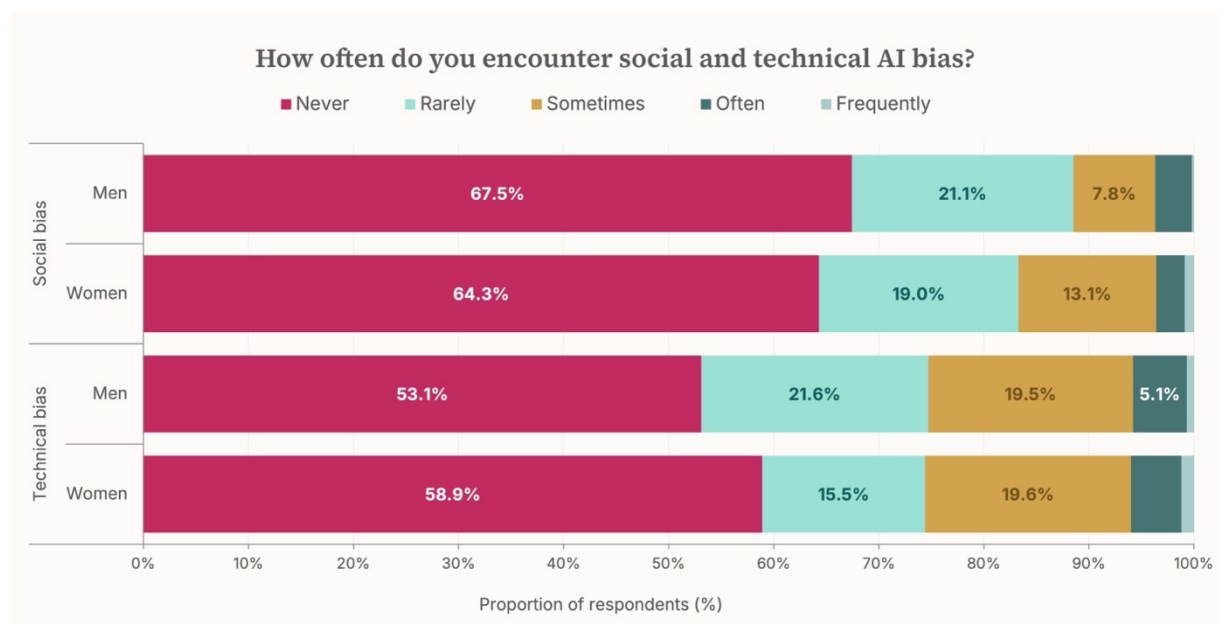
FIGURE 8: EXPERIENCE AND TYPES OF AI BIAS, BY GENDER



Note: Panel A: Based on 886 respondents (550 men, 336 women). No statistically significant gender difference. Panel B: Based on 335 respondents who selected at least one type of bias (213 men and 122 women). Respondents could select more than one type of bias; therefore, the percentages do not total 100%. Gender differences are statistically significant for technical bias (* $p < 0.05$) and socio-economic bias (* $p < 0.05$). For methodology, see Appendix B.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

FIGURE 9: FREQUENCY OF ENCOUNTERING SOCIAL AND TECHNICAL AI BIAS, BY GENDER



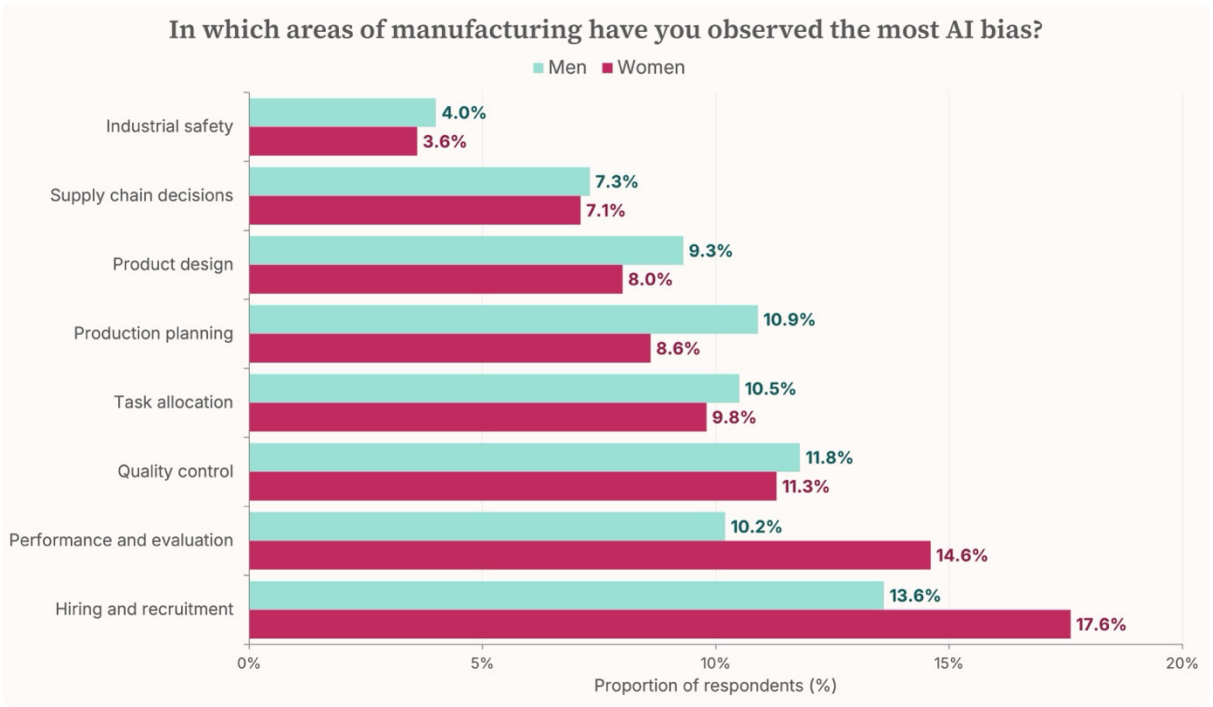
Note: Based on 886 respondents (550 men, 336 women). No statistically significant gender difference for social or technical AI bias. Values of less than 5% are not displayed. For methodology, see Appendix B.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

Instead, the distinction appears in the kinds of bias respondents recognise. Among the 335 respondents who selected at least one type of bias, 77.9% of men identified technical bias compared with 66.4% of women. Women were more likely to identify socio-economic bias (24.6% vs 14.6%) and gender bias (28.7% vs 21.6%), although only the socio-economic difference was statistically significant, alongside the difference in technical bias (Figure 8, Panel B).

There is less evidence of a gender difference in where bias was observed. Hiring and recruitment, performance evaluations, and quality control are among the areas most often selected, but none of the differences between women and men reaches statistical significance (Figure 10; see Box 5).

FIGURE 10: AREAS OF MANUFACTURING IN WHICH AI BIAS WAS OBSERVED, BY GENDER



Note: Based on 886 respondents (550 men, 336 women). Respondents could select more than one area; percentages therefore do not total 100%. “None observed” and “Other” responses are not shown. No statistically significant gender difference for any area. For methodology, see Appendix B.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

Box 5: How respondents described AI bias in hiring

Open-text responses provide examples of how respondents described AI bias in recruitment and CV screening. They reflect respondents’ own accounts and are illustrative rather than representative. Quotations have been lightly edited for spelling, grammar, punctuation and length.

“When sifting through CVs for a technical managerial position, AI seemed to prefer the male candidates. When I double-checked AI’s recommendations for the position, I found that a more suitable female candidate did exist among the CVs supplied.” – Woman, management role, SME manufacturer

“We stopped using an AI algorithm for hiring and recruitment because it has unconscious bias favouring male applicants over female.” – Woman, management role, large manufacturer

"When recruiting, we have a system which sifts out most suitable candidates, but we then manually look through the discarded candidates, as the human factor of a candidate who feels right but doesn't tick all the boxes comes into play." – Man, production and skilled-trades role, large manufacturer.

"We have had it in recruitment of personnel: screening out of candidates assessed to be female or showing flexible working patterns." – Woman, management role, large manufacturer

"When we were recently recruiting for a role, we were using AI to create a job advert and the AI model came up with language such as 'he will have knowledge' and 'his experience', which we had to correct before we made the advert live." – Man, professional role, SME manufacturer

"Selection of candidates: AI rejected on number of jobs, eliminating older candidates." – Woman, management role, SME manufacturer

"I used to work in HR for this business, and we have an AI system that filters people by certain qualifications and relevance; however, it would often filter out women, which was a remnant of older policies that we had within the business." – Man, administrative and customer-facing role, large manufacturer

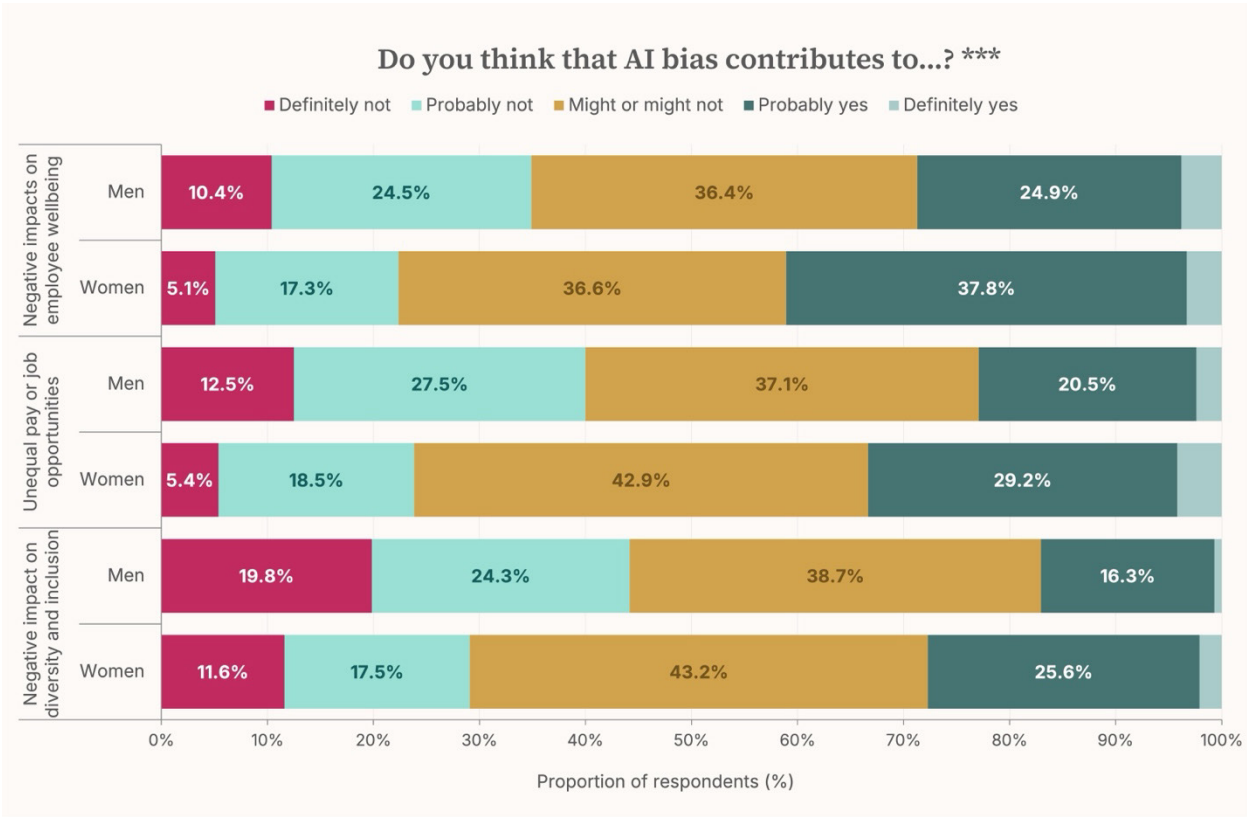
Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

3.3 Perceived social and workforce effects of AI bias

The gender differences became much more pronounced when respondents were asked about the consequences of AI bias. Women expressed greater concern about its effects on diversity, pay and job opportunities, and employee wellbeing. These differences persisted after accounting for occupational role, company size, age, AI use, and expertise. Concern about AI-related pay inequality is also already high among younger women: women aged 22–29 report levels of concern close to those of women in their 50s, despite facing a manufacturing gender pay gap of 7.6% compared with 20.0% for women aged 50–59, a difference of more than 12 percentage points.

When asked about social and workforce consequences, women consistently gave more negative assessments than men. Across three measures – diversity and inclusion, pay and job opportunities, and employee wellbeing – the gender differences were statistically significant (Figure 11). Overall, 41.1% of women said they believe that AI bias probably or definitely has a negative effect on employee wellbeing, compared with 28.7% of men. One-third of women (33.3%) said they believe it contributes to unequal pay or job opportunities, compared with 22.9% of men, while 27.7% reported a negative effect on diversity and inclusion, compared with 17.1% of men.

