# Resilient AI Adoption in Greater Manchester

*Pricing Risks, Place-Based Policy, and the Inclusive Growth Imperative*

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### About the Author

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### Acknowledgements and AI Statement

I am grateful to the University of Salford for funding this research as part of the University Fellow programme, and to colleagues and reviewers for constructive comments. For transparency, AI tools were used in parts of the research workflow. A local large language model (Llama 3.1) was used in the development of various indices. Several industry standard algorithms were used as part of our data analysis approach, particularly for the CrossWalking aspects. A trio of Large Language Models (Gemini 2.5 flash, GPT5 mini, Deepseek v3.1-terminus)[1] were accessed via API calls, to apply the Place Based AI Impact Scale to Manchester. GPT-5.4, Claude haiku-4.5, Gemini-3.1-flash-lite-preview, Deepseek-v-3.3 and Qwen3.5-flash-02-23 were used to develop a Manchester Specific 'AI Baseline'. GPT5-Pro, GPT-5.4, Claude Sonnet 4.5 & 4.6 were used to transcribe and edit dictated content.

I would also like to thank Dr James Ransom (UCL) and Dr Dan Olner (University of Sheffield) for extensive support with Manchester's AI exposure (industry and occupational) calculations.

[1]Knowledge cut-offs; January 2025, May 2024, July 2025 respectively.

# Abstract

Manchester's AI ecosystem (MAIES) has emerged as the largest in the UK outside London, combining vibrant startups, world-class university research, and active regional policy support. Yet the dominant framing of this success, centred on ecosystem size and headline growth metrics, obscures a set of structural risks that threaten its sustainability and equity. This report argues that Manchester needs to reorient its AI strategy around resilient and inclusive adoption and identifies three interlocking risks that demand immediate policy attention.

The first is **the AI pricing problem**. Since 2022, large AI vendors have pursued blitzscaling strategies, deliberately charging below cost-plus-margin prices to embed customer dependency before raising prices to sustainable levels (Mills & Whittle, 2025). Private sector dependencies upon AI technologies remain structurally weak, limiting vendors' capacity to recover full costs from commercial customers. In response, public-sector institutions are becoming an increasingly attractive target market, offering the political tractability and procurement scale that commercial markets have not yet provided. For Manchester's public institutions, this represents a significant and largely unacknowledged fiscal risk.

The second risk is **place-based fragility**. Applying the Place-Based AI Impact Scale (PBAIIS), AI Occupational Exposure (AIOE), and AI Industry Exposure (AIIE) measures to sub-regional data reveals that Manchester displays a distinctive vulnerability profile including microbusinesses concentrated in high AI-exposure sectors, employment clustered near the augmentation-versus-replacement threshold, and early evidence of dependency formation around subsidised AI pricing (Whittle et al. 2026). These patterns are likely replicated across Greater Manchester's other boroughs.

The third risk is **distributional**. Manchester's celebrated AI growth coexists with considerable inequality (e.g. a child poverty rate of 42%,[2,3] one of the highest in the UK). Without deliberate policy intervention, AI-driven productivity gains will compound existing inequalities rather than reduce them.

This report presents a restructured policy framework for building a resilient, equitable MAIES. Its recommendations are addressed to Manchester City Council (MCC), the Greater Manchester Combined Authority (GMCA), and the region's universities. It argues that the goal of policy must shift from growing the Manchester AI ecosystem to growing an AI ecosystem for the benefit of Manchester and its residents.

[2] https://www.manchester.gov.uk/the-council-and-democracy/council-policies-and-strategies/manchester-and-the-living-wage/manchester-a-living-wage-city-background

[3] With some higher estimates approaching 50% e.g. https://youngmanchester.org/entry/young-people-need-a-new-deal-how-different-can-manchester-be#:~:text=Manchester%20is%20a%20paradox%2C%20it,young%20people%20living%20in%20poverty

# Executive Summary

Manchester has secured its position as the UK's foremost regional AI hub outside London. It leads in Innovate UK AI funding, boasts research-active universities, and is rapidly emerging as a Global AI Hub[4]. These are tangible achievements, but they are not sufficient grounds for complacency.

Central Argument: The primary challenge for Manchester's AI ecosystem is no longer growth. It is resilience, the ability to absorb pricing shocks, platform dependencies, and distributional pressures without fracturing the gains already made.

This report identifies three strategic risks that current policy frameworks do not adequately address:

### Risk 1: The AI Pricing Shock

*Since 2022, AI vendors have charged below cost-plus-margin prices to build dependency. As venture capital subsidies thin and costs rise, vendors must shift to cost-recovery pricing. Organisations, including public-sector bodies in Manchester, that have embedded AI at subsidised prices may face significant disruption. Public institutions represent an increasingly attractive target for AI vendors, potentially at significant cost to the public purse.*

### Risk 2: Place-Based Structural Fragility

*Aggregate GM AI-readiness rankings mask significant sub-regional heterogeneity. Microbusinesses dominate employment in AI-exposed sectors. Many roles sit near the augmentation-replacement threshold, and early dependency formation on subsidised AI is already measurable. These patterns are likely repeated across and within Greater Manchester's ten boroughs.*

### Risk 3: The Distributional Deficit

*Manchester's paradox - a fast-growing AI ecosystem alongside significant inequality - will not resolve itself through market forces. Previous waves of automation have widened inequality; the current AI wave shows the same dynamics unless active redistribution mechanisms are embedded in the ecosystem's governance from the outset.*

To address these risks, this report makes ten policy recommendations (p21), organised under five strategic priorities: building pricing resilience; grounding policy in place-based evidence; reforming public procurement; investing in inclusive skills and the social economy; and strengthening participatory governance.

[4] https://eightfold.ai/company/press/press-releases/ai-workforce-consortium-finds-78-of-ict-roles-now-include-ai-technical-skills-while-human-skills-gain-priority-for-responsible-tech-adoption/

# 1. Introduction: Reframing Manchester's AI Opportunity

Manchester is widely recognised as the UK's leading regional AI city outside London. It outranks Oxford and Cambridge in AI readiness indices (SAS, 2024), leads all other UK city-regions in Innovate UK AI grant funding, and saw 77% of companies featured in the 2024 Greater Manchester Tech Climbers competition classified as AI-focused. Nearly 4,000 people work directly in AI companies[5] in the city-region. Manchester is leading Britain with a surge of new AI company registrations[6].

This success should be celebrated. But success creates its own risks, risks now embedded in the Manchester AI ecosystem. Discourse in Greater Manchester has been overwhelmingly growth-oriented with the implicit assumption that the benefits of AI growth will diffuse across the regional economy without requiring active intervention. This report argues that this framing is insufficient and, in some respects, misleading.

> The Manchester AI Ecosystem (MAIES) requires not just continued growth, but a shift in strategic orientation away from building scale to building resilience, and from simply generating AI activity and innovation, to directing it toward inclusive public value.

Three structural realities motivate this reframing. First, the pricing model on which the current AI boom has been built is unsustainable. AI vendors have been competing on subsidised prices, funded by venture capital, to build market share and customer dependency. As this subsidy diminishes, prices must rise, and those organisations most deeply embedded in current AI workflows will be most vulnerable to disruption. Manchester's public institutions are, for reasons elaborated below, increasingly attractive targets for AI vendors seeking to resolve what we term the AI pricing problem.[7]

Second, the distributional profile of AI's benefits within Manchester is deeply uneven and it does not appear to be self-correcting. Aggregate growth statistics obscure significant place-based heterogeneity, the risks and benefits of AI adoption vary sharply between sectors, firm sizes, and boroughs.

Microbusinesses, which represent significant employment in many sub-regions, are disproportionately exposed to AI displacement risk while lacking the resources to adopt AI strategically.
Third, Manchester's AI boom coexists with significant inequality. The claim that AI-driven growth will automatically lift living standards across the region is not supported by evidence from previous waves of technological change, which have consistently widened wage[8] and wealth inequality.

This report uses the term Manchester AI Ecosystem (MAIES) to describe the place-based system of firms, universities, policy institutions, intermediaries, and labour markets that together produce and consume AI goods, services, and capabilities within Manchester.

