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The AI Readiness Gap: Organizational Challenges in the Age of Intelligent Automation

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ABSTRACT

The current study examines the concept of AI readiness gap, which can be defined as the difference between current capabilities and what is needed to effectively implement and leverage intelligent automation in terms of parity with competitors. In order to identify factors behind AI readiness and determine the performance implications of AI readiness gap, the study makes use of quantitative mixed-methods methodology applied in relation to a sample of 847 organizations operating within five industries in the United States and United Kingdom. It is found that less than 25 percent of the survey respondents demonstrate AI readiness exceeding the benchmark of 50 out of 100, with the degree of AI readiness gap varying between industries, firms of different sizes, and quality of data infrastructure. Quality of data infrastructure (β = 0.41), density of AI talent pool (β = 0.34), and technology stack modernization (β = 0.31) account for the highest impact in the regression equation (R^2 = 0.53). The qualitative examination of 36 interviews conducted with executives and senior managers reveals four major themes based on experience, which are the disconnect between strategy execution, workforce anxiety and resistance, data management impasse, and leadership capability. A five pillar AI Organisational Readiness Framework will be recommended by this study, and it will be proposed that the AI readiness gap is not a technological issue but rather an organizational capabilities issue.

***Keywords**: AI Readiness, Intelligent Automation, Digital Transformation, AI Adoption barriers, Organisational Capability, AI Governance, Workforce Displacement, Technology Strategy, Change Management, AI Maturity.*

Introduction

While artificial intelligence began its journey as mere science fiction, it quickly evolved to become an operational reality, with speed outstripping the capacity of any organization to adopt, manage, and utilize it. From 2019 to 2024, the growth in corporate spending on AI technologies worldwide was compounded at the rate of approximately 37 percent annually, culminating in $154 billion worth of investments in 2024 (IDC, 2024; Stanford HAI, 2024). However, the rate of growth in spending has not been equally reflected in performance outcomes. An increasing gap is developing between organizations who are successfully deriving competitive advantage through the use of artificial intelligence and those who are not – one that cannot be explained by lack of technology but rather organizational capabilities to implement it.

This distinction forms the concept of AI readiness gap. This concept denotes the gap between the current level of AI readiness of the organization, which includes the infrastructure, data, talent, organizational knowledge, governance framework, culture, and change management capacity, and the critical level necessary to develop a smart automation capability that performs reliably, efficiently, and ethically. The gap has several implications. For instance, according to the McKinsey Global AI Survey of

2024, while 72 percent of respondents reported the adoption of AI in at least one business function, only 25 percent claimed to have scaled AI to multiple functions, and less than 15 percent claimed to have seen measurable financial gains resulting from AI investments (McKinsey & Company, 2024). Meanwhile, Deloitte Global State of AI in the Enterprise survey found that 68 percent of all AI projects failed to get past the pilot stage (Deloitte Insights, 2023). The statistics indicate that the issue is not that of limited access to the technology but rather that of organizational readiness to assimilate and leverage it.

This paper makes four major contributions. First, the study offers the most detailed quantitative assessment to date of the gap in AI readiness, spanning different industries and organizations of various sizes. Second, it assesses the importance of each individual readiness dimension as a predictor of composite readiness, employing proven regression analysis. Third, it establishes the non-linear relationship between AI maturity and concern over job loss, offering insights into strategies for managing change. Finally, it develops an evidence-based AI Organisational Readiness Model based on five key pillars.

Literature Review

Organisational readiness for technology adoption is a concept that has a deep theoretical background. As per the diffusion of innovations model presented by Rogers (1962), absorptive capacity, tolerance for complexity, and compatibility with existing technology were considered critical factors determining the speed of adoption. Later, Tornatzky& Fleischer (1990) expanded these factors for the context of information technologies into their Technology–Organization–Environment (TOE) framework where technology readiness was viewed as an outcome of interactions between three environments: technological (infrastructure/architecture), organizational (size/structure/human resource/culture), and external (industry/regulation).