FIGURE 11: PERCEIVED EFFECTS OF AI BIAS ON DIVERSITY, PAY AND JOB OPPORTUNITIES, AND EMPLOYEE WELLBEING, BY GENDER



Note: Based on 886 respondents (550 men, 336 women). Gender differences are statistically significant for all three effects (** $p < 0.001$). Women have approximately twice the odds as men of reporting concern on each measure, after adjusting for role, company size, and age (Model 1). These effects remain robust to further adjustment for AI use and expertise (Model 2). Values of less than 5% are not displayed. For methodology, see Appendix B.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

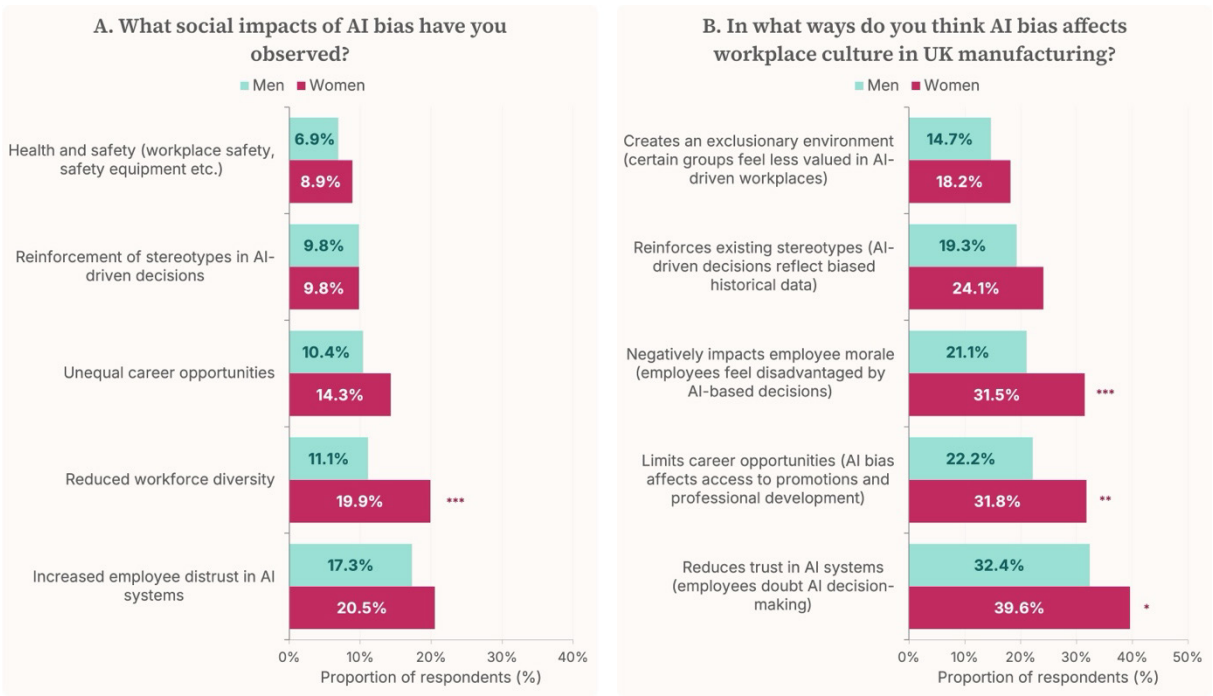
These differences remained after accounting for other respondent characteristics. After adjustment for occupational role, company size and age, women had approximately twice the odds of reporting concern on each of the three measures.⁵⁰ The results were robust to further adjustment for AI use and expertise, suggesting that the gender differences cannot be explained by differences in workforce composition or reported engagement with AI alone. At the same time, uncertainty was substantial: depending on the question, between 36% and 43% of respondents said they were unsure about the effects of AI bias.

Gender differences are also evident in reported impacts and perceptions of workplace culture (Figure 12). Among the specific social impacts listed, increased distrust in AI systems was reported most frequently, by 20.5% of women and 17.3% of men (Figure 12, Panel A). The clearest gender difference concerns workforce diversity: 19.9% of women reported having observed reduced diversity as an

⁵⁰ After adjusting for occupational role, company size, and age (Model 1), women have approximately twice the odds of reporting greater concern on each of the three social impact measures. The associations remained robust after further adjustment for AI use and expertise (Model 2). For methodology, see Appendix B.

effect of AI bias, compared with 11.1% of men. Differences in reported unequal career opportunities, stereotypes, and health and safety effects are smaller and not statistically significant.

FIGURE 12: REPORTED SOCIAL AND WORKPLACE-CULTURE EFFECTS OF AI BIAS, BY GENDER



Note: Based on 886 respondents (550 men, 336 women). Respondents could select more than one effect; percentages therefore do not total 100%. “None observed” and “Other” responses are not shown. Panel A: the gender difference is statistically significant for reduced workforce diversity (*** $p < 0.001$). Panel B: gender differences are statistically significant for employee morale (*** $p < 0.001$), career opportunities (** $p < 0.01$), and trust in AI systems (* $p < 0.05$). For methodology, see Appendix B.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

Women also expressed greater concern about the implications of AI bias for workplace culture. Around four in ten women reported that AI bias reduces trust in AI systems, compared with around one-third of men. Women were more likely to report that it limits career opportunities (31.8% compared with 22.2%) and negatively affects employee morale (31.5% compared with 21.1%). All three gender differences are statistically significant (Figure 12, Panel B; see Box 6).

Box 6: How respondents described AI bias in task allocation, performance evaluation, and representation

Open-text responses illustrate how respondents described AI bias in the allocation of work, performance evaluation and the representation of workers. They reflect respondents' own accounts and are illustrative rather than representative. Quotations have been lightly edited for spelling, grammar, punctuation and length.

"I have seen job allocation done by AI have all roles of a certain strength go to male workers." – Woman, management role, large manufacturer

"When assigning tasks, the AI tends to only ever provide lifting jobs to the male workers." – Man, production and skilled-trades role, large manufacturer

"AI bias in performance evaluation within manufacturing occurred in our factory. We used an AI system to assess worker productivity and determine promotions. The AI system tracked workers' output and compared it with historical performance data. However, the system was trained on historical data that did not account for different work conditions, such as varying task difficulty, shifts or machinery used by different workers." – Woman, management role, SME manufacturer

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

The age profile adds another dimension to the concern about AI-related pay inequality. The median manufacturing gender pay gap rises from 7.6% among employees aged 22–29 to 20.0% among those aged 50–59, an increase of 12.4 percentage points.⁵¹ Yet reported concern about AI-related pay inequality varies relatively little between younger and older women: 34.9% of women aged 22–29 expressed concern, compared with 39.0% of women in their 50s (Figure 13). The comparison does not show that younger women are anticipating their own future pay outcomes, but it does show that concern emerges well before the sector-wide pay gap reaches its highest levels.

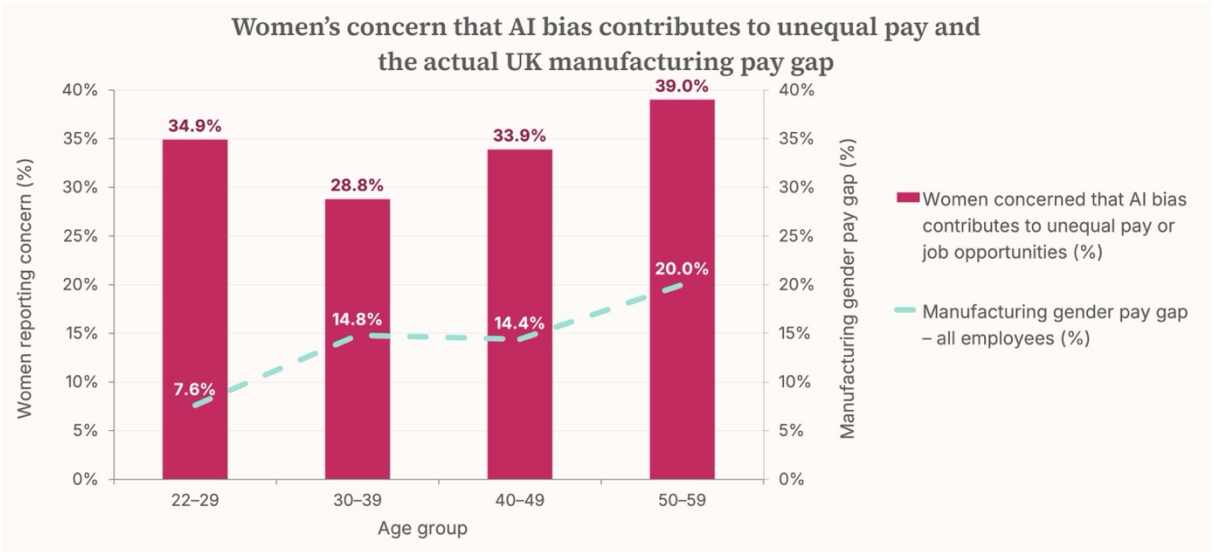
Although the questions are not directly comparable, women's greater concern about the effects of AI bias on pay, job opportunities and wellbeing is consistent with wider national evidence showing that women are less optimistic about AI's personal benefits and more concerned about its risks. In the ONS Opinions and Lifestyle Survey for June 2026, 41% of men but 31% of women agreed that AI would benefit them, while women were more likely than men to believe that AI brings more risks than benefits (42% compared with 34%). Men were also more likely to expect AI to improve their job prospects (11% compared with 7%) or increase their income (10% compared with 4%). Nearly half of adults aged 16–49 thought AI could put their job at risk, compared with 24% of those aged 50–69; the question was asked of all adults, regardless of employment status.⁵² Pew Research Center similarly found that 61% of UK adults expected AI to result in fewer jobs over the following 20 years, while 24% were unsure.⁵³

⁵¹ ONS (2025). Annual Survey of Hours and Earnings, Table 21.12. Manufacturing (SIC C), all employees, median hourly pay excluding overtime. 2025 provisional.

⁵² ONS (2026). Public opinions and social trends, Great Britain: June 2026. Opinions and Lifestyle Survey.

⁵³ Pew Research Center (2026). *Globally, More People Expect AI to Cause Job Loss Than Growth*.

FIGURE 13: WOMEN’S CONCERN ABOUT AI-BIAS-RELATED PAY INEQUALITY AND THE MANUFACTURING GENDER PAY GAP, BY AGE GROUP



Note: Based on 302 women respondents with valid age data aged 22–59. The left axis (bars) shows the percentage of women who responded “Probably yes” and “Definitely yes” to the question “Do you believe AI bias contributes to unequal pay or job opportunities in UK manufacturing?” The 18–21 and 60+ age groups are excluded because of small sample sizes. Differences in concern between age groups are not statistically significant. The right axis (line) shows the median manufacturing gender pay gap. For methodology, see Appendix B.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI; ONS (2025), Annual Survey of Hours and Earnings, Table 21.12, Manufacturing (SIC C), 2025 provisional.

3.4 Perceived economic and organisational effects of AI bias

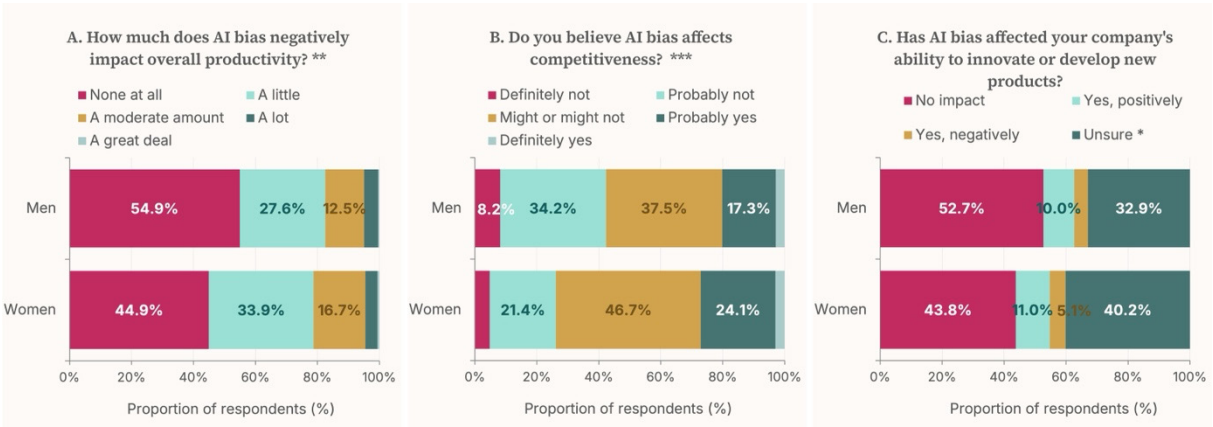
Women expressed greater concern about the economic consequences of AI bias, particularly for productivity and competitiveness, while several of the clearest differences in specific business impacts concern hiring and talent loss. Regarding innovation, the gender gap reflects greater uncertainty among women about whether AI bias affects their ability to innovate, rather than greater pessimism.

Women differed from men in how they assessed the implications of AI bias for business performance. Around 55% of women reported that AI bias has at least some negative effect on productivity, compared with 45% of men (Figure 14, Panel A; see Box 7). Women were also more likely to report an effect on competitiveness: 27.1% answered “probably” or “definitely” compared with 20.2% of men (Figure 14, Panel B). Both differences remained after adjustment for age, occupational role, and company size, and held after additionally accounting for AI use and expertise.

Read alongside Section 2, the productivity result raises an important policy question. Women are more concentrated in occupations likely to be reshaped by GenAI, yet the women in the survey were also more likely to report that AI bias has at least some negative effect on productivity. The combination suggests that achieving productivity gains from AI adoption will depend not only on deployment but also on how effectively bias and workforce concerns are addressed.

Responses on innovation show a different pattern. Women were more likely to be unsure whether AI bias had affected their company’s ability to innovate: 40.2% selected “unsure” compared with 32.9% of men (Figure 14, Panel C). Only 5.1% of women and 4.4% of men reported a negative effect. The adjusted analysis points in the same direction: the gender difference lies in uncertainty, not in a stronger belief among women that innovation has already been adversely affected.

FIGURE 14: PERCEIVED EFFECTS OF AI BIAS ON PRODUCTIVITY, COMPETITIVENESS, AND INNOVATION, BY GENDER



Note: Based on 886 respondents (550 men, 336 women). Panels A and B: gender differences are statistically significant for views on productivity (**p < 0.01) and competitiveness (**p < 0.001). Panel C: responses are not ordinal; tested separately. The gender difference is statistically significant for “unsure” response (* p < 0.05); no difference in negative impact. Values of less than 5% are not displayed. For methodology, see Appendix B.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

Box 7: How respondents described technical bias in quality control and production

Open-text responses illustrate how respondents described technical bias and related AI system failures in quality control and production. They reflect respondents’ own accounts and are illustrative rather than representative. Quotations have been lightly edited for spelling, grammar, punctuation and length.