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[5] The definition of AI companies here is vague. We consider the bulk of this employment to be in companies using AI to develop a product, service or saleable output. These are particularly vulnerable to AI price shocks. Roughly we calculate 1000 in pure AI roles and 3000 in AI related roles including data scientists etc.
[6] https://www.uktech.news/ai/manchester-leads-britain-in-surge-of-new-ai-companies-20251027
[7] Whilst unexplored in this report we note the risk of a wider economic downturn resulting from an AI investment crash is potentially increasing (Whittle & Mills, 2025).
[8] There is, at least some, doubt about the actual job creation potential of this wave of AI. See (Russell, 2021a, 2021b) or (Bessen, 2018). Generative AI is frequently efficient at the inefficient tasks of work (Mills & Spencer, 2025) it often does the aspects of a role which do not contribute directly to the objective of that role and result from the process of that role in a wider system. This is a larger debate outside the scope of this report, however we will also note a recent Guardian (Almeida 2026) report noting that in the UK as a whole, whilst AI has reportedly increased productivity by 11.5% it has resulted in net job losses. Incidentally other economies do not appear to be following this trend perhaps giving weight to Russell's (2021a) view that it is the wider economic context in which AI is deployed which will determine its complementary or substitutive nature.

# 2. The AI Pricing Problem: A Structural Threat

## 2.1 Blitzscaling and Below-Cost Pricing

The large-scale deployment of generative AI has been shaped by a distinctive commercial strategy termed blitzscaling. Supported by extraordinary volumes of venture capital funding, leading AI companies have offered their products at prices substantially below cost, that is, below the prices that would cover production costs while delivering a sustainable profit margin. This strategy prioritises rapid market capture over near-term profitability, with the expectation that embedded dependencies will, in due course, support a transition to full-cost pricing.[9]

**The AI Pricing Problem**

*Since 2022, the AI industry has pursued a blitzscaling strategy (Mills & Whittle, 2025). Supported by venture capital (VC) funding, many AI companies have charged substantially below cost prices for their technologies to win customers. AI companies now face a pricing problem. Data suggest private sector dependencies upon AI technologies are weak, undermining AI companies' capacities to raise price levels. Meanwhile, AI companies face upward pressure on both costs and margins, making the necessary price hikes greater than current dependencies can likely sustain.*

The economics of this model are becoming increasingly strained. AI infrastructure costs, chiefly compute and energy,[10] have not necessarily declined at the rate early projections suggested. The capital expenditure required to train and serve frontier AI models has grown substantially year-on-year, with the largest model providers spending tens of billions of dollars annually on infrastructure (Whittle & Mills, 2025).[11]

AI companies now face simultaneous pressure from both directions: costs are rising while the prospect of significant price increases is constrained by the weakness of customer dependencies.

## 2.2 Weak Private Sector Dependencies

For the blitzscaling model to successfully transition to cost-recovery pricing, customers must be sufficiently dependent on AI services that they cannot easily withdraw or substitute at reasonable cost. The evidence suggests that, at least in the private sector, this dependency remains shallower than AI vendors had anticipated.

Enterprise AI adoption evidence consistently reports that the majority of private sector AI projects remain at the pilot or proof-of-concept stage, with full operational integration into mission-critical workflows still limited to a minority of firms (Challapally et al., 2025).

Where integration has occurred, the switching costs are often lower than vendors would prefer, and many AI services are API-based, meaning that a firm's technology stack can, with effort, be redirected toward alternative providers or open-model alternatives. The modularity that makes AI accessible also makes it substitutable.

[9] We note that recently OpenAI's has offered investors a guaranteed 17.5% minimum return sitting against a financial backdrop of significant losses. Internal projections show the company is on track for $14 billion in losses in 2026 https://www.forbes.com/sites/josipamajic/2026/03/23/openai-offers-private-equity-firms-a-175-guaranteed-return-to-win-the-enterprise-ai-race-against-anthropic/

[10] Indeed should a sustained higher energy price occur (e.g. https://www.politico.eu/article/iran-crisis-could-hit-uk-manufacturing-in-months-ministers-warned/) then AI investment may slow and prices rise earlier than anticipated (e.g. https://www.theguardian.com/business/2026/mar/19/oil-prices-ai-boom-wto-iran-war-energy-global-economy)

[11] It is outside of the scope of this report for a full analysis, but there are indications of an increasing acceptance that 'scaling' the current AI paradigm may no longer yield significant results. See https://garymarcus.substack.com/p/breaking-expensive-new-evidence-that

This creates a structural bind for AI vendors. They cannot raise prices dramatically without risking customer churn to competitors or open-source alternatives. Yet they cannot sustain indefinitely the current below-cost pricing without either continued VC subsidy (which is of course finite) or a different category of customer that is both less price-sensitive and more structurally dependent.

## 2.3 The Public Sector as the AI Market of Last Resort

The logic of the AI pricing problem suggests the public sector as a potential 'saviour customer' of AI. Drawing on theories of policy entrepreneurship (Kingdon & Stano, 1984; Mills & Whittle, 2024) and documented patterns from both the UK and the United States, this report argues that public-sector institutions are emerging as a strategically critical market for AI vendors[12] facing the pricing bind described above.

Public-sector buyers operate under political pressures that differ in important respects from commercial procurement logic. While private-sector firms also face shareholder pressure to embrace technological modernisation, elected officials face a distinctive set of incentives to be seen to be embracing it. AI offers a readily legible narrative of efficiency, innovation, and future-readiness that holds considerable short-term political value. This political tractability means that public institutions may accept AI contracts at prices, and on terms, that a private sector buyer operating under sharper commercial discipline would reject.

> The promise of AI technologies is likely to hold significant short-term political value, enabling AI companies to charge public-sector bodies cost-plus-margin prices, resolving the pricing problem at the expense of the public purse.

From the vendor's perspective, public-sector contracts offer several advantages over private-sector equivalents: they tend to be larger in scale; they often involve multi-year commitments that reduce churn risk; they carry reputational benefits that can anchor commercial marketing; and crucially, they involve buyers who are operating under political pressures that create some tolerance for increased pricing (when this is still an overall cost reduction), particularly when that pricing is obscured within complex procurement processes.

## 2.4 Implications for Manchester's Public Institutions

For Manchester's public institutions including Manchester City Council, GMCA, NHS trusts, housing associations, Further Education colleges, and the city's universities, the AI pricing problem has direct and urgent implications.

These institutions are, for reasons of scale, civic visibility, and political ambition, highly attractive customers for AI vendors. Greater Manchester has been nationally prominent in its commitment to digital and AI modernisation. The region's public bodies have embraced AI as a component of service delivery, efficiency improvement, and regional economic leadership.

Public institutions that embed AI services at today's subsidised prices and then face cost-recovery pricing during the transition period may experience significant operational disruption. Budget commitments made on the basis of current AI pricing may prove undeliverable under true-cost conditions. And the services that may be cut to accommodate rising AI costs are, in many cases, precisely the services on which Manchester's most disadvantaged residents depend.

[12] This argument is advanced at the level of structural incentives and documented patterns of policy entrepreneurship. A systematic audit of AI contracts held by MCC, GMCA, GM NHS trusts, and the region's universities, covering price points, exit provisions, and vendor concentration, would be required to confirm the extent to which this dynamic is already operative locally. We are not currently aware of any such audit having been conducted, which is itself indicative of the governance gap this report identifies

### A Compounding Risk

*Organisations, including public bodies, that have integrated AI during the blitzscaling era have built workflows and operational models around the assumption of persistently low AI costs (Mills & Whittle, 2025; Whittle et al., 2026). If vendors shift to true pricing, organisations without contingency plans face not only higher costs but operational disruption.*

*This disruption will be exacerbated if talent pipelines are disrupted at early adoption stages. Quite simply a firm is dependent on AI if they no longer have the staff and expertise to do without.*

This is not an argument against public-sector AI adoption. AI can likely deliver real efficiency gains and service improvements. It is simply an argument for *resilient* adoption, including procurement that is evidence-based, contracts that include robust exit provisions, spending decisions that are stress-tested against true-cost pricing scenarios, governance structures that can assess value for money with substantive independence from the political incentives that drive procurement in the first place, and investment in the technical capability and process management required to switch providers or models over time where quality or cost considerations demand it.

# 3. Place-Based Economics and the AI Ecosystem

## 3.1 Why Place Matters

AI is not experienced uniformly (Ransom & Whittle, 2026; Ashraf et al., 2026). Its impacts on employment, productivity, inequality, and public services are mediated by the specific economic geography of the places in which it is adopted. The aggregate AI-readiness metrics that dominate policy discourse[13] which rank Manchester favourably relative to most UK city-regions, obscure the considerable variation in AI exposure and resilience that exists within the MAIES at the borough, sector, and firm-size level.

**Place Based AI**

*A place-based approach to AI recognises that the appropriate policy response depends on the specific configuration of economic actors, employment structures, and institutional capacities in each locality.*[14]

The policy interventions most likely to support resilient AI adoption in a borough characterised by microbusinesses in professional services are different from those appropriate for an area with a large manufacturing base, a health-economy anchor, or a significant creative industries cluster. A generic ecosystem-level strategy risks misallocating resources and missing the sub-regional dynamics that will ultimately determine whether Manchester's AI growth is genuinely inclusive[15].