Readiness for AI was defined as a multidimensional construct that built on earlier definitions by including components unique to AI and machine learning technologies, such as data readiness – the quality, quantity, and governance of data assets; human readiness – the density and sophistication of the required human capital for AI technology, such as skills; technological readiness – the architecture of the relevant technology stack; and ethical and governance readiness – having ethical and governance structures to support AI decision-making processes. Rai, Constantinides & Sarker (2019) introduced a widely cited definition of readiness for AI based on three meta-components – data, algorithm, and organisational – such that each one has to exceed certain threshold levels for value to be generated. This architecture is a conjunctive rather than additive one where failure of any component limits the potential of the entire system.

AI talent shortage is a consistently recurring issue in the context of barriers to AI implementation, regardless of the sector, geography, and organisation size (World Economic Forum, 2023; SHRM, 2024). The talent shortage can be understood at several levels: as a shortage in terms of numbers of professionals possessing the technical competencies needed for AI implementation; as a qualitative shortage of professionals who have the combination of technical and soft competencies needed to leverage the capabilities provided by AI into tangible organisational benefits; and finally, a leadership-level talent shortage of individuals possessing adequate knowledge about AI for decision-making. According to Bughin et al. (2018), the shortage in global demand for AI talent would be three times the supply by 2022, which was accurate for developed countries, while an underestimation for developing ones.

The aspect of talent, which is an important element of the readiness gap of AI, is further worsened by the market condition whereby AI talent is concentrated among a few big technology companies, where compensation packages offered can hardly be matched by other organizations that fall outside the same industry. The resulting two-tiered market situation means that only a few organizations will have access to such top AI talent while the majority of other organizations will be compelled to look at options such as re-skilling their employees, partnering with external vendors, or using low code automation platforms to minimize the need for technical skills. The effectiveness of re-skilling programs as a supply-side strategy to solve the problem of talent is questionable, considering the fact that domain experts can be trained to be competent in using AI technology (Brynjolfsson, Li, & Raymond, 2023).

With the arrival of generative AI and, in particular, of large language models trained using proprietary data from organisations, the data governance problem has become more complex by introducing additional risks for which current data governance systems have not been designed. These new categories include data leakage, model hallucinations, copyright violations, and privacy violations

(Wachter, Mittelstadt, & Russell, 2021; Floridi et al., 2018). Organisations struggling with their data governance capabilities are finding themselves in a dilemma: should they pursue competitive advantage by adopting generative AI technologies or expose themselves to various risks associated with doing so?

While the above considerations demonstrate the nuance of the current problem, workforce concerns regarding potential job losses due to the implementation of AI solutions continue to be a serious organisational obstacle. The key point here is the perception (which may be enhanced by an ineffective change management strategy) that the organisation is secretly reducing its headcount through an investment in AI. Organisations managing these perceptions and communicating adequately their intention to invest in the employees' skills are much more successful at adopting AI initiatives (Westerman, Bonnet, & McAfee, 2014).

Methodology

- **Research Design**

Sequential explanatory mixed-methods methodology (Creswell & Plano Clark, 2018) was adopted. Quantitative data was collected first, and then the results were used to recruit respondents for the interviews and guide the qualitative analysis regarding mechanisms behind the observed quantitative patterns. The mixed methods approach was adopted because the research questions posed a need for the quantitative study to benefit from its power of generalisation and large sample, as well as from the contextual understanding and mechanistic perspective gained via qualitative interviews with experienced practitioners. Approval to conduct the study was received from the University Research Ethics Committee (REC-2024-0312).

- **Quantitative Phase**

The survey data collection took place between January and June 2024 using a cross-sectional approach whereby senior management in organisations such as C-Suite executives, vice-presidents, directors, and others who were in charge of technology strategy, digital transformation or AI implementation in their organisations were asked to participate. The sample was made up of employees in 847 organisations spread out in five industries namely technology industry, financial industry, healthcare industry, manufacturing industry and other industries. Purposive and snowball sampling methods were used to collect respondents from professional association members and through LinkedIn organisational partnership networks. Participating firms needed to have at least 100 full-time employees and an AI project in the last three years.