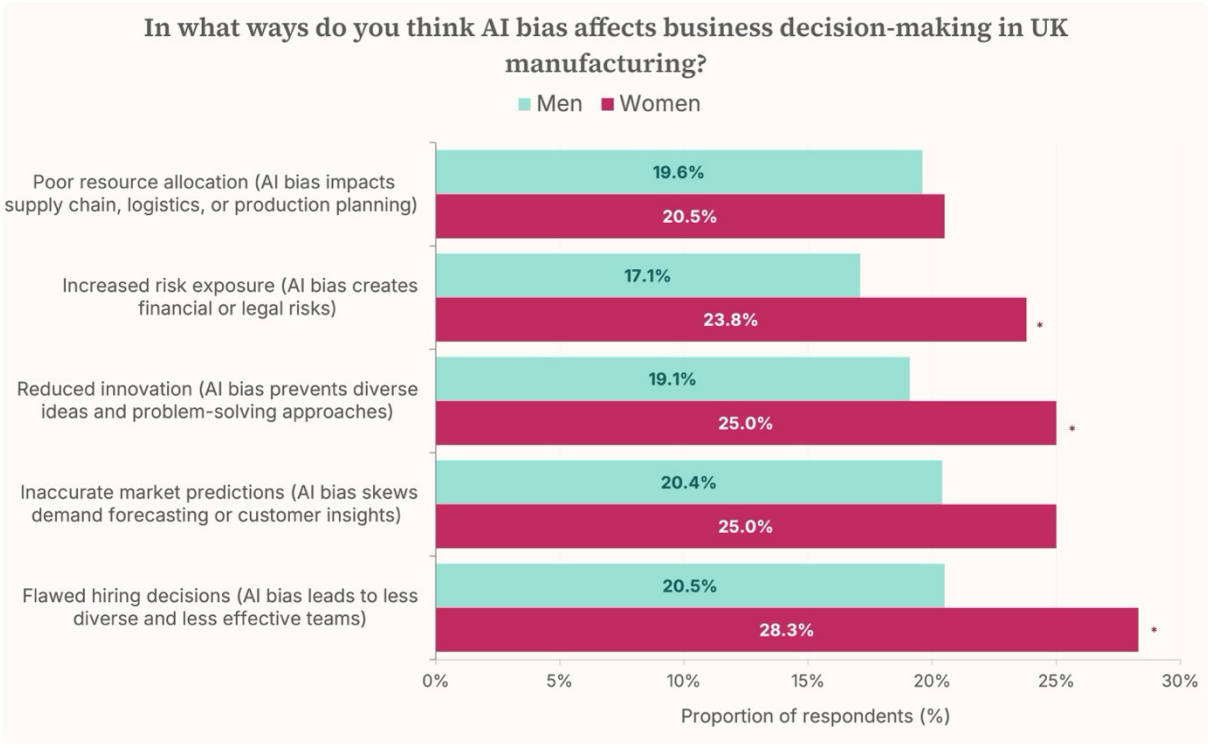
“On a sandwich production line, an AI system used to inspect the appearance of sandwiches can struggle to identify issues like uneven fillings when the sandwiches are made with different ingredients from new suppliers. We often experience teething issues, which leads to incorrect sorting and product rejection, which creates a lot of waste. More training and data is needed to reduce AI bias and improve accuracy in the food industry.” – Woman, administrative and customer-facing role, SME manufacturer

“Initially, the system was trained on parts produced using a specific polishing technique. However, when we introduced components from an alternative supplier, meeting the same food-safety standards but with slight variations in surface finish, the AI began falsely rejecting them as defective.” – Woman, professional role, large manufacturer

“Near the end of one of my shifts, one of our lines was completely halted due to the AI not wanting to pass a completed product. We had to disassemble one of the motors to allow the line to come back online, then had a technician reconfigure the AI to make sure the correct checks were being done.” – Man, administrative and customer-facing role, SME manufacturer

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

FIGURE 15: PERCEIVED EFFECTS OF AI BIAS ON BUSINESS DECISION-MAKING, BY GENDER



Note: Based on 886 respondents (550 men, 336 women). Respondents could select more than one effect; percentages therefore do not total 100%. “None observed” and “Other” responses are not shown. Gender differences are statistically significant for flawed hiring decisions (* $p < 0.05$), increased risk exposure (* $p < 0.05$), and reduced innovation (* $p < 0.05$). For methodology, see Appendix B.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

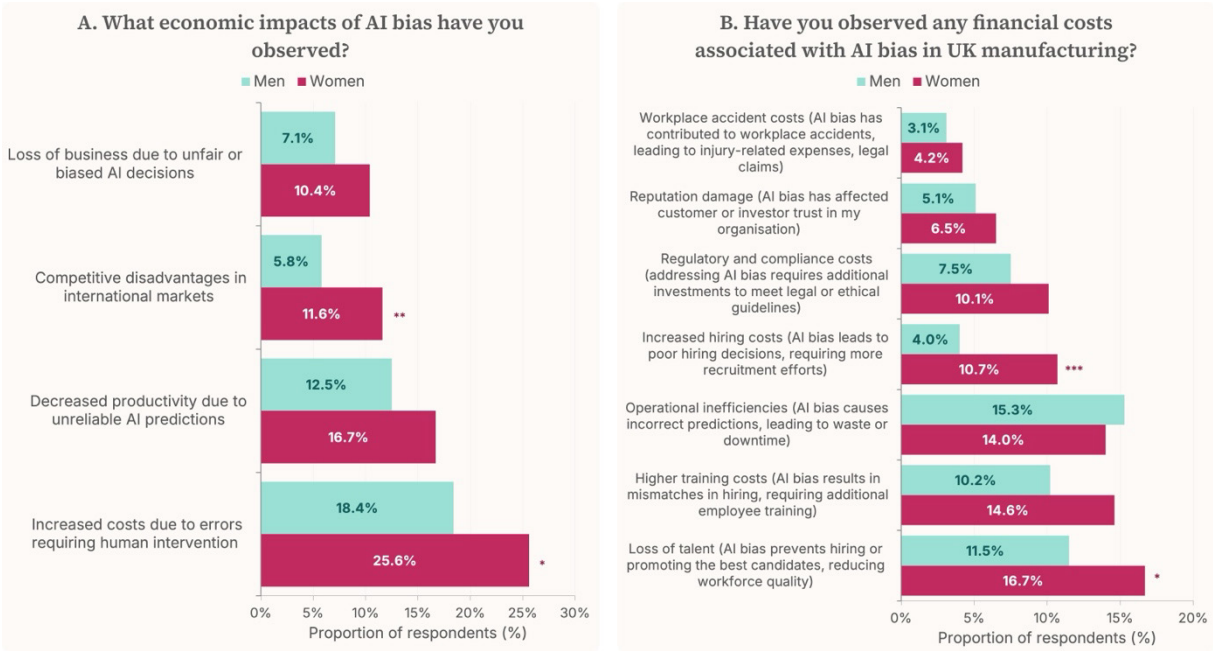
Looking beyond these broad performance measures, the perceived risks extend to business decision-making. Women were more likely than men to identify flawed hiring decisions (28.3% compared with 20.5%), reduced innovation (25.0% compared with 19.1%), and increased risk exposure (23.8% compared with 17.1%) as potential effects of AI bias (Figure 15). There was no statistically significant gender difference in reported concerns about inaccurate market predictions or poor resource allocation.

Reported economic consequences were less common than anticipated effects, but differences still emerged. Women were more likely to report increased costs from errors requiring human intervention (25.6% compared with 18.4%) and competitive disadvantages in international markets (11.6% compared with 5.8%) (Figure 16, Panel A).

Regarding the financial cost of AI bias, women were more likely to identify the increased hiring costs associated with poor AI-supported decisions (10.7% compared with 4.0% of men) and loss of talent through recruitment or promotion decisions (16.7% compared with 11.5%) (Figure 16, Panel B). Reports of operational inefficiencies, compliance costs, reputational damage, and workplace accident costs were broadly similar between women and men.

Overall, gender differences recurred across hiring and talent-related outcomes. Women were significantly more likely than men to identify flawed hiring decisions, increased hiring costs, and loss of talent as consequences of AI bias. This is important because it links perceptions of AI bias not only to fairness at work but also to recruitment quality, retention, and business performance.

FIGURE 16: REPORTED ECONOMIC IMPACTS AND FINANCIAL COSTS ASSOCIATED WITH AI BIAS, BY GENDER



Note: Based on 886 respondents (550 men, 336 women). Respondents could select more than one effect; percentages therefore do not total 100%. “None observed” and “Other” responses are not shown. Panel A: gender differences are statistically significant for increased costs (* $p < 0.05$) and competitive disadvantages (** $p < 0.01$). Panel B: gender differences are statistically significant for increased hiring costs (***) $p < 0.001$ and loss of talent (* $p < 0.05$). For methodology, see Appendix B.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

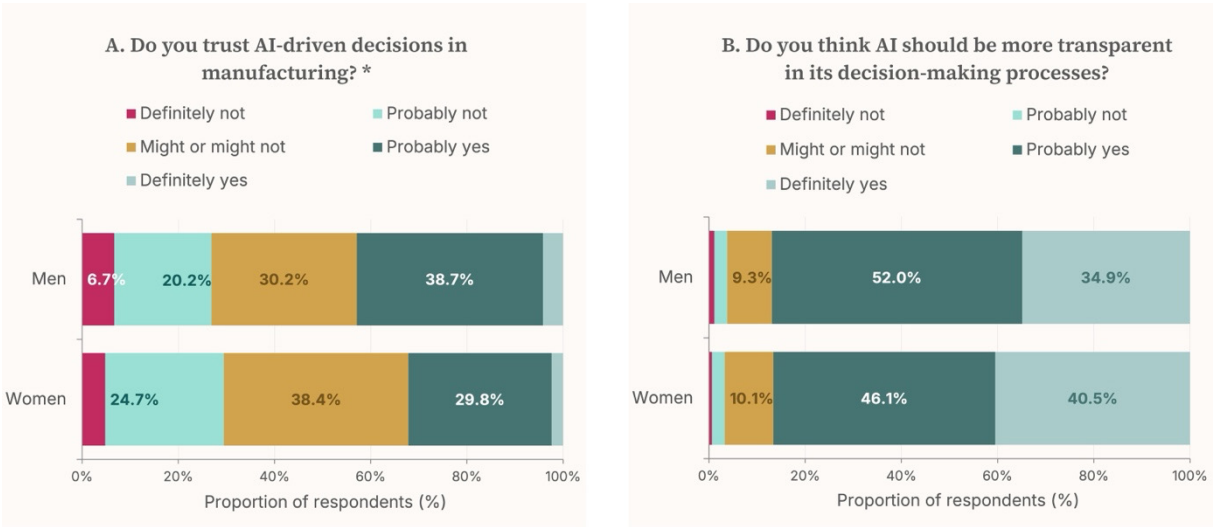
3.5 Trust in AI and governance

Women reported being less likely than men to trust AI-driven decisions, although this difference weakened once AI use and expertise were considered. Trust was similar among the youngest respondents, and the gap was widest among those aged 40–49. Women and men otherwise expressed similar views on transparency, regulation, and organisational preparedness. Greater perceived preparedness is associated with higher trust but not with lower concern about the effects of AI bias on pay and job opportunities.

Women reported being less likely than men to trust AI-driven decisions in manufacturing. Just under one-third of women (32.1%) said they would trust them (probably and definitely) compared with 42.9% of men (Figure 17, Panel A). This difference remained statistically significant after adjusting for role, company size, and age, but weakened once AI use and expertise were considered.⁵⁴

⁵⁴ The gender difference in trust was significant after adjusting for role, company size, and age (Model 1, * $p < 0.05$) but weakened after also adjusting for AI use and expertise (Model 2). For methodology, see Appendix B.

FIGURE 17: TRUST IN AI-DRIVEN DECISIONS AND SUPPORT FOR TRANSPARENCY, BY GENDER



Note: Based on 886 respondents (550 men, 336 women). Panel A: gender differences are statistically significant, and remain so after adjusting for role, company size, and age (Model 1, * $p < 0.05$), but weaken after additionally adjusting for AI use and expertise (Model 2, $p = 0.13$). Panel B: no significant gender difference. For methodology, see Appendix B.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

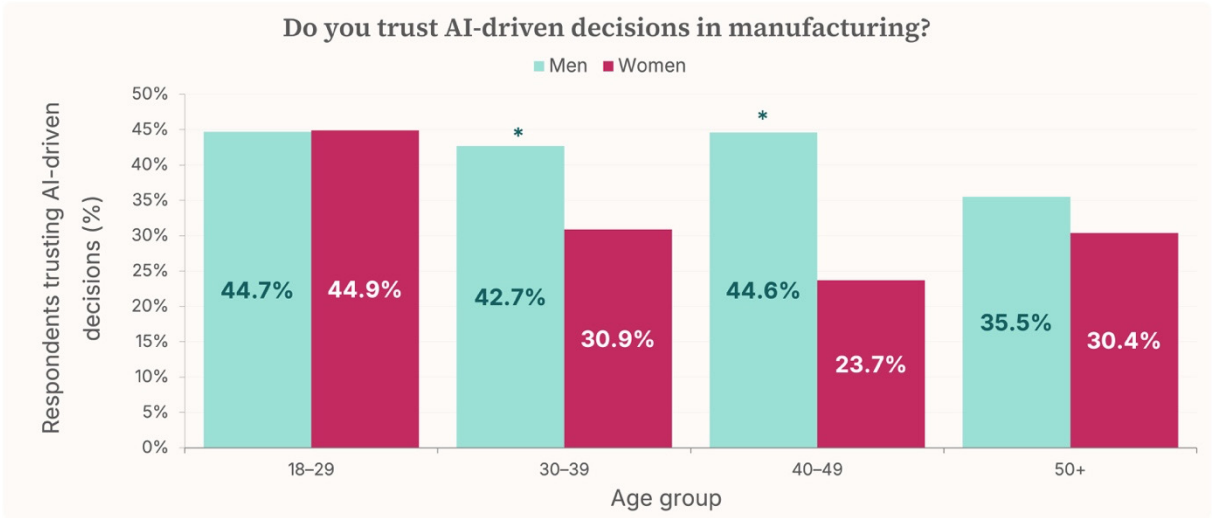
This distinguishes trust from the social impact findings in Section 3.3, where the gender gaps remain after all adjustments. The results suggest that differences in AI engagement may account for part of the gender gap in trust, which is consistent with wider evidence that familiarity with AI is associated with more positive attitudes towards it. A UK survey by the Tony Blair Institute for Global Change and Ipsos, for example, found that 56% of people who had never used AI viewed it primarily as a risk, compared with 26% of weekly users.⁵⁵

Age also mattered to respondents. Among those aged 18–29, women and men reported almost identical levels of trust (44.9% and 44.7%, respectively). A gap emerged among those aged 30–39, at 11.8 percentage points, and was widest among respondents aged 40–49, at 20.9 percentage points, before narrowing again among those aged 50 and over (Figure 18). The differences for the 30–39 and 40–49 groups were statistically significant, although these subgroup results should be interpreted with caution.

On the wider governance of AI, however, women and men largely agreed. More than eight in ten respondents in both groups said they believe AI systems should be more transparent: 86.9% of men and 86.6% of women. This was one of the strongest areas of consensus in the survey (Figure 17, Panel B). Views on regulation were also similar, with around a third of both women and men expecting AI regulations to help reduce bias (Figure 19, Panel B). Perceptions of organisational preparedness follow a similar broad pattern: roughly half of respondents in both groups believe their company is doing too little to prepare for the challenges associated with AI bias (Figure 19, Panel A). None of these measures shows a significant gender difference.