## 3.2 Ecosystem Strengths

Manchester's AI ecosystem is characterised by a distinctive concentration of assets. Understanding these strengths is essential both for appreciating the scale of the opportunity and for identifying the specific vulnerabilities that a resilience-oriented strategy must address.

In terms of investment and infrastructure, Manchester has attracted more Innovate UK AI grant funding than any other UK city-region. Initially The Greater Manchester AI Foundry, a £6 million multi-university programme, directly supported SME AI adoption. More recently, The Centre for Digital Innovation, the Manchester Turing Innovation Hub, and the selection of Greater Manchester as one of three UK Innovation Accelerator regions in 2023 (bringing around £100 million in national investment) collectively represent a significant infrastructure of public support for AI innovation.

The MAIES talent base is anchored by research-active universities. The University of Manchester, Manchester Metropolitan University (MMU), and close by, the University of Salford each host dedicated AI and data science research centres producing internationally excellent work. The University of Manchester's UKRI Centre for Doctoral Training in AI, funded as part of a £118 million national programme and delivered in partnership with the University of Cambridge, represents a particularly significant long-term investment in regional AI research capacity. UoM, MMU and UoS are members of

[13] We of course note that readiness in not necessarily preparedness.

[14] Manchester's AI ecosystem interacts even with 'non-AI' roles and tasks to make them more likely to incorporate Artificial Intelligence. Simply a manager in Manchester is *ceteris paribus* more likely to use AI in their job than a manager in lower AI exposed regions. Even if on paper they look like they are doing the same things (Ransom & Whittle, 2026).

[15] Whilst not covered in this report, post Covid significant public activity has moved online (e.g. see Mills, Whittle & Brown, 2021), there ae considerable implications of AI as a harm for (e.g. Muldoon 2026) and implications for digital inclusion (Whittle et al, 2026).

the Alan Turing Institute, and all five GM universities have committed to civic missions that extend their impact beyond the campus[16].

Bridging organisations, notably the Turing Innovation Catalyst Manchester (TIC), and the Centre for Digital Innovation, are critical connective tissue within the ecosystem. They translate research into commercial application, support SMEs in accessing AI capabilities, and create the cross-sector links on which ecosystem resilience depends. However, their focus is required to shift to inclusive AI growth, and to ensuring the ecosystem they have helped developed is resilient to the embedded and looming risks of this report.

## 3.3 Sub-Regional Heterogeneity

Aggregate ecosystem metrics do not capture the variation in AI risk and opportunity that exists within Greater Manchester (Whittle et al, 2026).

Next we apply the AI Occupational Exposure (AIOE) and AI Industry Exposure (AIIE) scales (adapted from Eloundou et al., 2023; cf. Felten, Raj & Seamans, 2021)[17] alongside the Place-Based AI Impact Scale (PBAIIS, Ransom & Whittle, 2026) to Manchester firm and labour market data.

> Greater Manchester needs a borough-level AI exposure audit, applying AIOE, AIIE, and PBAIIS, measures across all ten GM boroughs. Aggregate AI-readiness rankings are insufficient for evidence-based inclusive AI policy.

[16] It should be acknowledged that Greater Manchester's universities are not only solution providers in the AI ecosystem but are themselves significant AI consumers, in research computing, administrative systems, student-facing tools, and learning platforms, and are therefore subject to the same blitzscaling dependency and pricing risks that this report identifies for other public-sector institutions. The recommendations on procurement resilience (R1, R2) apply to universities as purchasers of AI services with equal force as they apply to local authorities and NHS trusts

[17] The underlying exposure indices were originally calibrated on US occupational classifications (O*NET) and AI capability benchmarks from a specific moment in the technology's development. Application to UK labour market data requires a SOC-to-O*NET crosswalk whose fidelity introduces some measurement noise at the margins of occupational categories. Furthermore, the rapid evolution of frontier model capabilities since the original calibration means that exposure scores should be interpreted as broadly indicative of relative positioning rather than as precise point estimates. The spatial and distributional patterns identified here are robust to reasonable recalibration assumptions, but readers should be cautious about over-interpreting small differences between individual MSOAs or occupational groups.

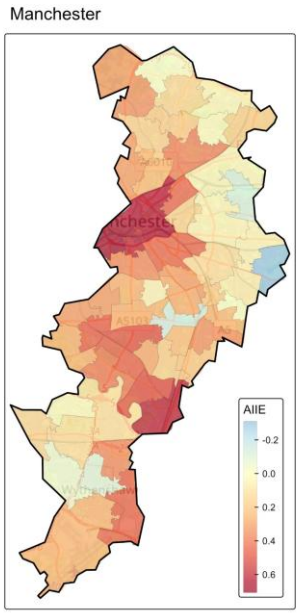


**Figure 1:** *AI Industry Exposure (AIIE) across Manchester MSOAs. Dark red (AIIE > 0.6) denotes high exposure; blue (AIIE < 0) denotes net-negative exposure. Source: Whittle et al. (2026).*

## Spatial Patterns and Policy Implications

Figure 1 presents AI Industry Exposure (AIIE) scores (Eloundou et al., 2023; Felten, Raj & Seamans, 2021) across Manchester's Middle Layer Super Output Areas (MSOAs), providing the most granular available picture of where AI-related industry risk and opportunity is concentrated within the city boundary. AIIE measures the degree to which the industrial composition of a given area is skewed toward sectors that are either highly exposed to AI capabilities or actively deploying them. A positive score indicates employment concentration in AI-exposed industries; a negative score indicates the reverse.

The spatial pattern is not unexpected. The highest AIIE scores, deep red, exceeding 0.6, are concentrated in Manchester city centre and a small number of secondary nodes in the southern corridor. These are areas characterised by high densities of professional services, financial services, and technology firms: sectors where AI exposure is both an indicator of augmentation opportunity for high-skill roles and of substitution risk for routine analytical and administrative tasks.

The mid-range orange band (AIIE 0.2-0.4) covers the majority of Manchester's surface area, including large residential areas in the north and east of the borough. This distribution carries an important policy implication. AI industry exposure is not confined to a small high-tech enclave. It extends into communities whose residents may not consider themselves part of the AI economy, and who are unlikely to have received the skills investment or awareness-raising that would allow them to navigate that exposure effectively.

The blue areas, particularly low AIIE scores, visible primarily on the eastern fringe and parts of Wythenshawe, represent communities where local industrial composition currently provides some degree of insulation from AI exposure. This should not be read as a measure of resilience in a broader sense. Negative AIIE typically reflects concentration in sectors that are less digitised or where AI capability has not yet penetrated, such as parts of social care, construction, and certain retail sub-sectors. These areas may experience delayed but significant AI exposure as capability diffuses and as cost pressures intensify the search for automated alternatives.

**A Tale of Two Manchesters**

*The AIIE map illustrates a spatial dimension of Manchester's paradox. The areas of highest AI industry exposure, city centre, the innovation corridor, established professional services clusters, broadly correspond to areas of relative economic advantage. The areas of lower current AI exposure, including parts of Wythenshawe and the eastern fringe, are disproportionately home to lower-income households.*

*This geography means that the first wave of significant AI-driven displacement risk falls on workers in high-exposure city-centre sectors, many of whom have the skills and mobility to adapt. The second wave, as AI diffuses into lower-exposure sectors, will fall on communities with fewer resources to respond. Without proactive place-based policy, the AIIE map may be charting the advance of a distributional shock that is gradual enough to evade political attention and disruptive enough to entrench inequality.*

The map also reinforces the case for the GM AI Exposure Audit covered in recommendation 3. Manchester city is one of ten Greater Manchester boroughs, and there is no reason to assume that its internal AIIE distribution is representative of, for example, Salford, Bolton, Rochdale, or Tameside. The policy interventions appropriate for a city-centre MSOA with AIIE above 0.6, augmentation support, pricing resilience planning, ethical procurement reform, are categorically different from those appropriate for a low-exposure peripheral community where the priorities are awareness-raising, basic digital skills provision, and sector-level contingency planning.

## Readiness-Adjusted AI Exposure: Manchester's Effective Risk Profile

Ransom & Whittle (2026) distinguish between technological exposure to AI, what AI can do to a task, and effective exposure, which accounts for the local ecosystem's capacity to translate that technological potential into actual workplace disruption. The base AIOE/AIIE scores are, by construction, place-blind, two cities with identical occupational profiles receive identical exposure scores regardless of whether one has a dense AI ecosystem and the other does not. The readiness adjustment addresses this limitation by incorporating local AI readiness as a multiplicative modifier on the exposure dimension.