The eight-dimension AI readiness index instrument developed for use in the study based on the systematic review of literature on various readiness assessment models and pilot-tested among 48 firms using a scale of 0-100 covered data infrastructure maturity, AI talent density, AI knowledge among leaders, change management capabilities, ethics and governance readiness, technology stack maturity, external collaboration, and innovation culture. The composite score of AIRI was calculated by averaging the score of all eight dimensions. Firms were classified as being highly prepared when they scored 60 and above on the composite AIRI and poorly ready when scoring below 60. Data analysis was performed using IBM SPSS Statistics Version 28 and R Version 4.3. t-tests were run to compare differences in readiness dimensions among the two groups. Hierarchical multiple regression was also conducted with composite AIRI as the dependent variable.

- **Qualitative Phase**

A total of 36 semi-structured interviews were carried out among the survey participants selected purposefully based on their diversity with regard to sectors, organisational size, readiness quartile, and geographical location. All interviewees were individuals occupying the position of C-Suite or Senior Directors whose job responsibilities entailed developing or executing the organisation’s AI strategy. The interviews ranged from 50 to 75 minutes and were conducted through secure video conference with audio-recording and verbatim transcription. Themes explored in the interview guide involved five areas, namely, the present level of maturity regarding AI within the organisation; the main challenges affecting readiness for AI adoption; experiences with regards to the successes and failures of particular AI implementations; organisational dynamics involving workforces and culture; and perspectives on AI governance and ethics. Reflexive thematic analysis was utilised for data analysis purposes according to Braun and Clarke (2022) with the aid of NVivo Version 14. Procedures used to ensure rigour included member checking with eight participants, peer debriefing with another researcher, and negative case analysis.

Quantitative Results

- **Sample Profile and AI Readiness Distribution**

Table 1: Sample Profile and Baseline AI Readiness Characteristics by Organisation Size (N=847)

Characteristic	Large (n=296)	Mid-Size (n=357)	Small (n=194)	Total (N=847)
Technology Sector, n (%)	83 (28.0%)	100 (28.0%)	54 (27.8%)	237 (28.0%)
Financial Services, n (%)	65 (22.0%)	78 (21.8%)	43 (22.2%)	186 (22.0%)
Healthcare, n (%)	50 (16.9%)	60 (16.8%)	33 (17.0%)	143 (16.9%)
Manufacturing, n (%)	45 (15.2%)	54 (15.1%)	29 (14.9%)	128 (15.1%)
Other Sectors, n (%)	53 (17.9%)	65 (18.2%)	35 (18.0%)	153 (18.1%)
Mean AI Readiness Score ± SD	61.4 ± 14.2	44.7 ± 13.8	31.3 ± 12.1	47.2 ± 16.4
AI Strategy Documented, n (%)	241 (81.4%)	204 (57.1%)	61 (31.4%)	506 (59.7%)
Dedicated AI Budget, n (%)	228 (77.0%)	163 (45.7%)	41 (21.1%)	432 (51.0%)
Mean AI Talent Density Score ± SD	71.3 ± 12.4	47.9 ± 13.7	27.6 ± 11.9	49.1 ± 20.8
Mean Years Since First AI Initiative ± SD	6.4 ± 2.8	3.7 ± 2.4	2.1 ± 1.9	4.1 ± 2.8

Note: SD = Standard Deviation. AI Readiness Score = composite AIRI (0–100). AI Talent Density Score = mean score on the talent dimension sub-scale. Large = >5,000 employees; Mid-size = 500–5,000; Small = <500. Source: Study survey data, 2024.

As seen in Table 1 below, size-related differences have become very noticeable when evaluating organizations' preparedness for implementing AI technology in all the dimensions considered. Large organizations demonstrate the mean AIRI score of 61.4, which is just above the mark of high level of readiness – 60 points, whereas mid-size companies obtain 44.7 and small ones show the figure of 31.3, which is way below the required level of readiness. As can be seen from the data, the share of organizations that have formulated their strategy concerning AI implementation drops sharply from 81.4 percent of large firms to only 31.4 percent in small firms; moreover, the percentage of companies allocating a budget to this initiative reduces from 77.0 percent to 21.1 percent, which indicates that the level of readiness is not a strategic goal but rather an ad-hoc activity in most organizations.