⁵⁵ Mökander, J. et al. (2025). What the UK Thinks About AI: Building Public Trust to Accelerate Adoption. Tony Blair Institute for Global Change / Ipsos. Survey of 3,727 UK adults.

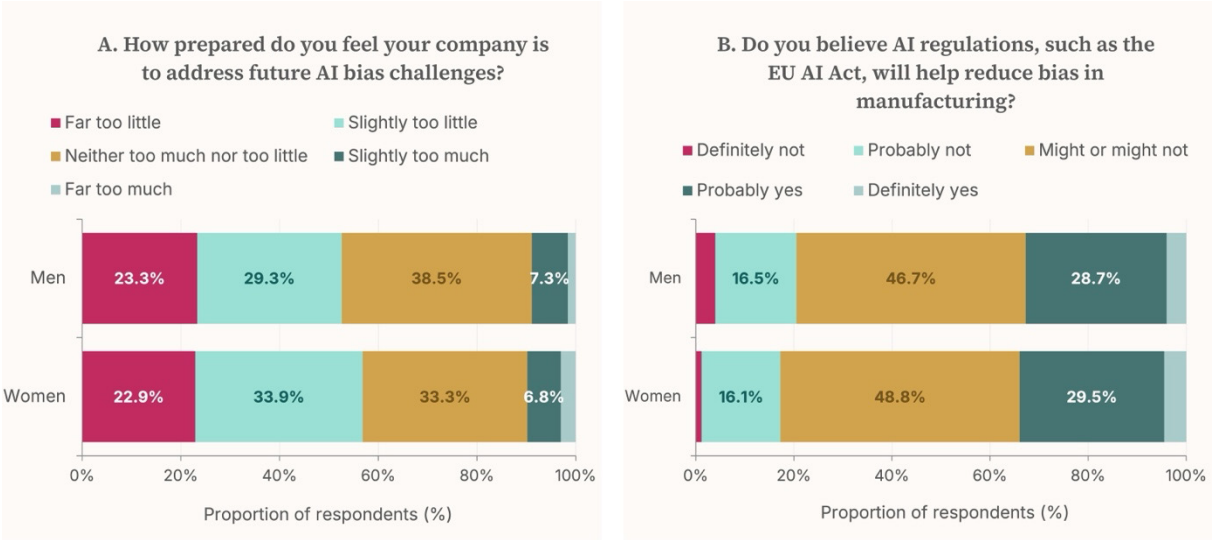
FIGURE 18: TRUST IN AI-DRIVEN DECISIONS IN UK MANUFACTURING, BY GENDER AND AGE GROUP



Note: Based on 857 respondents with valid age data (534 men, 323 women). Subgroup sample sizes: 18-29: 114 men, 69 women; 30-39: 192 men, 139 women; 40-49: 121 men, 59 women; 50+: 107 men, 56 women. "Probably yes" and "Definitely yes" combined. Gender differences are statistically significant for the 30-39 and 40-49 groups (* $p < 0.05$). 18-29 and 50+: no significant difference. This is a subgroup analysis, to be interpreted with caution. For methodology, see Appendix B.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

FIGURE 19: PERCEIVED ORGANISATIONAL PREPAREDNESS AND EXPECTATIONS OF AI REGULATION, BY GENDER

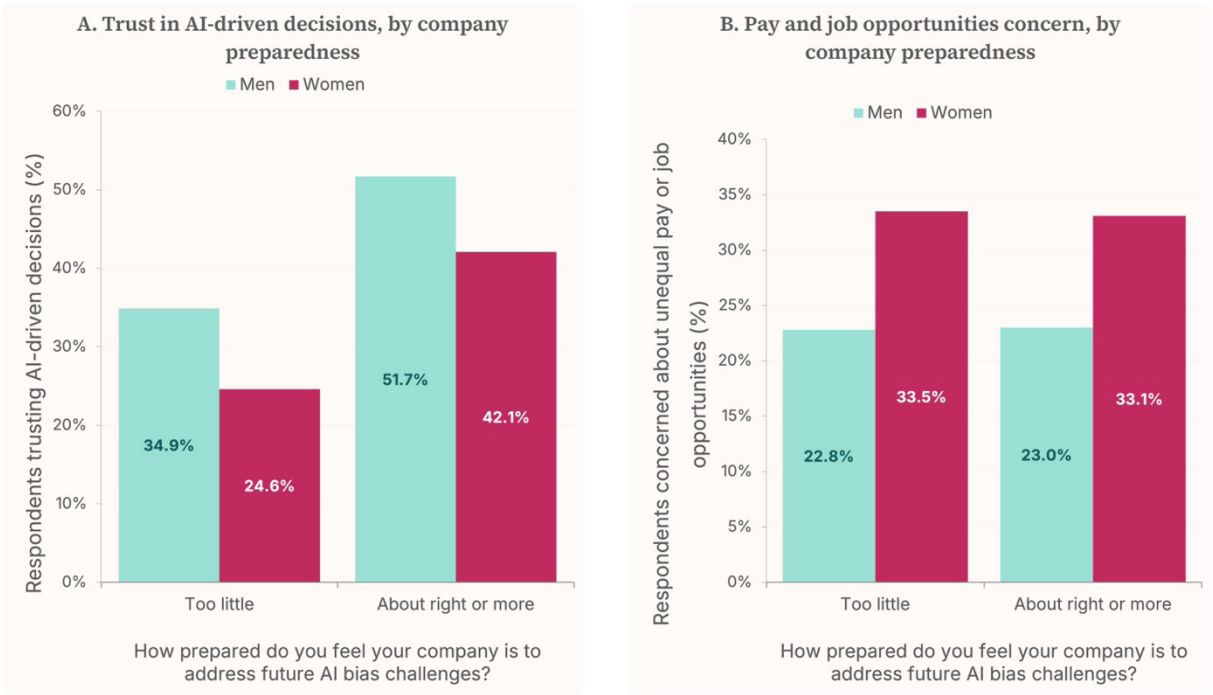


Note: Based on 886 respondents (550 men, 336 women). There are no statistically significant gender differences in either panel. Values of less than 5% are not displayed. For methodology, see Appendix B.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

Perceived organisational preparedness was nevertheless related to trust. Respondents who considered their company to be doing enough to prepare for AI bias said they were more likely to trust AI-driven decisions than those who thought it was doing too little, and this held for both women and men: trust rose from 24.6% to 42.1% among women and from 34.9% to 51.7% among men (Figure 20, Panel A). The gender gap of around ten percentage points persisted in both groups.

FIGURE 20: TRUST IN AI-DRIVEN DECISIONS AND CONCERNS ABOUT PAY AND JOB OPPORTUNITIES, BY GENDER AND PERCEIVED COMPANY PREPAREDNESS



Note: Based on 886 respondents (550 men, 336 women). Panel A: respondents answering "Probably yes" or "Definitely yes" to "Do you trust AI-driven decisions in manufacturing?". Panel B: respondents answering "Probably yes" or "Definitely yes" to "Do you think AI bias contributes to unequal pay or job opportunities?". "Too little" combines "Far too little" and "Slightly too little". "About right or more" combines "Neither too much nor too little," "Slightly too much", and "Far too much". Preparedness is positively associated with trust ($r = 0.27$, *** $p < 0.001$) but not with concern about pay and job opportunities ($r = 0.02$, not significant) or employee wellbeing ($r = -0.03$, not significant). Subgroup sizes: Too little: 289 men, 191 women; About right or more: 261 men, 145 women. For methodology, see Appendix B.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

Preparedness was not associated with concern about pay and job opportunities: concern did not decline as preparedness rose. Around one-third of women (33.5% and 33.1%) and just under a quarter of men (22.8% and 23.0%) expressed concern in both groups, and women were more concerned than men (Figure 20, Panel B). Across the full sample, preparedness was positively correlated with trust but not with concern about pay and job opportunities.⁵⁶ Organisational readiness and perceived fairness therefore appear to be distinct issues: greater preparedness may support confidence in the use of AI, but it does not in itself correspond to lower concern about its distributional or workforce consequences.

This distinction is relevant to the wider challenge of AI adoption in manufacturing. Make UK (2026) argues that many manufacturers still lack the organisational capabilities required to move from small-scale AI experimentation to wider business transformation.⁵⁷ As noted in Section 3.1, the share of manufacturing employers providing training fell between 2022 and 2024. The survey findings suggest that building those capabilities may be important for trust, but they should not be treated as a substitute for addressing fairness in how AI systems are designed and used. Young women are

⁵⁶ Spearman correlations: preparedness $\times$ trust $r = 0.27$ (*** $p < 0.001$); preparedness $\times$ pay $r = 0.02$ (not significant). For methodology, see Appendix B.

⁵⁷ Make UK (2026). *AI, Skills and the Future of the UK Manufacturing Sector*.

already as concerned about AI-related pay inequality as older women, despite facing a much smaller manufacturing pay gap (Figure 13). Preparedness may help build confidence in AI systems, but addressing concern about pay and opportunity requires a different set of responses.

These findings sit within a wider climate of caution about AI. In the ONS Opinions and Lifestyle Survey for June 2026, adults were asked which tasks, if any, they would trust AI to carry out; only 7% selected "decision-making in business".⁵⁸ In Pew Research Center's 37-country survey, 42% of UK adults felt more concerned than excited about the increased use of AI in daily life, while 49% felt equally concerned and excited and 8% felt more excited than concerned.⁵⁹ Although these general-population measures are not directly comparable with the manufacturing survey, they illustrate the wider challenge of building confidence in AI-supported decisions.

3.6 AI bias mitigation and challenges

Women and men identified broadly similar barriers to addressing AI bias, including unclear regulation, the complexity of detecting bias, and insufficient leadership awareness. One difference stands out: women were more than twice as likely as men to identify the under-representation of women in AI and manufacturing roles as a significant barrier. At the same time, most respondents said they are unaware of any measures their company is taking to address AI bias.

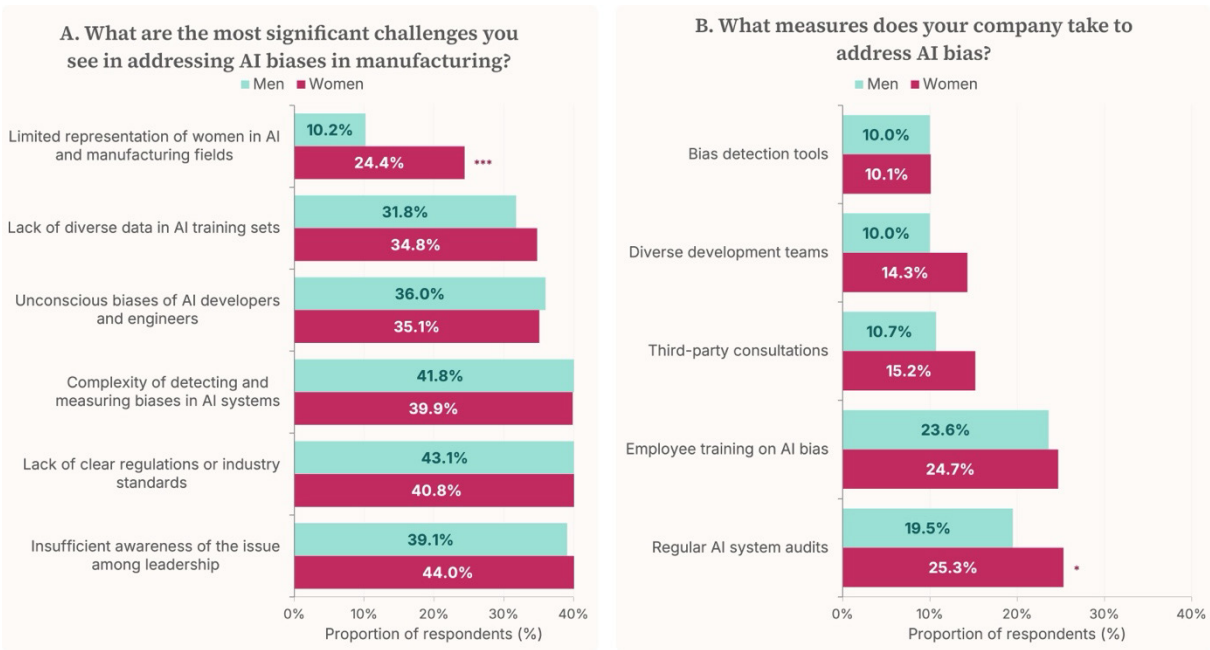
Across most of the challenges listed in the survey, women and men gave similar answers. A lack of clear regulation was identified by 43.1% of men and 40.8% of women, the complexity of detecting bias by 41.8% and 39.9%, respectively, and insufficient leadership awareness by 39.1% of men and 44.0% of women. But women were 2.4 times more likely than men to cite limited representation of women in AI and manufacturing roles as a significant challenge (24.4% vs 10.2%). This was the largest gender difference observed in the survey's multi-select items and was statistically significant (Figure 21, Panel A).

Awareness of organisational responses was limited more generally. More than half of respondents (58%) said they are not aware of any measures their company is taking to address AI bias. Where measures were reported, employee training was the most common (24%), followed by regular AI system audits (22%). Women were somewhat more likely than men to report regular audits (25.3% compared with 19.5%); under this analysis, this difference was statistically significant (Figure 21, Panel B).

⁵⁸ ONS (2026). Public opinions and social trends, Great Britain: June 2026. Opinions and Lifestyle Survey.

⁵⁹ Pew Research Center (2026). Globally, More People Expect AI to Cause Job Loss Than Growth.

FIGURE 21: CHALLENGES AND MEASURES IN ADDRESSING AI BIAS, BY GENDER



Note: Based on 886 respondents (550 men, 336 women). Respondents could select more than one response; percentages therefore do not total 100%. “None that I am aware of” and “Other” responses are not shown. Panel A: gender difference is statistically significant for limited representation of women (*** $p < 0.001$). Panel B: gender difference is statistically significant for regular AI system audits (* $p < 0.05$). All other items: no significant gender difference. For methodology, see Appendix B.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

3.7 Bringing the gender differences together

Taken together, the survey points to a clear divide. Women and men in UK manufacturing use AI at similar rates, report similar levels of expertise, and encounter AI bias at similar frequencies. Yet women are much more concerned about its social and economic consequences. The largest gaps are concentrated in areas that directly affect working lives – pay and job opportunities, wellbeing, diversity and inclusion, productivity and competitiveness – and persist after adjusting for occupational role, company size, age, AI use, and expertise.