Applied to Manchester, which tops the SAS AI Cities Index 2024 with a composite readiness score of 457 out of 700, Manchester's baseline weighted mean AI exposure score (1.41) is identical to the UK national mean, and only marginally above the North West regional average (1.39). Manchester's occupational mix, in other words, gives it roughly average national exposure to AI. The city's AI readiness profile changes this picture substantially: applying a +10 percent readiness modifier[18], Manchester's effective weighted mean exposure rises to 1.55, placing it just above London's unadjusted baseline of 1.54 (Ransom & Whittle, 2026).

[18] The readiness modifier is derived from Manchester's composite score on the SAS AI Cities Index 2024, normalised against the national distribution. We apply this as a multiplicative adjustment to the exposure dimension on the grounds that ecosystem density accelerates the translation of technological potential into workplace disruption. The specific magnitude of the modifier is necessarily approximate; alternative calibration approaches (e.g. using the normalised distance from the national mean, or weighting sub-components of the readiness index differentially) may yield somewhat different point estimates.

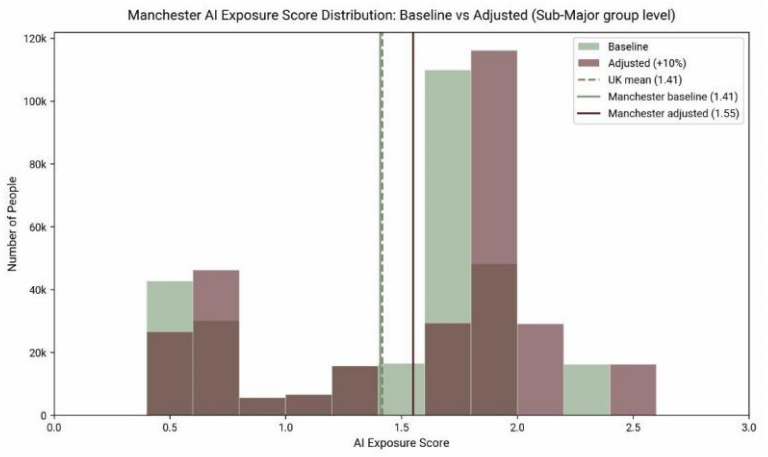


**Figure 2:** *Manchester AI Exposure Score Distribution, Baseline vs Readiness-Adjusted (+10%). Vertical lines show UK mean (1.41) and Manchester baseline (1.41) and adjusted (1.55) means. Source: Ransom & Whittle (2026).*

The significance of this result is twofold. First, it confirms that Manchester's headline AI ecosystem strength, typically cited as a growth story, also implies elevated effective AI exposure for its workforce relative to its occupational mix alone. Workers in Manchester are likely to encounter AI adoption faster and more extensively than their job titles would predict, precisely because the infrastructure to deploy AI is already dense and well-capitalised. Second, and critically for this report's argument about pricing risk, organisations that have adopted AI in a high-readiness environment are, by definition, further along the dependency-formation curve than those in lower-readiness cities. Manchester's position as the UK's highest-readiness city outside London makes it a leading indicator both of AI's benefits and of the pricing and dependency risks that follow rapid adoption.

Figure 2 illustrates the distribution shift clearly. The baseline distribution (green) is concentrated in the 1.5-2.0 exposure range, with a secondary cluster below 1.0. The readiness-adjusted distribution (brown) shifts rightward, with the modal bin moving from 1.5-2.0 to 2.0-2.5, a meaningful increase in the proportion of Manchester workers in occupations where AI can both substantially accelerate work and produce market-viable substitute outputs. This shift does not imply imminent mass displacement; rather, it indicates that the window in which AI augmentation transitions to substitution pressure is narrower in Manchester than the national average would suggest.

The sector-specific implications of this adjustment are also useful. Manchester's health professionals see their readiness-adjusted exposure score rise from 1.64 to 1.80, while their Minimum Viable Output (MVO) score remains at 0.64, well below the threshold at which AI can independently produce an acceptable output. The readiness adjustment implies greater productivity potential without a corresponding increase in displacement risk. Health professionals are in the augmentation zone regardless of adjustment, but the speed at which AI tools diffuse into clinical and administrative workflows will be higher in Manchester than elsewhere. For the MAIES, this points to health and public services as a priority arena for AI-augmentation support that is decoupled from displacement anxiety, and, relatedly, as a sector where the public-sector pricing dynamics described in Section 2 will be felt acutely as adoption deepens.

**The Readiness Paradox**

*Manchester's AI readiness is typically presented as an unambiguous competitive asset. The Ransom & Whittle (2026) readiness-adjustment framework reveals its dual nature, as the same ecosystem density that accelerates AI adoption also accelerates the translation of technological exposure into effective workforce risk.*

*High readiness means faster adoption, deeper dependency formation, and consequently greater vulnerability to the pricing transition described in Section 2. Manchester's effective exposure (1.55) exceeds its occupational-mix exposure (1.41) by 0.14 points, a gap that represents not simply growth potential, but a compressed timeline in which organisations must build resilience before the pricing environment changes.*

## Manchester: An Integrated Exposure Analysis

Figures 3 and 4, read together, provide the most comprehensive currently available evidence on AI exposure in Manchester. Figure 3 captures the demand-side, demonstrating how the firms and industries located within Manchester are positioned relative to AI capabilities, disaggregated by firm size. Figure 4 captures the supply-side, showing how the residents of Manchester's MSOAs are occupationally exposed to AI, based on the jobs they hold.

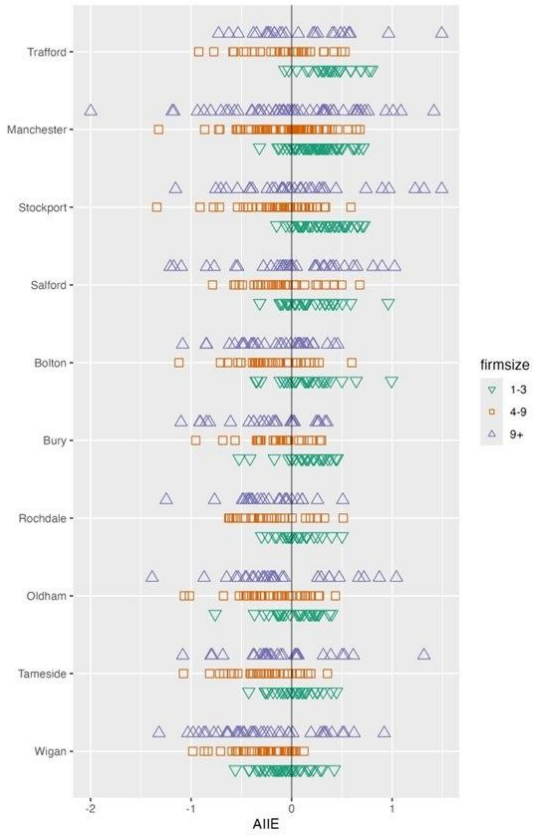


**Figure 3:** *AIIE by firm size across GM boroughs (Manchester = second row). Source: Whittle et al. (2026).*

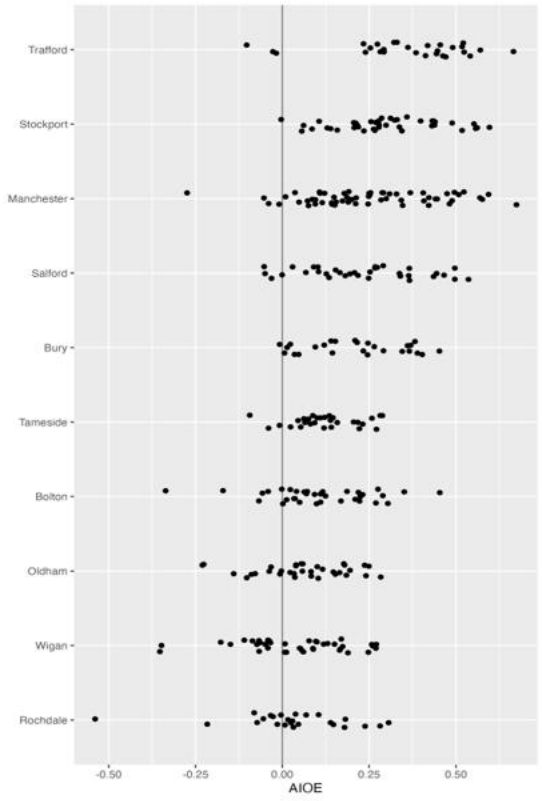


**Figure 4:** *AIOE for residents by MSOA across GM boroughs (Manchester = third row). Source: Whittle et al. (2026).*

## The Firm-Side Picture: What Industries Are Present in Manchester?

Focusing on the Manchester row in Figure 3, the dominant structural feature is the extreme lateral spread of larger firms (9+ employees, blue upward triangles) relative to all other GM boroughs. Manchester's 9+ firms extend from a leftward outlier approaching -1.0 AIIE, to rightward outliers at or beyond +1.5 AIIE, representing technology, financial services, or professional services firms that are among the most AI-

exposed in the entire GM economy. This spread exceeds that of every other borough, including Trafford, which displays the next widest large-firm range.