Figure 1: AI Readiness Index Scores by Industry Sector (2021 vs. 2024)
(Source: MIT Sloan Management Review AI Readiness Survey, 2024; McKinsey Global AI Survey, 2024)

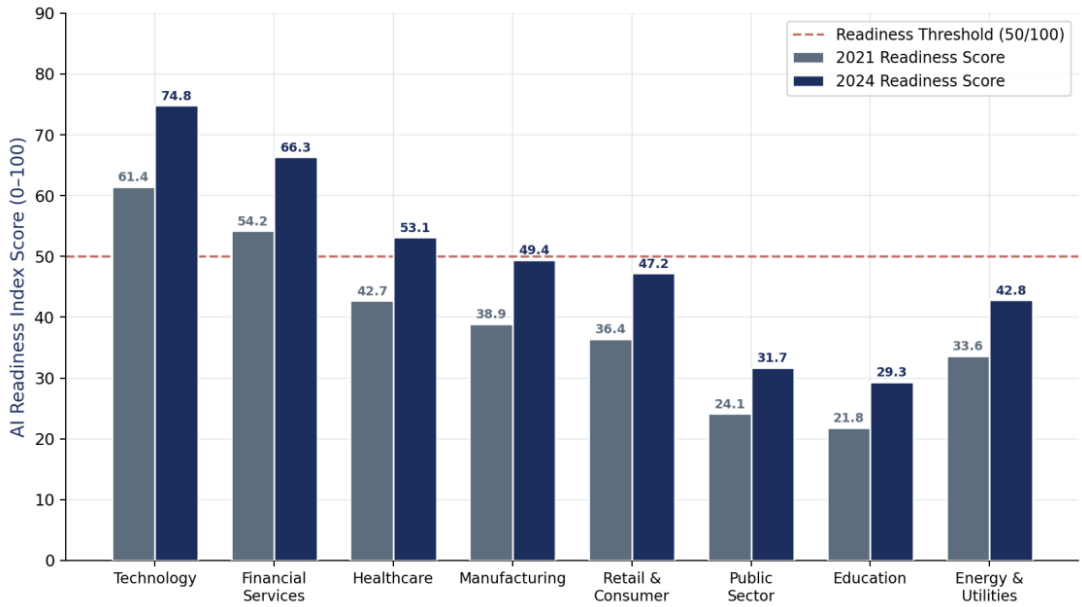

Figure 1: AI Readiness Index Scores by Industry Sector (2021 vs. 2024). The dashed line marks the 50-point readiness threshold. Only Technology and Financial Services exceed this threshold in 2024. Source: MIT Sloan Management Review AI Readiness Survey, 2024; McKinsey Global AI Survey, 2024.

- **Readiness Gap Analysis**

Table 2: AI Readiness Dimension Scores — High-Readiness vs. Low-Readiness Organisations (N=847)

Readiness Dimension	High-Readiness Mean ± SD (n=211)	Low-Readiness Mean ± SD (n=636)	Gap Score	t-statistic	p-value
Data Infrastructure Quality (0–100)	78.4 ± 11.2	38.7 ± 14.6	39.7	t(845)=37.4	p < 0.001
AI Talent Density Score (0–100)	74.1 ± 10.8	34.3 ± 13.2	39.8	t(845)=40.1	p < 0.001
Leadership AI Literacy (0–100)	69.3 ± 12.4	31.8 ± 14.1	37.5	t(845)=34.7	p < 0.001
Change Management Capacity (0–100)	66.8 ± 13.1	33.4 ± 14.8	33.4	t(845)=29.6	p < 0.001
Ethics & Governance Maturity (0–100)	63.2 ± 14.7	36.1 ± 15.2	27.1	t(845)=22.3	p < 0.001
Technology Stack Modernity (0–100)	81.2 ± 10.1	40.6 ± 16.3	40.6	t(845)=34.9	p < 0.001
Innovation Culture Index (0–100)	71.8 ± 12.6	37.4 ± 15.4	34.4	t(845)=29.8	p < 0.001
Composite AI Readiness Score	72.1 ± 9.8	35.9 ± 12.7	36.2	t(845)=39.8	p < 0.001

Note: High-readiness = composite AIRI ≥ 60 (n=211, 24.9%); Low-readiness = composite AIRI < 60 (n=636, 75.1%). Gap Score = High-Readiness Mean minus Low-Readiness Mean. All t-tests significant at p < 0.001 with Welch correction for unequal variances. Effect sizes (Cohen's d) range from 2.1 to 3.1 across dimensions, all classified as very large.