The trust and understanding results add nuance. First, the gender gap in trust became weaker when AI use and expertise were included in the analysis, suggesting that engagement may explain part of the difference; trust was also almost identical among the youngest respondents and widest mid-career. Second, the gender difference in perceived understanding of AI bias similarly decreased after accounting for AI use and expertise. Training and hands-on engagement may therefore help narrow specific gaps in confidence and understanding, although the survey cannot establish causality.

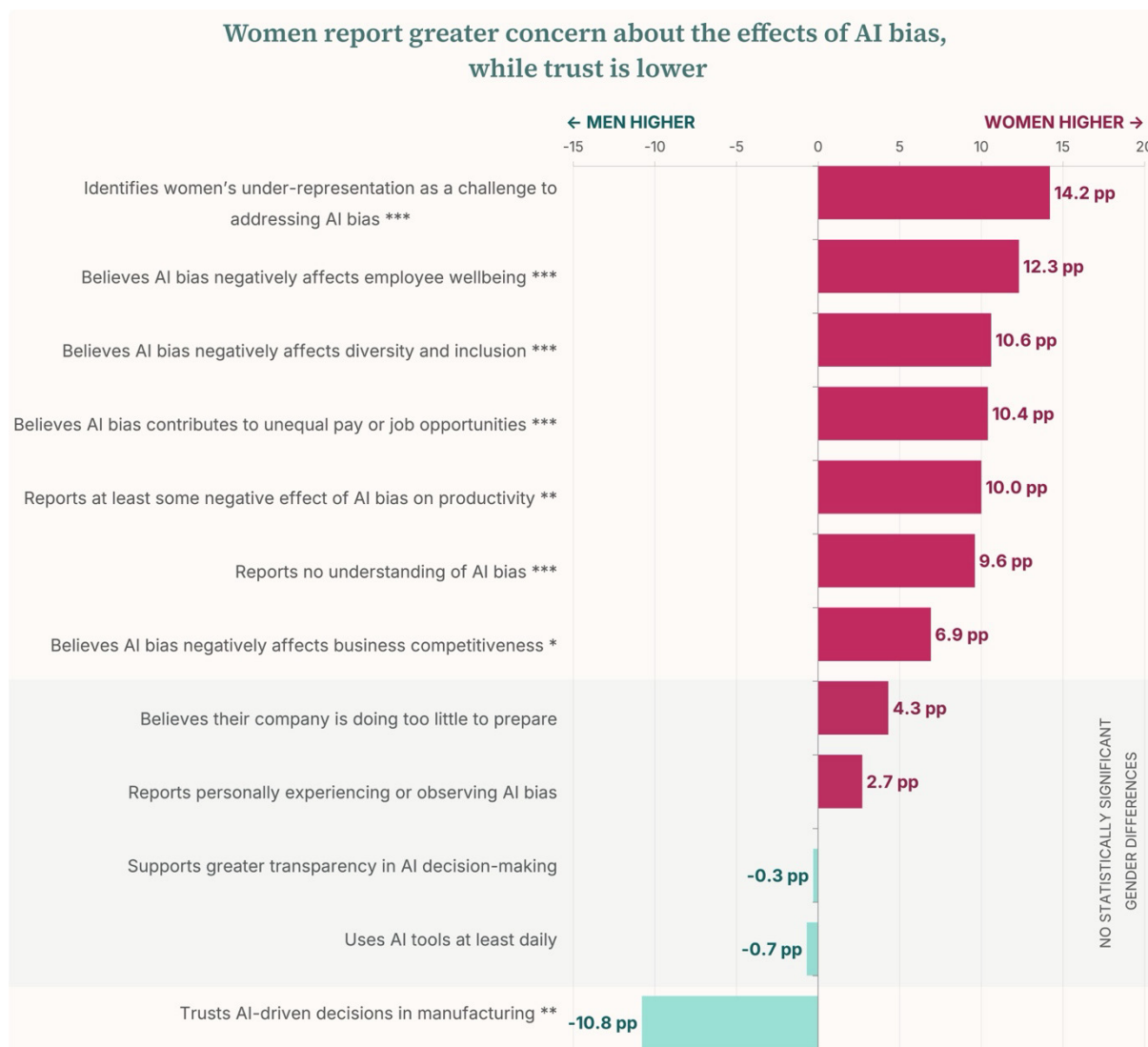
The differences in concern, by contrast, remained after accounting for AI engagement. After adjustment for occupational role, company size, and age, women had approximately twice the odds of reporting greater concern about pay and job opportunities, wellbeing and diversity; the differences remained robust even after further adjustment for AI use and expertise. This suggests that these

differences cannot be explained simply by lower familiarity with AI. Concern about AI-related pay inequality is already high among younger women, despite the much smaller sector-wide manufacturing gender pay gap faced by this age group. Women were also 2.4 times more likely than men to identify the limited representation of women in AI and manufacturing roles as a key challenge in addressing AI bias – the largest gender difference across the survey’s multi-select items.

Organisational preparedness adds another part of the picture. Respondents who consider their company to be better prepared reported being more likely to trust AI-driven decisions. Preparedness was not, however, associated with lower concern about pay and job opportunities. Training and organisational readiness may therefore strengthen confidence in AI and improve understanding, but they are unlikely on their own to address concerns about fairness. These concerns point to a broader set of organisational responses, including inclusive AI design and governance, greater transparency around workforce decisions, and stronger representation of women in the roles involved in developing, deploying, and overseeing AI systems.

Figure 22 summarises these patterns. The largest women-higher differences concern women’s under-representation as a challenge to addressing AI bias, perceived negative effects on employee wellbeing, diversity and inclusion, pay and job opportunities, productivity and business competitiveness, and lower reported understanding of AI bias. There is a substantial difference in trust in AI-driven decisions in the opposite direction. By contrast, perceived organisational preparedness, reported experience of AI bias, support for greater transparency, and daily AI use show no statistically significant gender difference.

FIGURE 22: SELECTED GENDER DIFFERENCES IN PERCEPTIONS OF AI BIAS ACROSS KEY INDICATORS



Note: Based on up to 886 respondents (550 men and 336 women). Bars show the percentage point difference between women and men in the proportion selecting the specified response or combined response categories. Positive values indicate a higher proportion among women; negative values indicate a higher proportion among men. The representation item was part of a multiple-response question. Statistical significance is based on chi-square tests with Yates' correction: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Items without stars show no statistically significant gender difference. For methodology, see Appendix B.

Source: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

AI and women's career pathways in UK manufacturing

What the evidence shows about
how AI may shape access to
work and progression after entry

4



4 AI and women's career pathways in UK manufacturing: a review of the evidence

Artificial intelligence can shape a career long before a formal employment decision is made, and its influence does not end once someone is hired. Section 4 reviews the evidence that helps explain how AI may influence access to manufacturing work and opportunities after entry. It considers five linked areas: gender differences in exposure to AI; in adoption and use; gender bias in AI models; recruitment and career guidance; and AI-enabled work organisation, management, and automation. The evidence base is expanding quickly but remains uneven. Much of the strongest gender-specific work is economy-wide or international, while manufacturing studies often concern earlier forms of automation rather than generative AI. The discussion therefore carefully distinguishes between experimental findings, cross-sector evidence, and research that is specific to manufacturing.

4.1 Gendered exposure to AI and generative AI

Section 2 established that women in UK manufacturing are more concentrated in occupations with higher estimated exposure to GenAI. International research places that result within a wider pattern in which occupational segregation shapes who is most exposed to current GenAI capabilities. Exposure is useful for locating where task content may change, but it does not show who has access to the technology, how intensively it is used, or whether employers reorganise work around it.

The international evidence also cautions against treating gendered exposure as a uniform measure of vulnerability. The ILO finds higher GenAI exposure among women in many countries because of their concentration in clerical, administrative, and business support work.⁶⁰ The OECD reaches a broadly compatible, though more qualified, conclusion. Its 2024 policy brief, drawing on evidence from 22 countries, finds that female and male workers face roughly the same occupational exposure to AI overall, but are distributed differently across highly exposed occupations.⁶¹ In either case, the implications depend partly on what happens after technical exposure: whether workers gain access to AI tools, training, and opportunities to use them in ways that build capability and experience.⁶² Exposure and vulnerability are also not the same thing. As noted in Section 2.5, US evidence illustrates this: most of the highly exposed workers are in professional roles with strong capacity to adapt, while among the smaller group with both high exposure and low capacity to manage a job transition, 86% are women, concentrated in clerical and administrative roles.⁶³

Seen alongside the UK manufacturing analysis, this wider evidence helps explain why exposure can have a gendered pattern even within a sector that is not highly exposed overall, and why access to tools, training, and career opportunities becomes important in terms of how that exposure is experienced. What the published literature does not show is how GenAI exposure is distributed

⁶⁰ International Labour Organization (2026). *Gen AI, occupational segregation and gender equality in the world of work*. ILO Research Brief. DOI: 10.54394/00033798.

⁶¹ OECD (2024). *Algorithm and Eve: How AI will impact women at work*. OECD. DOI: 10.1787/a1603510-en.

⁶² OECD (2024). *Algorithm and Eve: How AI will impact women at work*. OECD. DOI: 10.1787/a1603510-en.

⁶³ Manning, S. et al. (2026). *Measuring US Workers' Capacity to Adapt to AI-Driven Job Displacement*. Brookings Institution.

between women and men within the sector's occupational structure. Economy-wide studies therefore establish the relevance of the question but do not answer it for manufacturing.

4.2 Gender differences in AI adoption, use, and perceptions

Whether or not technical exposure translates into a meaningful change at work depends partly on whether people can access and use the tools. Workers may be in highly exposed occupations without having access to AI tools, and adoption can be shaped by training, employer policies, knowledge, and perceptions of usefulness or risk. A growing body of evidence suggests these factors differ by gender. In Denmark, Humlum and Vestergaard studied around 18,000 workers across 11 highly exposed occupations and found that women were 16 percentage points less likely than men in the same occupation to have used ChatGPT for work. The gap narrowed but persisted when comparing workers within the same workplace and controlling for detailed task mixes, falling to around 12 percentage points. Employer restrictions and a perceived need for training were among the barriers reported.⁶⁴

Evidence from the United States points in the same broad direction, although estimates vary. A nationally representative survey published by the National Bureau of Economic Research (NBER) found that men were around nine percentage points more likely than women to use GenAI at work. A BIS study using the New York Federal Reserve's Survey of Consumer Expectations found that 50% of men and 37% of women had used GenAI in the previous 12 months. Conventional demographic characteristics explained relatively little of this difference; self-assessed knowledge was the largest measured contributor, alongside perceptions of opportunities, risks, privacy, and trust. The studies do not show that an adoption gap exists everywhere, but they suggest that similar exposure does not necessarily translate into similar use.⁶⁵

Manufacturing-specific evidence is thinner, although the OECD's employer and worker surveys provide a useful starting point. Conducted in 2022, they covered 5,334 workers and 2,053 firms in manufacturing and finance across 7 countries, including the United Kingdom. The OECD found that AI users were more likely to be male than non-users in both sectors; separately, it estimated that 29% of all manufacturing workers and 42% of finance workers in the survey could be considered AI users. These figures pre-date the rapid diffusion of ChatGPT and relate to a broader generation of workplace AI, so they should not be read as a current GenAI estimate. They nevertheless show that workplace AI was already established in manufacturing and that use was not evenly distributed across worker groups. The published results do not provide a simple male-versus-female adoption rate for the combined sample, nor can they show whether gender differences in UK manufacturing reflect occupation, seniority, training, access to technology, or other organisational factors.⁶⁶

⁶⁴ Humlum, A. and Vestergaard, E. (2025). The unequal adoption of ChatGPT exacerbates existing inequalities among workers. *PNAS*. DOI: 10.1073/pnas.2414972121.

⁶⁵ Bick, A. et al. (2025). The Rapid Adoption of Generative AI. *NBER Working Paper*, 32966. DOI: 10.3386/w32966;

Aldasoro, I. et al. (2024). The gen AI gender gap. *BIS Working Papers*, No. 1197. <https://www.bis.org/publ/work1197.htm>

⁶⁶ Lane, M. et al. (2023). The impact of AI on the Workplace: Main findings from the OECD AI surveys of employers and workers. *OECD Social, Employment and Migration Working Papers*, No. 288. DOI: 10.1787/ea0a0fe1-en.

4.3 AI, gender bias, and access to work

4.3.1 Representation and access to opportunities

A separate body of research asks whether the very AI systems that help people find work opportunities reproduce gendered associations. Controlled experiments with large language models repeatedly identify occupational gender stereotypes. Kotek and colleagues found that the models they tested were much more likely to associate occupations with stereotypically corresponding genders, while UNESCO and IRCAI documented broader differences in how women and men were described and linked to work. Such findings do not demonstrate discrimination in an employment process, but they matter because the same models can sit upstream of job advertising, career guidance, screening, and other employment applications.⁶⁷

Similar patterns appear when LLMs generate professional material. Wan and colleagues found gendered differences in model-generated reference letters, including more communal language for women and more agentic or role model language for men. A separate pre-registered study of 1,400 ChatGPT-generated recommendation letters also found recurring communal and socially oriented language for female names, although some effects varied with the prompt. The concern is not simply stylistic. Repeated differences in how competence, agency, and leadership potential are described could shape perceptions of suitability, particularly for technical or senior roles. At the same time, these studies use simulated documents and do not show how often such differences change real hiring or promotion outcomes.⁶⁸

AI can also shape access before an application is submitted. Lambrecht and Tucker's field experiment on online STEM advertising found that a gender-neutral careers advert was shown to fewer women because the platform was optimising delivery costs and younger women were more expensive to reach. Imana and colleagues later found a gender skew in Facebook job-advert delivery that could not be explained by qualifications, although they did not find the same pattern on LinkedIn. The wider lesson is that unequal visibility can emerge from the optimisation logic of a platform even when an employer has not chosen to target one gender.⁶⁹

How a vacancy is written can influence a different part of the same decision, namely whether people see themselves as plausible candidates. Mao and colleagues developed a large-scale language model approach to identify and mitigate gender and age bias in Australian job advertisements, while Dikshit and colleagues used contextual language modelling to examine gendered language in STEM vacancies. He and Kang provide stronger evidence on the consequences. Across four laboratory and

⁶⁷ Kotek, H. et al. (2023). Gender bias and stereotypes in Large Language Models. *Proceedings of the ACM Collective Intelligence Conference*, 12–24. DOI: 10.1145/3582269.3615599; UNESCO and IRCAI (2024). Challenging systematic prejudices: an investigation into bias against women and girls in large language models. <https://unesdoc.unesco.org/ark:/48223/pf0000388971>

⁶⁸ Wan, Y. et al. (2023). "Kelly is a Warm Person, Joseph is a Role Model": Gender Biases in LLM-Generated Reference Letters. Findings of the Association for Computational Linguistics: EMNLP 2023. DOI: 10.18653/v1/2023.findings-emnlp.243; Kaplan, D.M. et al. (2024). What's in a Name? Experimental Evidence of Gender Bias in Recommendation Letters Generated by ChatGPT. *Journal of Medical Internet Research*. DOI: 10.2196/51837.