The 4-9 employee band (orange squares) tells a different story. In Manchester as in every other GM borough, small businesses are massed in a tight corridor close to the zero baseline, extending no further than approximately ±0.5 AIIE. This compression reflects that smaller firms tend to concentrate in service sectors, accountancy, consulting, hospitality, retail, health and social care support, whose AI exposure is moderate and broadly uniform regardless of location. Manchester's small business population is, in industry-composition terms, essentially indistinguishable from that of Salford or Bury, despite operating within a dramatically different large-firm AI context.

Manchester's microbusinesses (1-3 employees, green inverted triangles) cluster from approximately -0.5 to just above zero, with a centre of mass slightly below the AIIE baseline. This near-neutral to mildly negative positioning reflects concentration in personal services, creative freelance work, sole-trader professional services, and similar activities, sectors where AI exposure is currently moderate but where competitive pressure from AI-enabled larger firms is growing.

## The Resident Side: Who Actually Lives in Manchester and What Do They Do?

Figure 4 examines how exposed people's occupations are to AI. Manchester's MSOA distribution is the third from the top of the chart, and it displays greater internal spread than any other GM borough. The large majority of Manchester's MSOAs record AIOE scores between 0.00 and 0.50, consistent with a workforce in which most residents work in roles that are moderately amenable to AI productivity enhancement, administrative functions, analytical roles, customer-facing professional services, health administration, without being at the frontier of AI substitution risk.

Two outlier MSOAs require specific attention. The first is Manchester's deep negative outlier, recording AIOE below -0.25, the lowest single MSOA reading visible for the borough and among the lowest in the entire GM chart. This MSOA contains a residential population whose occupational profile is heavily weighted toward low-AIOE roles. This is not an economically marginal area in a simple sense as low AIOE does not mean low income or low employment, but it does mean that the current wave of AI development is unlikely to arrive in this community through the productivity augmentation channel. When AI does penetrate these roles, it may arrive through competitive and cost-reduction channels driven by forces external to the community itself[19].

The second outlier is Manchester's high positive MSOA, recording AIOE approaching 0.65–0.70. This is the highest resident AIOE value visible in Manchester's distribution and one of the highest in the GM chart outside Trafford. This is an area with high concentrations of software, data, financial, or professional services workers, residents whose occupations are not only AI-exposed but where AI tooling is already embedded in daily workflows. This MSOA sits, in occupational terms, in the zone where augmentation is well established and where the policy questions are about deepening the quality of that augmentation and managing the pricing transition rather than initiating AI awareness.

## Reading the Two Charts Together: The Commuter-Exposure Disconnect

The most significant insight from placing Figures 3 and 4 in direct comparison is the degree to which the firm-side and resident-side exposure profiles diverge for Manchester. The city hosts some of the most AI-exposed large employers in Greater Manchester, 9+ firm outliers at AIIE above +1.0, yet the majority of Manchester's residential MSOAs record AIOE scores in the moderate 0.0–0.40 range. If the workforce of Manchester's high-AIIE firms were drawn primarily from Manchester's own residential population, we would expect the AIOE chart to mirror the rightward skew of the AIIE firm distribution. It does not.

[19] This reflects that AI does not need to be producing outputs at a human parity level to impact job roles (Ransom & Whittle, 2026), and that if AI impacts *demand* for those roles, rather than substituting the tasks directly, it will result in labour substitution.

This divergence reflects a well-documented feature of city-region labour markets, the workers in Manchester's most AI-exposed large firms are not predominantly Manchester residents. They commute in, from Trafford, Stockport, and Salford, whose AIOE distributions do skew more noticeably rightward, or they are drawn from a national talent pool that does not register in local residential Census data. This commuter-exposure disconnect and underexplored policy implication. The productivity gains generated by AI adoption in Manchester's most AI-exposed firms will accrue first to workers who are not, in the main, Manchester residents[20]. The Manchester Council Tax base, the Manchester labour market, and the Manchester communities that host these firms will bear the infrastructure and social costs of a high-intensity AI economy without necessarily capturing commensurate wage and employment benefits within the city boundary.

> Manchester's AIIE and AIOE profiles diverge in a way that most GM boroughs do not. High firm-side AI exposure in the city centre coexists with moderate resident-side occupational exposure across most MSOAs. The productivity gains of Manchester's AI-intensive large employers are flowing primarily to commuter-resident workers in neighbouring boroughs, not to Manchester's own residential communities. This is the spatial mechanism through which AI growth can simultaneously occur and deepen intra-city inequality.

## Policy Implications: Targeting Requires Sub-City Resolution

The combined reading of Figures 3 and 4 establishes that Manchester is not one AI story but at least three, running concurrently within the same city boundary. The first story is that of the high-AIIE large employer in the city centre, deploying AI rapidly, competing for commuter talent, and exposed to the pricing transition risks described in Section 2. The second story is that of Manchester's small and microbusinesses, whose near-zero AIIE belies their competitive exposure to AI-enabled rivals and whose residents cluster in the moderate-AIOE MSOAs that form the bulk of Figure 4's Manchester distribution. The third is that of Manchester's lowest-AIOE residential communities, the deep-negative MSOA outlier and the MSOAs in the 0.0-0.10 range, whose residents are currently insulated from AI by occupational profile but who face the risk of indirect displacement as AI-enabled efficiency gains in adjacent sectors reshape service demand and employer behaviour.

Effective AI policy for Manchester City Council must engage with all three stories simultaneously, and it cannot do so at the borough level alone. The interventions appropriate for a city-centre MSOA with AIOE above 0.60, skills deepening, augmentation tooling, pricing resilience support for employers, are categorically different from those appropriate for a low-AIOE residential MSOA where the immediate priority is awareness, foundational digital literacy, and protection from indirect displacement effects. The GM AI Exposure Audit recommended in R3 is the minimum evidential infrastructure required to target these three stories with proportionate and effective policy responses.

Manchester's small and microbusinesses (figure 3) are the least AI-equipped firms in the city's most AI-intensive economy. They require not only generic AI literacy and skills support, but specific guidance on how to navigate an environment in which their large-firm competitors are moving rapidly, and in which the pricing transition in frontier model markets is simultaneously raising the cost of the very tools that might otherwise allow them to compete. Manchester's AI strategy should treat its small business population as a significant AI vulnerability in the ecosystem. These firms whose failure, under competitive AI pressure, would most directly harm the residential communities that Figure 4's AIOE distribution represents.

[20] This inference is drawn from the divergence between firm-side AIIE and resident-side AIOE distributions across GM boroughs. It is consistent with well-documented travel-to-work patterns in city-region labour markets but has not been confirmed through direct linkage of commuting flow data (e.g. Census travel-to-work tables) to occupational exposure scores at the individual level. Confirming the mechanism would be a natural priority for the GM AI Exposure Audit recommended in R3.

## The Augmentation–Substitution Frontier: Where Manchester's Workforce Actually Stands

The preceding analysis has established where AI exposure is highest across Greater Manchester's firms, sectors, and residential communities. A further and more decisive question for policy is: what kind of AI exposure? The distinction between augmentation, where AI tools enhance human productivity without displacing employment, and substitution, where AI outputs are of sufficient quality to render human involvement unnecessary, is the central hinge on which the distributional consequences of AI adoption turn. Figure 5 maps Manchester's occupational groups against this augmentation/substitution frontier.