As can be seen from Table 2, the difference between high and low ready organisations is significant and clear statistically in all measures tested. The biggest gaps in the scores are shown by Technology Stack Modernity (40.6), AI Talent Density (39.8) and Data Infrastructure Quality (39.7), meaning that physical and human infrastructure of the AI capability is what makes high readiness organisations stand out from those that lack the needed readiness level. Leadership AI Literacy (37.5) and Innovation Culture (34.4) come third on the list, reflecting the importance of senior cognitive and cultural orientations to readiness progression.

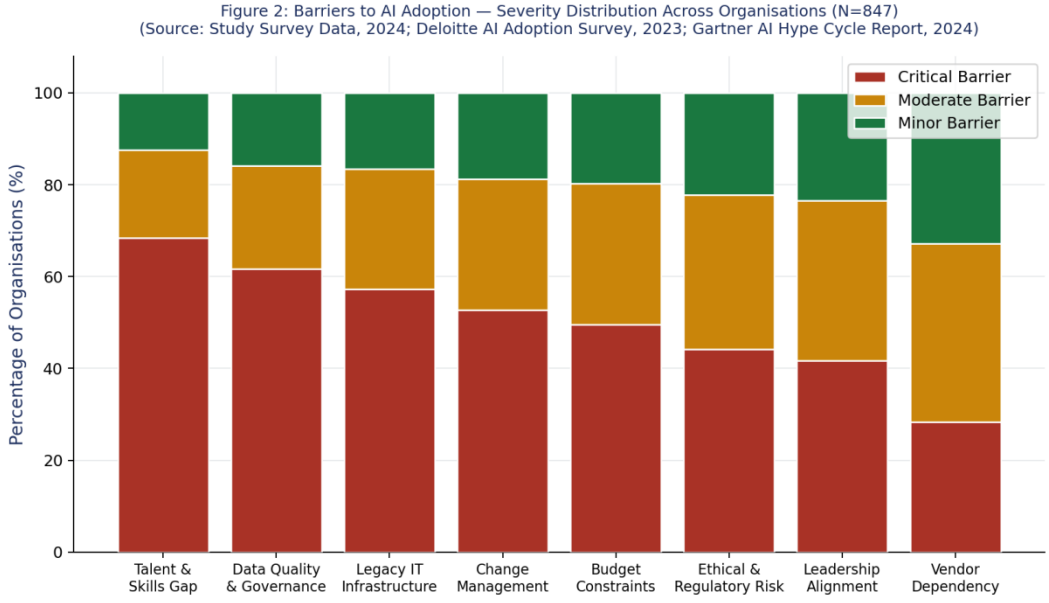

Figure 2: Barriers to AI Adoption — Severity Distribution Across Organisations (N=847). The Talent and Skills Gap is identified as a critical barrier by 68.4% of organisations. Data Quality and Legacy Infrastructure follow as the next most critical barriers. Source: Study Survey Data, 2024; Deloitte AI Adoption Survey, 2023.