⁶⁹ Lambrecht, A. and Tucker, C. (2019). Algorithmic Bias? An Empirical Study of Apparent Gender-Based Discrimination in the Display of STEM Career Ads. *Management Science*, 65(7). DOI: 10.1287/mnsc.2018.3093; Imana, B. et al. (2021). Auditing for Discrimination in Algorithms Delivering Job Ads. *Proceedings of The Web Conference 2021*, 3767–3778. DOI: 10.1145/3442381.3450077.

field studies involving 37,920 observations, replacing stereotypically masculine terms with gender-neutral alternatives increased the gender diversity of applicant pools. This concerns how opportunities are presented rather than how candidates are screened, but it is relevant to manufacturing and engineering because both remain male-dominated labour markets.⁷⁰

4.3.2 Screening and assessment

Once an application has been submitted, removing names or declared sex does not necessarily make automated matching gender-blind. Parasurama and Sedoc analysed 709,000 resumes from IT firms and found that applicant gender could be predicted with an AUROC⁷¹ of around 0.75 using simple text features and around 0.80 using transformer-based models. In separate obfuscation experiments, they found that substantial gender-related information remained even after removing explicit identifiers and other potentially gender-linked features. Earlier research on resume search engines also found gender-related differences in ranking, although no evidence that inferred gender was being used explicitly as a ranking feature. Anonymising names or declared sex therefore does not necessarily make algorithmic matching gender-blind, because resumes contain other features correlated with gender.⁷²

Evidence on LLM-based matching and screening is less consistent. Wilson and Caliskan found that male-associated names were favoured much more often than female-associated names in simulated retrieval tests, with pronounced intersectional effects. Lippens, using 34,560 vacancy–CV combinations, found that gender identity influenced ChatGPT evaluations especially in gender-atypical roles, although female candidates were not rated lower on average. Armstrong and colleagues also identified stereotype-related differences in GPT-3.5 resume assessment. Other studies report smaller or different effects: Iso and colleagues found reduced bias in newer models on explicit gender and race attributes, while Chaturvedi and Chaturvedi report male-favouring callback recommendations in several open source models, particularly in higher-wage and male-dominated occupations. Bias can therefore arise, but its direction and magnitude are not stable across models, occupations, or methods. For employers, this makes context-specific testing more informative than assumptions based on a single model audit.⁷³

⁷⁰ Mao, R. et al. (2023). Developing a Large-Scale Language Model to Unveil and Alleviate Gender and Age Biases in Australian Job Ads. *IEEE International Conference on Big Data*. DOI: 10.1109/BigData59044.2023.10386083; Dikshit, M. et al. (2024). Investigating Gender Bias in STEM Job Advertisements. *Proceedings of the 5th Workshop on Gender Bias in Natural Language Processing*, 179–189. DOI: 10.18653/v1/2024.gebnlp-1.11; He, J. and Kang, S. (2025). Debiasing job ads by replacing masculine language increases gender diversity of applicant pools. *PNAS*, 122(7). DOI: 10.1073/pnas.2409854122.

⁷¹ AUROC (Area Under the Receiver Operating Characteristic curve) is used to evaluate and compare how well a binary classification model separates two different classes

⁷² Parasurama, P. and Sedoc, J. (2022). Gendered Language in Resumes and its Implications for Algorithmic Bias in Hiring. *Proceedings of the 4th Workshop on Gender Bias in Natural Language Processing*, 74. DOI: 10.18653/v1/2022.gebnlp-1.7; Chen, L. et al. (2018). Investigating the Impact of Gender on Rank in Resume Search Engines. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 651, 1–14. DOI: 10.1145/3173574.3174225.

⁷³ Wilson, K. and Caliskan, A. (2024). Gender, Race, and Intersectional Bias in Resume Screening via Language Model Retrieval. *Proceedings of the Seventh AAAI/ACM Conference on AI, Ethics, and Society*, 7(1), 1578–1590. DOI: 10.1609/aies.v7i1.31748; Lippens, L. (2024). Computer says “no”: Exploring systemic bias in ChatGPT using an audit approach. *Computers in Human Behavior: Artificial Humans*. DOI: 10.1016/j.chbah.2024.100054; Armstrong, L. et al.

Studies that follow more than one stage of a hiring decision reinforce this point. Gerszberg and colleagues found that the LLMs they tested were more likely to hire and rate as more qualified a female version of an otherwise identical candidate, while still recommending lower pay for her. Nghiem and colleagues, using more than 750,000 prompts across 40 occupations, likewise found that names signalling race and gender affected hiring and salary recommendations, with salary recommendations varying by as much as 5% between demographic subgroups despite identical qualifications. These are controlled model audits rather than observations of employer behaviour, but they show why a system can appear fair at one stage and still produce unequal treatment at another.⁷⁴

Assessment can extend beyond CV screening to recorded interviews, voice, and behavioural signals. Booth and colleagues compared models built from verbal, paraverbal, and visual features in pre-recorded interviews with 733 participants. Combining these modalities produced small gains in predictive accuracy while increasing measured bias and reducing fairness relative to the least-biased verbal model. Hickman and colleagues show a related risk at the transcription stage, where automatic speech recognition systems used in scored interviews can perform differently across demographic groups. A recent multidisciplinary review reaches a similar conclusion, treating video interviewing as a distinct fairness challenge alongside advertising and resume screening. None of this establishes that automated interviews systematically disadvantage women in UK manufacturing, but it does show that adding richer data can create additional routes for demographic information to enter an assessment.⁷⁵

These issues are no longer confined to academic model audits. UK regulatory evidence confirms that automated recruitment is already a practical governance issue (see Box 8). In 2024 the Information Commissioner's Office audited providers and developers of AI-powered recruitment tools used for sourcing, screening, and selection, and issued almost three hundred recommendations. Problems included insufficient accuracy testing, filtering functions involving protected characteristics, attempts to infer gender or ethnicity from names, excessive data collection, and weak transparency. The ICO returned to the issue in March 2026 through Recruitment Rewired, based on voluntary engagement with more than thirty employers, and called for clearer transparency, meaningful human involvement, and stronger fairness monitoring.⁷⁶

(2024). The Silicon Ceiling: Auditing GPT's Race and Gender Biases in Hiring. *EAAMO 2024: Proceedings of the 4th ACM Conference on Equity and Access in Algorithms, Mechanisms, and Optimization*, 2, 1–18. DOI: 10.1145/3689904.3694699; Iso, H. et al. (2025). Evaluating Bias in LLMs for Job-Resume Matching: Gender, Race, and Education. *Proceedings of the 2025 Conference of NAACL: Human Language Technologies*, 3 (Industry Track), 672–683. DOI: 10.18653/v1/2025.naacl-industry.55; Chaturvedi, S. and Chaturvedi, R. (2025). Who Gets the Callback? Generative AI and Gender Bias. arXiv:2504.21400.

⁷⁴ Gerszberg, N. et al. (2026). Quantifying Gender Bias in Large Language Models: When ChatGPT Becomes a Hiring Manager. arXiv. <https://arxiv.org/abs/2604.00011>; Nghiem, H. et al. (2024). "You Gotta be a Doctor, Lin": An Investigation of Name-Based Bias of Large Language Models in Employment Recommendations. *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, 7268–7287. DOI: 10.18653/v1/2024.emnlp-main.413.

⁷⁵ Booth, B. et al. (2021). Bias and Fairness in Multimodal Machine Learning: A Case Study of Automated Video Interviews. *Proceedings of the 2021 International Conference on Multimodal Interaction*, 268–277. DOI: 10.1145/3462244.3479897; Hickman, L. et al. (2025). Automated speech recognition bias in personnel selection: The case of automatically scored job interviews. *Journal of Applied Psychology*, 110(6), 846–858. DOI: 10.1037/apl0001247; Fabris, A. et al. (2025). Fairness and Bias in Algorithmic Hiring: A Multidisciplinary Survey. *ACM Transactions on Intelligent Systems and Technology*, 16(1), 1–54. DOI: 10.1145/3696457.

⁷⁶ Information Commissioner's Office (2024). AI tools in recruitment: Audit outcomes report; Information Commissioner's Office (2026). Recruitment rewired: an update on the ICO's work on the fair and responsible use of automation in recruitment. <https://ico.org.uk/about-the-ico/what-we-do/recruitment-rewired/>.

Since 5 February 2026, the Data (Use and Access) Act 2025 has permitted solely automated decisions producing legal or similarly significant effects on a wider range of lawful bases where special-category data are not involved, subject to safeguards including information about the decision, the opportunity to make representations, human intervention and the ability to contest the decision.⁷⁷ Neither the ICO's work nor the legislation quantifies the effects on women applying for manufacturing roles. The ICO's findings nevertheless show that governance problems identified in research are already present in parts of UK recruitment, while the legislation sets out the safeguards required when solely automated systems affect applicants.

Box 8: Key law, guidance, and standards for AI in employment

AI used in recruitment, workforce management, and other employment decisions is covered by existing equality and data protection law, alongside newer AI-specific regulation and guidance. The table highlights the main frameworks that are relevant to manufacturers.

Instrument	What it means for AI and employment	Practical application
Equality Act 2010	Existing equality law applies when AI is used in recruitment, promotion, pay, performance, or other employment decisions. AI-supported criteria or processes can still create direct or indirect discrimination.	Review criteria and outcomes for unequal effects and retain evidence and meaningful routes to review.
UK GDPR + Data (Use and Access) Act 2025	Where AI processes personal data, existing data protection principles continue to apply. Safeguards are required around significant decisions made solely by automated processing, including the provision of information, the right to make representations, human intervention, and the ability to contest the decision.	Map data, lawful basis, and decision process; explain relevant uses; provide routes to correction and human review.
DSIT Responsible AI in Recruitment	UK Government guidance covers AI used across sourcing, screening, interviewing, and selection, including procurement, impact assessment, bias testing, transparency, and human oversight.	Use as a practical reference when buying, configuring, or deploying AI-supported recruitment systems.
ICO recruitment audits + Recruitment Rewired	The ICO has examined recruitment AI in practice and identified issues including weak accuracy testing, use of protected-characteristic data, demographic inference, excessive data collection, limited transparency, and inadequate human involvement.	Turn findings into assurance questions for suppliers and internal recruitment processes, including testing, DPIAs, transparency and review.
EU AI Act	Where the Act applies, certain employment and worker-management systems are treated as high risk. This includes AI used for recruitment and selection and some systems used to make decisions affecting workers. Annex III employment rules apply from 2 December 2027.	Check territorial scope and the specific use case rather than assuming either universal UK applicability or no relevance to UK firms.
ISO/IEC AI standards	ISO/IEC 42001, 42005, and 23894 provide frameworks for AI governance, impact assessment and risk management; TR 24027 and TS 12791 address bias assessment and treatment.	Use to structure assurance and monitoring. Voluntary standards alone do not demonstrate that a system is fair or legally compliant.

Source: Equality Act 2010; UK GDPR, as amended by the Data (Use and Access) Act 2025, s. 80; DSIT (2024). Responsible AI in Recruitment; ICO (2024). AI Tools in Recruitment: Audit Outcomes Report; ICO (2026). Recruitment Rewired; Regulation (EU) 2024/1689 (AI Act), as amended by Regulation (EU) 2026/1744; ISO/IEC 42001:2023, 42005:2025, 23894:2023, TR 24027:2021 and TS 12791:2024.

⁷⁷ Data (Use and Access) Act 2025, c. 18, s. 80 (inserting Articles 22A–22D into the UK GDPR); The Data (Use and Access) Act 2025 (Commencement No. 6 and Transitional and Saving Provisions) Regulations 2026, SI 2026/82, regs. 2(o) and 5.

4.3.3 Career guidance and pathways

AI-mediated guidance may influence career pathways even earlier, by shaping which fields or roles people are encouraged to consider; it may also affect professional development after entry. Blair-Loy and colleagues found that two established career assessment tools were less likely to recommend engineering occupations to women than to men among students already studying engineering, even after accounting for academic performance, satisfaction, and intended persistence. Research on LLM-based guidance points in a similar direction, but with more nuanced results. Zheng identified demographic disparities in ChatGPT college-major recommendations. Castro Souto and Padilla Castillo found that the fields suggested to women and men did not differ significantly overall, yet female users received more traditionally feminised professional examples and caregiving traits, whereas male users more often received technical or leadership-oriented examples. Not all systems show this pattern: in a study of an AI career recommender for professional training, Pröbster and colleagues found that women and men were about equally likely to receive STEM recommendations, even though men rated their own skills higher. Taken together, this literature suggests that AI may shape not only the options people are shown but also the way technical and leadership pathways are framed as realistic or appropriate, although whether it does so varies across systems.⁷⁸

4.4 AI, work organisation, and opportunities after entry

4.4.1 Work organisation, task allocation, and progression

After entry, the literature shifts from access to the organisation of work and the conditions under which people can build skills, visibility, and progression. The OECD's manufacturing and finance surveys provide the most directly relevant cross-country evidence. Workers using AI reported being generally positive about its contribution to performance and some working conditions, while also raising concerns about job loss and work intensity. In manufacturing, male AI users were somewhat more likely than female users to report improvements across several outcomes, although the published gender differences were not statistically significant, and occupation explained part of the wider gap in the pooled data. Training and worker consultation were associated with more favourable experiences of adoption, suggesting that organisational practice matters alongside the technology itself.⁷⁹

This point is especially important in algorithmic management, where data-driven systems can allocate, monitor, or evaluate work. An OECD survey of more than six thousand firms across six countries found

⁷⁸ Blair-Loy, M. et al. (2024). Steering Women out of Engineering: Career Assessment Tools as a Technology of Self-Expressive Segregation. *Sociological Inquiry*, 94(4), 830–853. DOI: 10.1111/soin.12612; Shaner, C. et al. (2024). Assessing Implicit Gender Bias in Large Language Models for STEM Career Guidance Applications. *IEEE Integrated STEM Education Conference*. DOI: 10.1109/ISEC61299.2024.10664821; Zheng, A. (2025). Dissecting bias of ChatGPT in college major recommendations. *Information Technology and Management*, 26(4), 625–636. DOI: 10.1007/s10799-024-00430-5; Castro Souto, L. and Padilla Castillo, G. (2026). Gender bias in LLMs: analyzing AI responses on STEM career guidance. *Cuadernos.info* 64. DOI: 10.7764/cdi.64.98546; Pröbster, M. et al. (2025). Bias in AI Recommender Systems: Examining Gender Disparities in STEM and Non-STEM Career Recommendations for Professional Development. *Artificial Intelligence in HCI: 6th International Conference, AI-HCI 2025, Proceedings, Part II*, 78–96. DOI: 10.1007/978-3-031-93415-5_5.