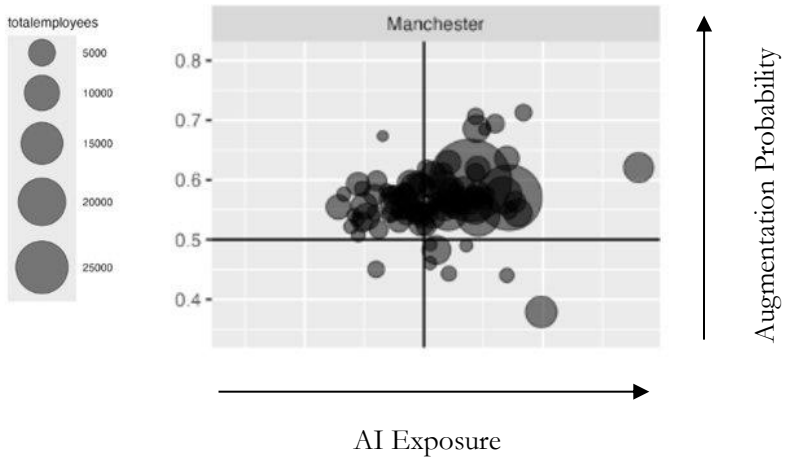


**Figure 5:** *Manchester occupational groups plotted by AIIE and an Augmentation / Automation probability. (see Whittle et al. 2026).*

Figure 5 plots Manchester's occupational groups on two dimensions simultaneously. The x-axis captures AIIE. The y-axis the estimated probability of a worker being augmented by Artificial Intelligence (or conversely replaced). Bubble size represents the total number of workers in each group. Simply the more to the right a worker is the more AI exposed their role is, the higher they are, the more likely they are to use AI to be more productive than be replaced by it. Workers in the lower right quadrant are at the greatest risk of replacement, workers in the upper right quadrant are more likely to use AI to increase their productivity, rather than simply be replaced by it. Workers in the left quadrants are less likely to be exposed to AI at all. The further one is in the quadrant, from the midpoint, the more likely the outcome.

The distribution of Manchester's workforce across this quadrant space is the most direct available evidence on the augmentation / automation balance in the city. The dominant feature of Figure 5 is the large cluster of bubbles, representing the majority of Manchester's total employment, positioned quite centrally away from any definite outcomes. This cluster sits, decisively, in the augmentation zone, occupational groups where AI exposure is real and where AI tools can meaningfully accelerate and enhance work, but where current AI output quality does not meet the threshold required for wholesale human substitution. The current Manchester picture is one where the majority of workers are primed for using AI rather than being replaced by it, but are close to the replacement category. For policy the focus is one of both moving workers further into the augmentation zone *via* skills and inclusion programmes *and* via infrastructure and procurement, lowering the zone boundary bringing more workers into the augmentation zone. However, the pricing transition described in Section 2 is precisely the kind of cost pressure that could trigger this threshold rising organisations that have embedded AI at subsidised prices, facing a step-change increase in costs, will face strong incentives to accept lower-quality AI outputs rather than reintroduce human labour at higher cost.

### The Augmentation Zone is Not Permanent

*Manchester's workforce currently sits, in aggregate, in the augmentation zone, a positive finding. AI is predominantly acting as a productivity tool rather than a replacement technology in the city's occupational profile.*

*But the augmentation zone is not a stable resting place. It is a dynamic threshold determined by three factors that are all currently in motion: AI capability (improving rapidly), MVO acceptance standards (susceptible to cost pressure), and human skill levels (dependent on sustained investment).*

*Policy that does not actively manage all three factors simultaneously is not preserving the augmentation equilibrium. The pricing transition, in particular, is the mechanism most likely to push Manchester's majority-cluster occupations across the substitution threshold in the near term.*

The bulk of Manchester's workforce sits in the augmentation zone, but near its edge, and that the pricing dynamics described in Section 2 represent the most immediate mechanism by which the equilibrium could shift. Pricing resilience (Recommendations R1 and R2) is a workforce protection priority.

**Manchester vs the Rest of Greater Manchester: A Direct Comparison**

Figure 6 extends the augmentation-substitution analysis to place Manchester workers (red) in direct comparison with firms across the remaining GM boroughs (blue).

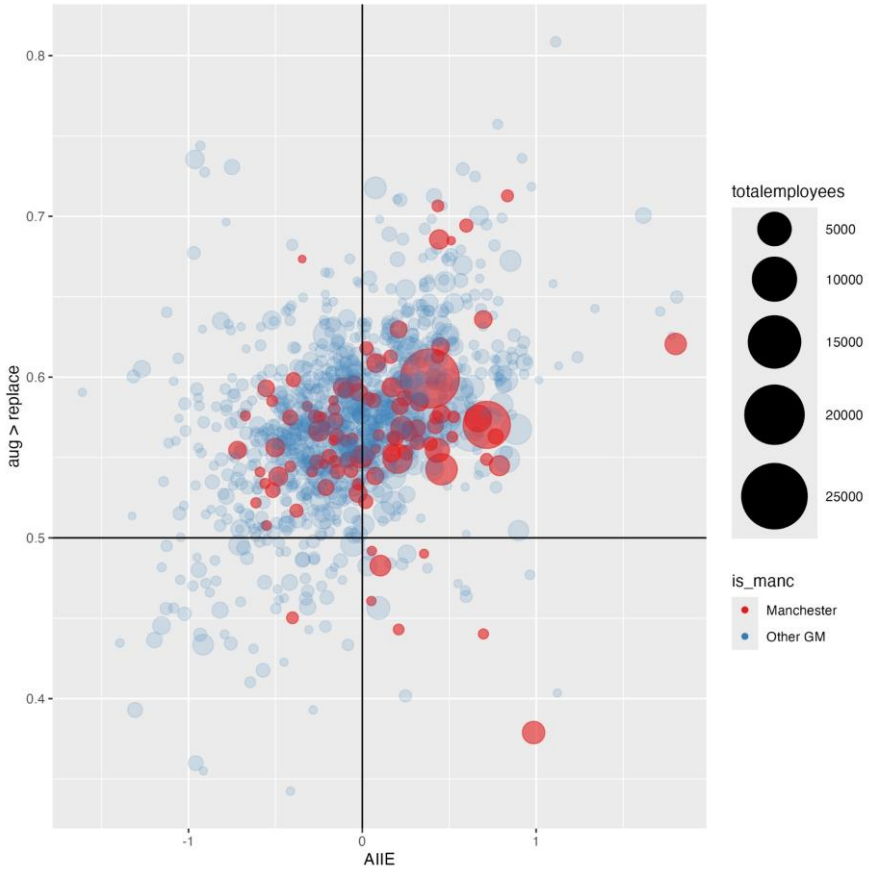


**Figure 6:** *AIIE (x-axis) versus augmentation probability, aug > replace (y-axis), for Manchester (red) and Other GM boroughs (blue). Bubble size = total employees. Quadrant lines at x=0 (mean AIIE) and y=0.5 (augmentation threshold).*

The first feature of Figure 6 is the horizontal differentiation between Manchester and the rest of Greater Manchester. The Manchester distribution is pulled decisively rightward along the AIIE axis relative to the Other GM distribution. Manchester's firms are, in aggregate, located in more AI-exposed industries than their equivalents elsewhere in the city-region. This is consistent with the city-centre concentration of professional services, financial technology, digital media, and data-intensive businesses established in Figure 1. The Other GM distribution spreads more symmetrically around x=0, with substantial mass in negative AIIE territory, sectors such as manufacturing, logistics, retail, and social care that are less currently AI-exposed.

The second critical feature is the vertical positioning. Both Manchester and Other GM distributions sit predominantly above the y=0.5 augmentation threshold, a finding that replicates and reinforces the city-region level result from Figure 5 and is broadly encouraging. The centre of mass of the entire scatter is in the upper half of the chart, indicating that across Greater Manchester's employer base, the probability that AI adoption will augment rather than replace workers is, on balance, above the threshold. However, the degree of comfort this provides should not be overstated. The majority of the employment-weighted mass sits between y=0.5 and y=0.65, a narrow band. There is no large concentration of bubbles in the upper reaches of the chart (above y=0.75) that would indicate deep, structural insulation from substitution risk.

The centre of gravity for both Manchester and Other GM employment sits above the augmentation threshold, but only just. With augmentation automation probabilities clustering between 0.5 and 0.65, the city-region's workforce occupies a structurally precarious position, in the augmentation zone, but within reach of the boundary that separates augmentation from substitution.