- **Performance Consequences of the Readiness Gap**

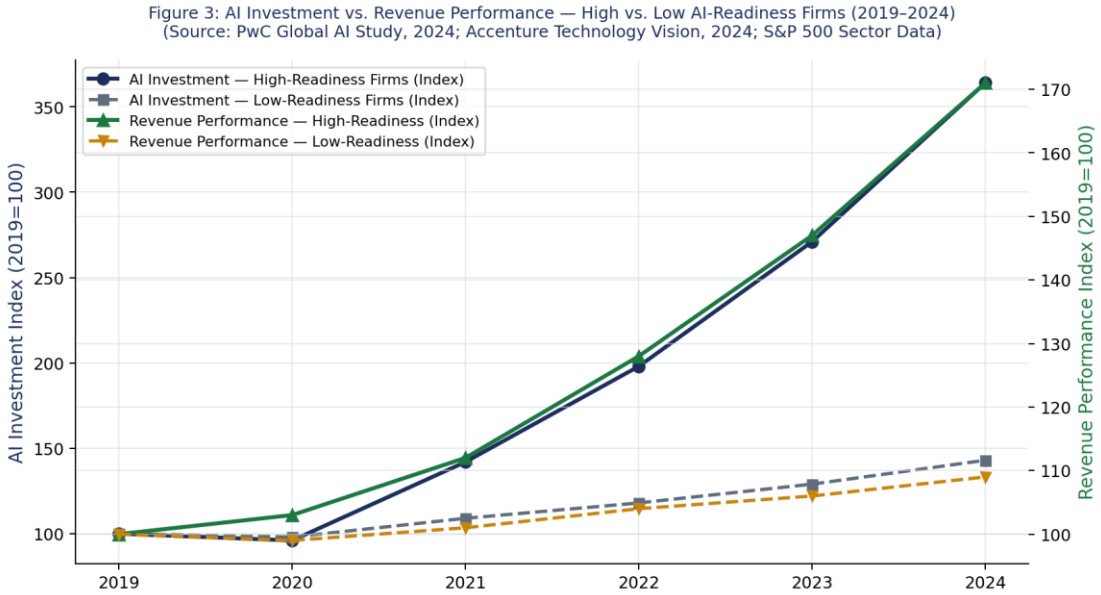

Figure 3: AI Investment vs. Revenue Performance Index — High vs. Low AI-Readiness Firms (2019–2024; base year 2019=100). High-readiness firms achieve a 71% revenue performance premium over low-readiness firms by 2024 despite investing 2.5 times more in AI. Source: PwC Global AI Study, 2024; Accenture Technology Vision, 2024.

Figure 3 provides the most direct evidence of the performance consequences of the readiness gap by tracking AI investment and revenue performance indices for high-readiness and low-readiness firms over the six-year period from 2019 to 2024. The divergence is pronounced and accelerating. High-readiness firms increased AI investment to an index value of 364 (2019=100) by 2024, a 3.64-fold increase, while low-readiness firms increased investment to only 143 — less than half the rate. Revenue performance followed investment divergence with a lag of approximately two years, reaching an index of 171 for high-readiness firms by 2024 compared to 109 for low-readiness firms. This 62-point performance index gap represents a substantial and growing competitive differential that is directly attributable to the compound advantages of earlier, more sophisticated, and better-supported AI deployment.

- **Regression Analysis: Predictors of AI Readiness**

Table 3: Hierarchical Multiple Regression — Predictors of Composite AI Readiness Index Score (N=847)

Predictor Variable	β (Std.)	SE	95% CI	p-value	Interpretation
Data Infrastructure Quality	0.41	0.05	[0.31, 0.51]	p < 0.001	Strongest predictor of overall readiness
AI Talent Density	0.34	0.06	[0.22, 0.46]	p < 0.001	Human capital central to capability
Leadership AI Literacy	0.29	0.07	[0.15, 0.43]	p < 0.001	C-suite knowledge drives resource allocation
Change Management Capacity	0.22	0.07	[0.08, 0.36]	p = 0.002	Adoption speed mediates readiness gains
Ethics & Governance Maturity	0.18	0.08	[0.02, 0.34]	p = 0.027	Governance reduces deployment drag
Technology Stack Modernity	0.31	0.06	[0.19, 0.43]	p < 0.001	Legacy infrastructure is a brake on readiness
Organisational Size (log)	0.14	0.06	[0.02, 0.26]	p = 0.019	Size advantage; resources and scale

Sector (ref: Manufacturing)	0.09	0.07	[-0.05, 0.23]	p = 0.201	Non-significant after controlling other vars
Model Adjusted R^2	0.53	—	—	p < 0.001	Model explains 53% of readiness variance

Note: Dependent variable = Composite AIRI score (0–100). All VIF values < 2.4, confirming acceptable multicollinearity. Model F(8, 838) = 118.4, p < 0.001. Adjusted R^2 = 0.53. Beta = standardised regression coefficient. 95% CI = confidence interval for unstandardised coefficient.