⁷⁹ Lane, M. et al. (2023). The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers. *OECD Social, Employment and Migration Working Papers*, No. 288. DOI: 10.1787/ea0a0fe1-en.

such systems already in widespread use, with managers reporting perceived improvements in decision quality alongside concerns about accountability, explainability, and workers' health. ILO and JRC case studies in logistics and healthcare describe similar trade-offs but provide little gender-specific evidence on progression. A recent simulation by Parziale and colleagues illustrates one mechanism that deserves attention: across 3,000 software-team decisions using 3 LLMs, demographic signals affected both team selection and task assignment even after expertise-related factors were considered, and technical and leadership roles were distributed unevenly. The study is not evidence from a manufacturing workplace, but it shows how AI-supported allocation could influence who accumulates the experience and visibility that later matter for progression.⁸⁰

Promotion introduces a related interaction between algorithmic recommendations and managerial judgement. In an experimental study, Ghasemaghaei and Kordzadeh found that an unfair algorithmic recommendation against a more-qualified woman reduced managers' perceptions of distributive fairness and influenced their willingness to accept the recommendation; trust in the system also shaped their responses. Because the study used a simulated promotion decision, it cannot tell us how deployed systems affect promotion outcomes in practice. It does, however, underline that fairness depends not only on what a model recommends but also on how managers interpret, challenge, and rely on that recommendation.⁸¹

The limited gender-specific evidence also cautions against assuming that algorithmic management will always worsen existing inequalities. In a field study of 220,085 service calls, Gu and colleagues found that replacing human supervision with an algorithmic supervisor improved female agents' performance relative to male agents on the study's service measures. This is an important counter-example because it comes from a real workplace, although one service setting cannot establish what would happen in manufacturing. The broader implication is that outcomes depend on the design of the system, the measures it rewards, and the organisational context in which it is used.⁸²

4.4.2 Technical systems and automation

Technical performance can also vary across demographic groups and operating conditions. The National Institute of Standards and Technology (NIST) evaluations of face recognition systems, for example, have found demographic differences in error rates whose magnitude varies substantially by algorithm, application, and image quality, reinforcing the importance of testing systems in the context in which they will be used.⁸³

⁸⁰ Milanez, A. et al. (2025). Algorithmic management in the workplace: New evidence from an OECD employer survey. *OECD Artificial Intelligence Papers*, No. 31. DOI: 10.1787/287c13c4-en; Rani, U. et al. (2024). Algorithmic Management practices in regular workplaces: case studies in logistics and healthcare. ILO/JRC. DOI: 10.2760/712475; Parziale, A. et al. (2026). Once Upon a Team: Investigating Bias in LLM-Driven Software Team Composition and Task Allocation. *ICSE-SEIS 2026: Proceedings of the IEEE/ACM 48th International Conference on Software Engineering*, 77–88. DOI: 10.1145/3786581.3786930.

⁸¹ Ghasemaghaei, M. and Kordzadeh, N. (2025). Ethics in the Age of Algorithms: Unravelling the Impact of Algorithmic Unfairness on Data Analytics Recommendation Acceptance. *Information Systems Journal*, 35(4), 1166–1197. DOI: 10.1111/isj.12572.

⁸² Gu, W. et al. (2025). Algorithmic Supervisor and Employee Performance. *Production and Operations Management*, 34(10). DOI: 10.1177/10591478251331095.

⁸³ Grother et al. (2019). Face Recognition Vendor Test (FRVT) Part 3: Demographic Effects. NISTIR 8280. National Institute of Standards and Technology. DOI: 10.6028/NIST.IR.8280.

Manufacturing also has a longer research tradition on industrial automation and robotics. Although this work does not examine GenAI, it shows how new technologies can interact with gendered occupational structures. The findings are mixed. Brussevich and colleagues estimated that women were more likely than men to work in routine, automation-prone jobs across 30 countries. Blanas and colleagues found that software and robots reduced labour demand for women particularly in manufacturing, while Aksoy and colleagues found that robot adoption increased earnings for both sexes but widened the gender pay gap across 20 European countries. Other studies were more positive: German plant-level evidence found modestly positive effects on female employment, while recent Chinese firm-level research reports higher female employment shares and a narrower pay gap among lower-skilled workers. The variation matters because it shows that technological effects depend on tasks, skills, and institutional context; robotics evidence cannot simply be carried across to GenAI.⁸⁴

The workplace literature is therefore stronger on immediate changes in tasks, productivity, working conditions, and management processes than on longer-term careers. There is still relatively little causal evidence on whether access to AI tools and training affects women's promotion, pay progression, movement into higher-value tasks, or retention, and less still that is specific to UK manufacturing. Exposure and adoption measures therefore tell only part of the story about opportunities after entry.

4.5 Synthesis and gaps in the evidence for UK manufacturing

The literature provides a clear basis for examining AI through a gender lens, but it does not point to a single outcome. Women are disproportionately represented in many occupations with high GenAI exposure, and several studies find lower adoption among women even within exposed occupations. The evidence points to a series of mechanisms operating at different stages of a career. Advertising systems can influence which vacancies are seen; the language of job adverts and career guidance can shape signals of belonging; resumes can retain gender-related information even after explicit identifiers are removed; and matching, screening, and interview systems can introduce differences during assessment. After entry, algorithmic management can affect how work is allocated, monitored, and evaluated. None of these mechanisms produces the same outcome in every setting, and some field evidence shows women benefiting from particular forms of automation or algorithmic supervision. AI appears to interact with existing patterns of work, skills, and organisational practice rather than producing the same effect in every setting. A 2026 scoping review of 13 empirical studies on AI and women's career development reaches a similar conclusion: the evidence is stronger for the design and auditing of career-related systems than for sustained effects on progression and retention.⁸⁵

⁸⁴ Brussevich, M. et al. (2019). Is Technology Widening the Gender Gap? Automation and the Future of Female Employment. *IMF Working Paper*, 19/91, 1. DOI: 10.5089/9781498303743.001; Blanas, S. et al. (2019). Who is afraid of machines? *Economic Policy*, 34(100), 627–690. DOI: 10.1093/epolic/eiaa005; Aksoy, C. et al. (2021). Robots and the gender pay gap in Europe. *European Economic Review*, 134. DOI: 10.1016/j.euroecorev.2021.103693; Deng, L. et al. (2023). Robots and Female Employment in German Manufacturing. *AEA Papers and Proceedings*, 113, 224–228. DOI: 10.1257/pandp.20231040; Wang, X. et al. (2025). Robots and gender inequality: Evidence from Chinese firms. *Asian Economic Journal*, 39(3), 279–312. DOI: 10.1111/asej.12355.

⁸⁵ Portell-Fonolla, S. et al. (2026). Artificial intelligence applications supporting women's career development: a scoping review. *International Journal for Educational and Vocational Guidance*. DOI: 10.1007/s10775-026-09807-0.

For UK manufacturing, the remaining gaps are more specific. International exposure studies do not show in detail how GenAI exposure is distributed between women and men across the sector's occupations and functions. Recruitment studies identify credible mechanisms, supported by experiments and regulatory evidence, but provide little direct evidence on whether AI-enabled advertising, matching, screening, or assessment changes women's application, shortlisting, or hiring outcomes in UK manufacturing. Evidence is also limited on whether women and men have comparable access to AI tools and training, and on how differences in use affect progression, pay, or retention. These gaps matter because the technologies grouped under "AI" – GenAI, predictive hiring systems, algorithmic management, and industrial robotics – operate through different mechanisms. The analysis in this report begins to close part of that gap by combining sector-specific exposure data with workforce survey evidence, while leaving clear priorities for future monitoring and research.

Resetting the default: actions for inclusive AI adoption in UK manufacturing

Five priorities for organisations and policymakers

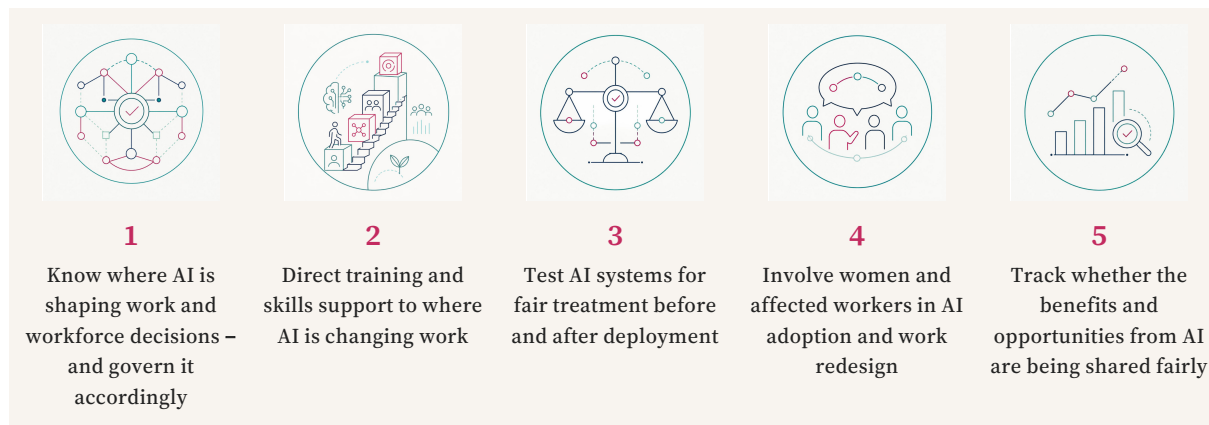


5 Resetting the default: actions for inclusive AI adoption in UK manufacturing

Artificial intelligence is not affecting all parts of the manufacturing workforce in the same way: women are more concentrated in some of the occupations with higher generative AI exposure, while the survey shows similar overall levels of AI use but greater concern among women about the consequences of AI bias for pay, wellbeing, diversity, and opportunity. The wider evidence is mixed: AI can reproduce gender bias in recruitment and assessment, but effects vary across systems and settings. At the same time, exposure does not inevitably translate into disadvantage. Outcomes will depend on how organisations introduce AI, redesign work, build workforce capability, and govern systems that influence employment and progression. In this context, “resetting the default” means ensuring that AI adoption widens access to skills, fair treatment, participation, and progression rather than reproducing existing inequalities in the structure of work.

The findings point to five areas where action by organisations and policymakers could ensure that the benefits of AI adoption in manufacturing are shared fairly across the workforce (Figure 23). This is consistent with the International Labour Organization’s April 2026 tripartite conclusions on AI in manufacturing, which emphasise that outcomes depend on organisational decisions, not technology alone, and that social dialogue is essential to shaping those decisions.⁸⁶ The level of action should reflect the use case, organisational capacity, and significance of the decision or change involved.

FIGURE 23: FIVE AREAS OF ACTION FOR INCLUSIVE AI ADOPTION IN UK MANUFACTURING



1. Know where AI is shaping work and workforce decisions – and govern it accordingly

How AI is introduced will shape the distribution of its benefits as much as the underlying technology. Manufacturers need enough visibility over adoption to understand which tasks and groups of workers are affected, while job and workflow design determine whether new tools mainly remove routine

⁸⁶ ILO (2026). Conclusions and recommendations: Technical meeting on challenges and opportunities for promoting decent work, productivity and a just transition arising from artificial intelligence in the manufacturing industry.

activity, add new responsibilities, or open different routes for progression. The ILO places social dialogue alongside skills and productivity in its manufacturing conclusions, and OECD evidence similarly points to the value of training and consultation when work is reorganised around AI.⁸⁷

For organisations

- ❑ **Maintain visibility and accountability:** Keep an organisation-wide view of significant AI uses that affect workers or applicants, including their purpose, the tasks and groups affected, and the accountable owner. This should include relevant embedded or supplier-provided AI features, not just standalone systems.
- ❑ **Consider workforce effects early:** Assess likely changes to job content, workload, autonomy, skills requirements, and progression while adoption choices and workflows can still be changed.
- ❑ **Use role redesign to widen opportunity:** Where AI reduces routine tasks, consider whether roles can be redesigned to give workers access to more skilled, higher-value, or developmental work, supported by internal mobility where roles change substantially. Where consolidation or substantial change is likely, plan appropriate transition support.

For policymakers and the manufacturing ecosystem

- ❑ **Integrate workforce planning into adoption support:** Publicly supported manufacturing AI programmes should address work design, skills, and responsible AI governance alongside technology selection and implementation.
- ❑ **Provide practical support for smaller firms:** Develop proportionate tools and sector guidance that help SMEs assess task change, redesign work, and connect adoption with existing skills, careers, and workforce-development provision.

2. Direct training and skills support to where AI is changing work

Higher GenAI exposure is concentrated in administrative, clerical, and selected professional work, while the survey suggests that greater engagement with AI is associated with stronger understanding and trust. The ILO calls for skills development and lifelong learning across the manufacturing workforce, and the recent fall in sector training provision strengthens the case for linking AI adoption more closely to workforce development.⁸⁸

National provision is beginning to expand. The government–industry AI Skills Boost programme offers free, Skills England-benchmarked foundation courses and aims to equip 10 million UK workers with AI skills by 2030. Skills England has also introduced an AI and automation practitioner apprenticeship, open to employers across all sectors.⁸⁹ These initiatives provide useful economy-wide foundations

⁸⁷ Lane, M. et al. (2023). The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers. *OECD Social, Employment and Migration Working Papers*, No. 288. DOI: 10.1787/ea0a0fe1-en; ILO (2026). Conclusions and recommendations: Technical meeting on challenges and opportunities for promoting decent work, productivity and a just transition arising from artificial intelligence in the manufacturing industry.