**Four Zones, Four Policy Responses**

*Figure 6 effectively divides Greater Manchester's employer base into four strategically distinct groups, each requiring a different policy response.*

*Upper-right: The Augmentation Zone. Manchester-concentrated advanced sectors. Policy priority, augmentation support, ethical AI procurement, pricing resilience planning, and skills deepening to maintain the augmentation advantage.*

*Upper-left: Other GM employers in lower-exposure sectors where AI is arriving slowly but augmentation outcomes remain probable. Policy priority, proactive AI awareness and foundational skills investment before exposure intensifies.*

*Lower-right: The Automation Zone. Manchester's outlier large employer and several smaller firms are here now. Policy priority, urgent skills transition, alternative employment pathway investment, and regulatory scrutiny of AI deployment decisions.*

*Lower-left: Peripheral Other GM employment in sectors where AI has not yet arrived but where, when it does, the occupational profile implies substitution risk. Policy priority, long-term resilience building and proactive sector diversification.*

## 3.4 Platform Dependency and Concentration Risk

A structural vulnerability that deserves particular attention is the MAIES's dependency on a small number of large foundational model providers. Many MAIES firms build products and services on APIs provided by OpenAI, Anthropic, Google, and a small number of others. This platform dependency ties the ecosystem to external roadmaps, pricing decisions, and potential terms-of-service changes entirely outside local control. The Competition and Markets Authority has identified vendor lock-in and ecosystem concentration as key competition risks in AI foundation models;[21] these risks apply with equal force at the regional level.

For MAIES firms, platform dependency amplifies the pricing risk described in Section 2. Not only are their customers exposed to pricing transitions, but the firms themselves are exposed to upstream pricing changes from frontier model providers. A simultaneous increase in frontier model API costs and downstream customer pressure, both foreseeable as blitzscaling subsidies unwind, would compress margins significantly across the MAIES.

MAIES strategy should explicitly map where key dependencies lie and develop contingency capacity accordingly. This is not an argument against using frontier models, as they dramatically lower barriers to AI innovation. Building resilience alongside adoption, for example maintaining awareness of open-source alternatives, participating in consortium models, and treating current low API costs as a temporary subsidy rather than a structural feature of the business environment, will allow MAIES organisations to continue to be competitive in a rapidly changing environment.

## 3.5 The wider economic context

The MAIES operates within a challenging macroeconomic environment. Inflation, while easing from its 2022 peak, has left costs persistently elevated.[22] The cost of commercial and residential property in Manchester has risen in line with the city's economic success, narrowing the cost advantage that has historically made Manchester an attractive location for tech talent relative to London. Real wages have stagnated or fallen in many sectors, creating pressure on consumer demand for AI-enabled products and services, while simultaneously making Manchester a less clearly attractive destination for highly paid tech workers.

These macroeconomic headwinds reinforce the case for a resilience-oriented strategy. Many MAIES firms, particularly those in early and mid-growth stages, carry high burn rates and remain dependent on venture funding. A sustained tightening of VC conditions, coinciding with the pricing transition in frontier model markets, could produce a rapid and disruptive correction in the MAIES. The region's AI strategy must build in financial prudence, diversified funding sources, and explicit stress-testing against adverse scenarios, not only the optimistic projections that dominate current planning documents.

Finally, looming economic pressures may force a greater pressure on cost reduction as a primary AI driver. Ransom & Whittle (2026) note that in this circumstance cost rather than quality can dominate decision making, accelerating automation over augmentation, although the elasticity of this relationship will vary considerably across occupational groups.

[21] https://www.gov.uk/government/publications/cma-ai-strategic-update/cma-ai-strategic-update
[22] At the time of writing a further increases in energy and goods prices are anticipated.

# 4. AI, Inequality, and the Inclusive Growth Imperative

## 4.1 Manchester's Paradox

Manchester's economic paradox is the starkest possible illustration of why growth-oriented AI policy is insufficient. For example Manchester has one of the fastest-growing AI ecosystems in Europe *and* one of the highest child poverty rates in the UK, with 42% of children and young people living in poverty. The dynamics that make Manchester attractive for high-growth technology companies, dense networks, skilled labour, world-class universities, public investment in innovation infrastructure, do not automatically benefit the households whose children make up that 42%.

Access to the benefits of AI within Greater Manchester is itself uneven. Digital exclusion remains significant, disadvantaged neighbourhoods have lower rates of device ownership, internet connectivity, digital skills, and representation in technology employment. AI is not a route to shared prosperity if those who stand to benefit most from new employment opportunities, improved public services, and enhanced productivity are excluded from access to the digital infrastructure that underpins it.

> Manchester's AI strategy must be explicitly framed as an inclusive growth strategy. The goal is not only to grow the Manchester AI ecosystem. The goal is to grow an AI ecosystem for the benefit of Manchester.

## 4.2 The Automation Threshold and Place-Based Risk

Understanding the distributional risks of AI in Manchester requires moving beyond aggregate exposure metrics to place-specific analysis. The PBAIIS framework (Ransom & Whittle, 2026) provides a methodological basis for this, weighting standard AI exposure metrics by local economic characteristics and by considering whether AI can produce a minimum viable output (MVO) that renders a human unnecessary for a given task.

PBAIIS analysis reveals that employment is concentrated near the augmentation threshold, the point at which outcomes depend critically not on AI capability alone, but on managerial choices, worker capability, and governance decisions. This means that policy choices matter enormously at the margin. The same technological capabilities, deployed under different governance conditions, can produce radically different outcomes for employment, income distribution, and social mobility (Russell, 2021b).

The MVOQ extension of this framework (Whittle *et al*, 2026) is particularly relevant for policy[23]. When cost pressure leads organisations to accept a lower-quality AI output rather than maintain human-quality standards, roles that would otherwise be augmented shift toward substitution. This substitution effect, driven not by AI capability but by cost-driven managerial decisions, is potentially the primary driver of inequality-inducing AI adoption in many MAIES sectors.

[23] The MVO framework is not fully operationalised in this report. A comprehensive application would require MVO scoring across Manchester's principal occupational groups, mapping the quality threshold at which AI output becomes acceptable as a substitute for human labour in each case. A more complete MVO mapping for Manchester is a priority for subsequent work and would substantially strengthen the empirical basis for the augmentation-zone arguments advanced in this report.

## 4.3 Three Scenarios

The trajectory of AI adoption in the MAIES can be understood through three plausible scenarios, which represent different combinations of policy choice and market dynamics (developed from Whittle *et al.*, 2026):

| | Strong Scenario | Mid Scenario | Weak Scenario |
|---|---|---|---|
| **Description** | AI treated as a public good. Shared infrastructure, open access, universal upskilling. Broad-based prosperity. | Market-driven adoption creates a two-tier landscape: advanced AI for well-resourced organisations; basic tools for smaller firms and lower-income residents. | MAIES becomes dependent on proprietary systems. Costs rise as subsidised access ends. Inequality entrenched. |
| **Current trajectory** | *Active governance intervention required* | **Evidence suggests current trajectory** | *Pricing shock could push here without intervention* |

Sub-regional evidence (figures 1-6) suggests the MAIES currently sits closer to the Mid scenario[24]. Without the governance interventions recommended in this report, pricing shocks, both from frontier model providers and from the public-sector AI pricing dynamic described in Section 2, could push the region toward the Weak outcome. This trajectory is not fixed, policy decisions and the wider economic conditions, over which we have little control, will determine the outcome.

[24] The scenario framework is intended as a heuristic for structuring policy discussion rather than as a predictive model. We do not specify formal transition dynamics between scenarios, and the claim that the MAIES currently approximates the Mid scenario is a qualitative judgement based on the aggregate evidence presented, not on a defined set of diagnostic indicators. For the scenario framework to function as a monitoring tool, identifiable leading indicators and trigger points for each transition would need to be developed, a task beyond the scope of this report but one that the Manchester Inclusive AI Taskforce (R8) could usefully take on.

# 5. Policy Recommendations: Building a Resilient and Inclusive MAIES

The following ten recommendations are addressed jointly to Manchester City Council, the Greater Manchester Combined Authority, and the region's universities. They are organised under five strategic priorities, and presented in order of urgency given the structural risks identified in this report.

These recommendations are not a replacement for existing Manchester AI strategy commitments. They are a complementary set of additional measures that the current growth-oriented framing of AI policy has not adequately addressed.

## Priority A: Pricing Resilience

**R1**

### Build Resilience Against AI Pricing Shocks

MAIES organisations, particularly SMEs and public-sector bodies, should be supported to stress-test their dependence on commercial AI services. Analysis of Salford City Region (Whittle *et al.*, 2026) finds that many organisations have integrated AI during a period of artificially low blitzscaling prices, building workflows and business models around the assumption of persistent low costs.

GM policy should require: (a) regular AI cost stress-testing, modelling scenarios of (at least) five-fold or greater price increases; (b) exploration of open-weight and consortium-based AI alternatives; (c) treating current low AI costs as temporary savings to be reinvested in resilience; and (d) consideration of shared public AI infrastructure as a long-term hedge against vendor dependency.

**R2**

### Reform Public Sector AI Procurement

Public institutions in Greater Manchester face distinctive exposure to the AI pricing problem. Procurement practices must be redesigned to account for this risk.

Contracts for AI services should include: robust exit provisions and interoperability requirements; mandatory value-for-money assessments benchmarked against open-source alternatives; independent evaluation of pricing against cost-plus-margin estimates; and multi-year cost trajectory projections that account for the end of blitzscaling subsidies.

An AI Procurement Review Board, drawing on independent academic expertise, should assess all significant public AI contracts for pricing sustainability, vendor lock-in risk, and social value.

## Priority B: Place-Based Evidence

**R3**

### Conduct a Greater Manchester AI Exposure Audit

Apply AIOE, AIIE, PBAIIS, and MVOQ measures to borough-level firm and labour market data across all ten GM boroughs. This would identify where the augmentation-versus-replacement threshold is most precarious, where microbusiness concentration compounds vulnerability, and which geographic sub-areas face the greatest substitution risk.

Aggregate AI-readiness rankings can mask significant intra-borough heterogeneity (Whittle *et al.*, 2026). Such an audit would provide the evidential foundation for equity-targeted skills investment and business support, and should be updated annually as AI capabilities and adoption patterns evolve.

## Priority C: Inclusive Skills and the Social Economy

**R4**

### Target Digital Skills Investment at Underrepresented Groups

Expand and target AI and digital literacy training into minority and disadvantaged communities. Education should focus on both how to use AI and what AI means, developing a critical understanding of AI's social, economic, and ethical dimensions, not merely tool-level proficiency.

Policy should actively support partnerships between schools, Further Education, adult learning, and universities to integrate AI and digital literacy training within wider educational provision. Subsidies or incentives should be used to encourage under-represented groups to enter AI training. The Digital Inclusion Action Plan's existing commitments must be extended to cover AI literacy in this broader sense.

**R5**

### Strengthen the Social Economy and 4th Sector

Go beyond support for traditional tech startups by empowering social enterprises, cooperatives, and community organisations to participate in AI innovation. Provide AI adoption grants or 'innovation vouchers' to small businesses and non-profits with demonstrable social value, enabling them to leverage AI for community benefit.

Encourage cross-sector partnerships, AI firms working with housing associations, health providers, and social care organisations, to embed AI benefits in public services and the social economy. A dedicated AI for Social Good fund, administered through GMCA, should explicitly favour organisations whose primary purpose is community benefit rather than commercial return.

## Priority D: Equity-Driven Funding and Procurement

**R6**

### Embed Inclusion and Equity in AI Funding Decisions

Public investments in AI should require social value commitments. AI companies receiving city or regional contracts should be required to demonstrate inclusive hiring practices, community engagement plans, and fair pay standards.

Procurement of AI systems by local government must follow transparency and equity criteria: tools must be fair, transparent, explainable, and auditable. Policymakers should set explicit targets for diversity and social value in funded AI projects, ensuring that equal growth is a core rather than incidental component of innovation support.

**R7**

### Foster Public Good AI Initiatives

Not all AI activity will be, or should be, commercial. The city-region and its anchor institutions (the Greater Manchester University Network, NHS trusts, housing associations) should co-create AI projects that directly serve the public interest.

Manchester should formalise a Civic AI approach in which residents and public bodies co-diagnose policy problems and co-create or co-design AI solutions. The People's Panel on AI, already led by colleagues at MMU, should be formalised as a standing body with defined powers to shape public-sector AI procurement and deployment decisions.

# Priority E: Governance and Accountability

**R8**

### Establish a Manchester Inclusive AI Taskforce

Create a permanent Manchester Inclusive AI Taskforce composed of City Leaders, Academia, Trade Union Representatives, Employers, Business Leaders, and Manchester Citizens. This body would track key indicators, diversity in AI employment, skills gaps, ethical AI use in public services, and, crucially, the impact of the MAIES on the wider Manchester economy and society.

**R9**

### Promote Ethical AI Standards and a Manchester AI Charter

Develop and promote a Manchester AI Charter for private businesses, complementing the People's Charter for AI and building on the model of Manchester's existing fair work and decent work charters. The Charter should address: transparency and explainability in AI systems; fairness and non-discrimination in AI-mediated decisions; job quality standards in AI-enabled roles; and commitments to community engagement in AI deployment.

Universities should play a leading role in developing and updating the Charter's content, drawing on their expertise in AI ethics, labour market economics, and community engagement.

**R10**

### Invest in Regional AI Infrastructure and Social Research

Steer targeted research investment toward AI applications that directly address Manchester's social challenges: determinants of poor health outcomes, environmental resilience, social care innovation, and urban mobility. Consider developing local compute infrastructure under community or public ownership, which could support AI research capacity while returning gains to the public purse.

Further research is urgently needed on the Manchester economics of AI: what does AI mean, specifically, for each of Greater Manchester's ten boroughs? The implications of AI are place-based, and the evidence base for place-sensitive policy is currently insufficient.

# Annex: MCC, GMCA, and the Universities

Building a resilient, equitable AI ecosystem in Greater Manchester requires collective action that moves beyond the growth-oriented framing that has characterised AI policy to date. The following outlines how three key actors, Manchester City Council (MCC), the Greater Manchester Combined Authority (GMCA), and Greater Manchester's universities, should translate the recommendations in this report into concrete responsibilities.

## Manchester City Council

As the democratic body for the city, MCC holds the soft power to convene stakeholders, legitimise a shared vision for AI for good, and embed equity into the technology agenda. MCC's procurement authority and direct relationships with community organisations make it the critical actor in translating inclusive AI commitments from aspiration into practice.

MCC should: lead the establishment of the Manchester Inclusive AI Taskforce and the formalisation of the People's Panel on AI as standing governance bodies; reform AI procurement practices to incorporate the pricing resilience and social value requirements set out in Recommendations R1, R2, and R6; extend the Digital Inclusion Action Plan to encompass AI literacy in its fullest sense; and act as an enabler for mission-oriented AI innovation through targeted support, data sharing, and convening, redirecting the energy of the MAIES toward the city's most pressing social challenges.

## Greater Manchester Combined Authority

GMCA's scale and strategic remit give it the capacity to integrate resilient AI adoption into region-wide economic planning in ways that no individual borough council can achieve alone. GMCA should ensure that AI-related investment decisions, including decisions on how to allocate Innovation Accelerator funding and the Adult Education Budget, are assessed against inclusive growth criteria, not merely ecosystem growth metrics.

GMCA should: commission the GM AI Exposure Audit recommended in R3; develop and maintain GM-wide ethical AI standards for public service delivery; expand AI and digital skills training programmes with an explicit focus on reaching underrepresented communities in all ten boroughs; and convene a Greater Manchester AI Network, bringing together universities, employers, community organisations, and local authorities, to drive the collaborative, place-sensitive AI governance that the current moment requires.

## Greater Manchester's Universities

The region's universities carry a dual responsibility: as engines of AI innovation and as civic institutions with a commitment to social good that extends beyond the campus. All five Greater Manchester universities have committed to a Civic University Agreement with GMCA and local authorities; this commitment must be enacted in the AI domain with the same ambition that has characterised their contributions to other civic priorities.

Universities should: extend AI education beyond specialist programmes to deliver universal AI literacy (with a focus on preparedness, not simply readiness), including for community audiences; orient research investment toward AI applications in public health, social care, environmental resilience, and economic inequality; provide independent ethical leadership on AI governance, developing the Manchester AI Charter, staffing oversight bodies, and ensuring procurement scrutiny is evidence-based; and support inclusive entrepreneurship by directing university incubation capacity toward social enterprises and cooperatives, not only toward commercial ventures. University Business Schools should review their programmes to ensure they do not funnel students into the automation zone but prepare them for the augmentation zone. This is a move beyond simple operator provisioning (e.g. teaching AI user skills) to teaching those skills as a foundation for making decisions about AI (see Whittle & Ransom 2026).

## Conclusion

*Greater Manchester stands at a critical juncture in its AI development. The ecosystem has achieved real and impressive scale. But scale is not the same as resilience, and growth is not the same as equity.*

*The AI pricing problem, platform dependency, sub-regional fragility, and the distributional deficit are not problems that the market will resolve. They are problems that require deliberate, evidence-based, place-sensitive policy intervention, beginning now, while the MAIES is still in a position to shape the terms of AI adoption rather than simply absorb their consequences.*

*Manchester's status as a thriving AI hub is not simply the end of the process. It is a potential means to supporting more equal development across the city's economy, requiring a decisive policy shift from growing the Manchester AI ecosystem to growing an AI ecosystem for the benefit of Manchester.*

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