⁸⁸ Department for Education and Skills England (2025). Employer Skills Survey 2024. Official Statistics; ILO (2026). Conclusions and recommendations: Technical meeting on challenges and opportunities for promoting decent work, productivity and a just transition arising from artificial intelligence in the manufacturing industry.

⁸⁹ Department for Science, Innovation and Technology (2026). AI Skills Boost: Explainer; Skills England (2026). AI Apprenticeship to Close Digital Skills Gap Holding Back Millions of Workers.

but are not tailored specifically to manufacturing. Make UK reports that 50% of manufacturers say staff lack time to train, while 49% struggle to identify the right AI skill standards for their roles.⁹⁰

For organisations

- ❑ **Extend role-specific AI learning beyond technical specialists:** Administrative, clerical, customer-facing, and selected professional roles should have access to training that is relevant to the tasks that are likely to change.
- ❑ **Provide practical access as well as training:** Give workers protected learning time, opportunities to practise, and access to suitable tools rather than relying on informal self-learning.
- ❑ **Match support to the scale of change:** Use upskilling where AI changes tasks within an existing role; where change is more substantial, consider reskilling, career guidance, internal mobility, and transition support.

For policymakers and the manufacturing ecosystem

- ❑ **Broaden and tailor AI skills support:** Build on national programmes with manufacturing-specific, modular and work-based learning for non-technical roles experiencing task change, alongside continued investment in advanced technical and AI skills.
- ❑ **Plan skills support before roles change:** Help employers identify likely changes to tasks and skill requirements early, so that upskilling, reskilling, and transition support can begin before substantial role changes occur.

3. Test AI systems for fair treatment before and after deployment

The case for stronger assurance is greatest where AI materially influences access to work, pay, performance, progression, or other consequential workforce outcomes. UK guidance already emphasises impact assessment, fairness testing, supplier assurance, transparency, and meaningful human involvement in AI-supported recruitment.⁹¹

For organisations

- ❑ **Identify consequential workforce systems:** Apply stronger assurance where AI materially influences recruitment, pay, performance, progression, task allocation, or access to work.
- ❑ **Assess, test, and monitor proportionately:** For higher-impact uses, consider impact assessment, context-specific testing, ongoing monitoring, and supplier assurance, covering accuracy, relevant fairness risks, and known limitations.
- ❑ **Preserve meaningful human judgement, transparency, and routes to review:** Reviewers should have sufficient information and authority to reach a different decision. Workers and applicants should be able to understand when AI materially contributes to a consequential decision, correct relevant information, and request human consideration where appropriate.
- ❑ **Define escalation and intervention routes:** Identify in advance who has responsibility and authority to investigate, pause, modify, or withdraw a system where monitoring identifies persistent errors or unequal outcomes.

⁹⁰ Make UK (2026). *AI, Skills and the Future of the UK Manufacturing Sector*.

⁹¹ Information Commissioner's Office (2026). Recruitment rewired: an update on the ICO's work on the fair and responsible use of automation in recruitment. <https://ico.org.uk/about-the-ico/what-we-do/recruitment-rewired/>; Information Commissioner's Office (2024). *AI Tools in Recruitment: Audit Outcomes Report*. Information Commissioner's Office; Department for Science, Innovation and Technology (2024). *Responsible AI in Recruitment*. UK Government.

For policymakers and the manufacturing ecosystem

- ❑ **Translate existing requirements into manufacturing practice:** Provide practical guidance on applying employment, equality, data protection, and responsible AI expectations to recruitment and workforce management uses.
- ❑ **Support assurance proportionate to organisational capacity:** Building on the ICO's procurement questions and DSIT's Responsible AI in Recruitment guidance, develop manufacturing-specific procurement questions, impact assessment templates, and worked examples of testing and meaningful human involvement that smaller firms can use in practice.
- ❑ **Promote coherence across guidance:** Align responsible AI, employment, equality, and data protection guidance so firms can work from a coherent set of expectations rather than navigating parallel or overlapping compliance processes.

4. Involve women and affected workers in AI adoption and work redesign

The transition will be more credible and more informed when the people whose work is changing are involved early enough to influence it. This has a particular gender dimension in manufacturing because women are disproportionately represented in several of the occupations with the highest GenAI exposure. The survey adds a further signal: 24.4% of women, compared with 10.2% of men, identify the limited representation of women in AI and manufacturing roles as a significant barrier to addressing AI bias. ILO research on occupational segregation similarly calls for gender equality and women's representation to be embedded in the design, deployment, and governance of GenAI.⁹²

For organisations

- ❑ **Involve women and affected workers early:** Create opportunities to influence procurement, deployment, workflow change, and role redesign while important choices remain open.
- ❑ **Use consultation to understand workforce effects, not just risk:** Consider workload, autonomy, skill development, and progression alongside technical performance.
- ❑ **Broaden participation in AI-enabled opportunities:** Ensure women are represented in AI projects, testing, and oversight and can access newly created responsibilities and internal progression routes.

For policymakers and the manufacturing ecosystem

- ❑ **Support worker voice and social dialogue:** Embed meaningful participation in publicly supported AI adoption and workforce transition programmes, focusing on women in exposed occupations.
- ❑ **Widen routes into emerging work:** Use manufacturing skills and careers policy to strengthen women's pathways into digital, technical, professional, and leadership roles as occupational structures change.

5. Track whether the benefits and opportunities from AI are being shared fairly

The survey provides a detailed baseline on current use, perceptions, and concerns, but it cannot show how AI will affect careers over time. The literature review identifies the same gap, particularly for

⁹² International Labour Organization (2026). *Gen AI, occupational segregation and gender equality in the world of work*. ILO Research Brief. DOI: 10.54394/00033798.

longer-term effects on access to training, higher-value work, pay, progression, and retention in UK manufacturing.

For organisations

- ❑ **Monitor access to AI-enabled opportunities:** Track access to tools, employer-supported training, AI projects, and newly created responsibilities alongside conventional measures of adoption and productivity.
- ❑ **Follow relevant workforce outcomes:** Where AI materially affects work or employment decisions, examine recruitment, task allocation, performance, progression, pay, wellbeing, and retention, including patterns by sex and occupational group where the data allows.
- ❑ **Use disparities as a trigger for review:** Persistent differences alone do not establish discrimination or causation, but they can indicate where closer investigation of training, process design, or governance is warranted.
- ❑ **Keep entry and progression routes under review:** Where administrative and support roles are substantially redesigned, check whether routes into professional, technical, or managerial careers are being narrowed, so that changes to career pathways are identified early without assuming exposed roles will disappear.

For policymakers and the manufacturing ecosystem

- ❑ **Improve sector-level evidence:** Track AI adoption, access to employer-supported training, and transitions into AI-enabled work by gender, occupation, and business function rather than relying only on aggregate firm-level measures.
- ❑ **Develop longitudinal evidence on career outcomes:** Support research on higher-value work, progression, pay, and retention, and evaluate whether public adoption and skills programmes are reaching workers in more exposed occupations.

Appendix A

Occupational exposure analysis: data and methods

A.1 Data sources

Source	What it provides	Period
ILO Working Paper, 140 (Gmyrek, P. et al., 2025), Annex Table A1	Mean and standard deviation of task-level exposure scores and official exposure classification for 427 ISCO-08 four-digit occupations	2025
ILO harmonised microdata (ILOSTAT)	UK manufacturing employment by ISCO-08 major group and sex, aggregated across ISIC Rev.4 divisions 10–33	UK LFS 2025
ONS Annual Population Survey workplace analysis T10c via Nomis	UK manufacturing employment by SOC2020 major group and sex; SIC 2007 Section C	Jan–Dec 2025
ONS Annual Population Survey, four-digit occupation by sex and four-digit industry tables	Detailed SOC2020 by SIC 2007 occupational pattern in manufacturing and whole-economy SOC4 sex-composition priors; many industry cells suppressed	Apr 2025–Mar 2026
ONS SOC2020 Volume 2 coding index, Version 13	Job titles coded to SOC2020 and ISCO-08, used to link the two classifications	Dec 2025

A.2 Method

The ILO gradients are derived from the mean (μ) and standard deviation (σ) of task-level exposure scores. Gradient 4 requires $\mu \geq 0.60$ and $\mu - \sigma \geq 0.50$; Gradient 3 requires $0.50 \leq \mu < 0.60$ and $\mu + \sigma \geq 0.50$; Gradient 2 requires $0.40 \leq \mu < 0.50$ and $\mu + \sigma \geq 0.50$; and Gradient 1 requires $\mu < 0.40$ and $\mu + \sigma \geq 0.50$. Occupations meeting none of these conditions are not significantly exposed.

Figure 3 uses the ILO classification directly and combines occupation counts with ILO-harmonised UK manufacturing employment by major occupational group and sex. Figure 4 links SOC2020 occupations to ISCO-08 using the ONS coding index and applies the corresponding ILO classification. Published detailed SOC manufacturing cells cover about 38% of sector employment; within each major group, the observed occupational pattern is scaled to the Annual Population Survey total.

Where a SOC2020 occupation links to more than one ISCO-08 occupation, the links are weighted by the number of ONS coding-index job-title records. Sex-specific estimates apply each major-group gradient distribution to published female and male employment totals, capturing differences between major occupational groups but not additional segregation within them. Occupations without an ILO classification, representing under 1% of mapped employment, are retained separately as “Not classified”.

A.3 Sensitivity and limitations

Three linking approaches were tested: weighting across all linked ISCO occupations by title records; assigning each SOC occupation to its most common ISCO link; and using the occupational assignments in the Greater London Authority's 2026 analysis.⁹³ The estimated share of UK manufacturing employment in Gradients 1–4 is 28–29% across the three approaches. The main limitations are that coding-index title-record shares are not employment weights; suppressed detailed cells require the occupational pattern to be inferred within major group; and the ILO index measures technical potential rather than adoption or employment outcomes.

⁹³Dwan-O'Reilly, J. (2026). London's workforce exposure to generative artificial intelligence. *GLA Economics Working Paper*, 103. Greater London Authority.

Appendix B

Survey methodology

B.1 Data source

The gender analysis presented in this report draws on: Roupakia, Z. (2026). AI Bias in Manufacturing: A UK Workforce Survey. Noetic AI.

B.2 Survey design and administration

The survey was designed and conducted by Zoi Roupakia (Noetic AI). It was administered using Qualtrics, with participants recruited through Prolific between January and September 2025. It comprised 34 substantive questions covering demographics, AI use and adoption, understanding and experience of AI bias, its perceived social and economic effects, organisational preparedness, trust, and attitudes towards regulation and transparency.

B.3 Sample

The final sample included 890 UK-based manufacturing professionals. Respondents were screened for current employment in the UK manufacturing sector. The sample consisted of 550 men, 336 women, 3 respondents who identified as non-binary, and 1 who preferred not to state their gender. The gender comparisons presented in this report draw on up to 886 respondents: 550 men (62%) and 336 women (38%). The other four respondents were not included in gender comparisons because the numbers were too small to support separate analysis.

Respondents spanned a range of roles, from production and skilled trade occupations to senior management; company sizes, from micro-enterprises to firms with 250 or more employees; and levels of manufacturing experience. No weighting was applied. The original occupational categories were informed by the broad structure of the ONS Standard Occupational Classification. For the analysis, they were consolidated into four role families: managers and directors; professional and associate professional roles; production and skilled trades; and administrative, sales, and service roles.

B.4 Denominators

Percentages were calculated separately for women and men, based on the number who provided a valid response to each question. The relevant sample is reported in figure and table notes when it differs from the maximum of 336 women and 550 men. For questions allowing more than one answer, percentages show the share of respondents who answered the question and selected each option. Respondents could therefore appear in more than one category, and percentages do not necessarily total 100%. Respondents who did not answer the question were excluded from the denominator. Explicit responses such as "none", "none observed", or "none of the above" were treated as valid responses.

B.5 Statistical analysis

The analysis proceeded in three stages. First, responses from women and men were compared using counts, percentages, and percentage point differences. A positive difference indicates the response was more common among women; and a negative difference indicates it was more common among men. Second, statistical tests were used to assess whether the observed differences were likely to reflect more than sampling variation. Questions with ordered response categories were assessed using Mann–Whitney U tests. Categorical responses were assessed using Pearson chi-square tests, with the Yates continuity correction applied to two-by-two tables. Where significance stars are shown, * denotes ($p < 0.05$), ** denotes ($p < 0.01$), and *** denotes ($p < 0.001$). And third, selected headline outcomes were examined using regression models to assess whether differences between women and men remain after accounting for other characteristics:

- Model 1 accounts for age, manufacturing role, and company size.
- Model 2 additionally accounts for AI use frequency and self-reported AI expertise.

Both models use 857 respondents with valid age information and complete information for the other variables included. Results are estimated as odds ratios with 95% confidence intervals. For ordered outcomes, an odds ratio above one indicates that women were more likely than men to select a higher response category; an odds ratio below one indicates they were less likely to do so. The innovation question was analysed separately because its response options do not form an ordered scale.

Associations between ordered survey responses were assessed using Spearman correlations. These show whether responses tend to vary together; they do not establish that one causes the other. Reported p-values have not been adjusted for the number of comparisons undertaken. Individual results close to the 0.05 threshold should therefore be interpreted cautiously and alongside the size and consistency of the difference.

Stars in panel titles indicate a statistically significant gender difference across the full response distribution, assessed using Mann–Whitney U tests. Stars beside individual bars indicate a difference in the proportion selecting that response, assessed using chi-square tests with Yates correction. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.6 Limitations

Respondents were recruited from an online research panel rather than a random sample of UK manufacturing professionals. The findings describe patterns within the survey population and should not be read as nationally representative estimates. The survey captures self-reported experiences and perceptions of AI bias, not direct measurements or independent audits of AI systems. As the survey was conducted at one point in time, associations between trust, preparedness, AI use, and other factors should not be interpreted as evidence of cause and effect. Some analyses by age and occupational role contain relatively small subgroups and are treated as exploratory.

Noetic AI is an independent AI and emerging technology policy intelligence lab and advisory practice, founded in 2025 by Zoi Roupakia. It works with governments, international organisations, and mission-led institutions on AI policy, innovation systems, industrial transformation, and public sector adoption, translating complex technology questions into evidence, strategy, and practical policy tools. Contact info@noeticai.co