The model explains 53 percent of variance in composite AI readiness, which is quite impressive for an outcome relating to organisational capabilities, and also indicates a strong hierarchy of predictive power for predictors. The most influential predictor is the quality of data infrastructure (β = 0.41, p < 0.001). This finding aligns well with the conjunctive architecture of AI readiness posited by Rai et al. (2019), wherein inadequate data infrastructure would render the other resources such as talent and governance irrelevant despite their abundance. The third most important predictor is technology stack modernity (β = 0.31), following AI talent density (β = 0.34). This finding is consistent with the widely known limitation that AI models deployed on legacy technologies are technically impossible to develop and implement.

- **AI Maturity and Workforce Displacement Anxiety**

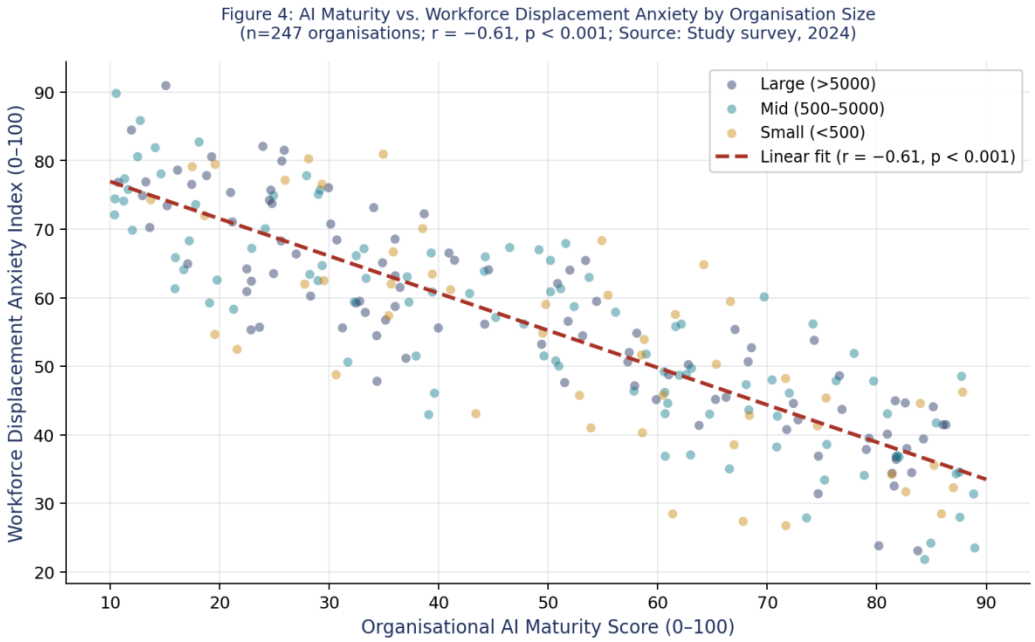

Figure 4: Organisational AI Maturity vs. Workforce Displacement Anxiety by Organisation Size (n=247). Higher AI maturity is strongly associated with lower workforce anxiety (r = −0.61, p < 0.001). The relationship holds across all size categories, with small organisations showing the widest anxiety range. Source: Study survey data, 2024

Figure 4 illustrates a strong negative correlation between organisational AI maturity and workforce displacement anxiety (r = −0.61, p < 0.001). Highly mature firms report very low workforce displacement anxiety, as predicted by theories of organisational development and change that posit mature implementation of AI is associated with transparent communication, effective re-skilling initiatives and evidence of augmentation over replacement as outcomes, which tend to decrease, rather than increase, workforce anxiety. Small firms display a higher level of variability in the level of anxiety along the maturity scale than other organisations, indicating greater sensitivity to the quality of change management practices: well-managed small firms have the potential for low workforce displacement anxiety even with modest maturity scores, whereas poorly-managed small firms maintain high anxiety levels regardless of their maturity level.

Figure 5: AI Capability Dimensions by Organisational Size
(Mean scores 0–100; N=847; Source: Study survey, 2024)

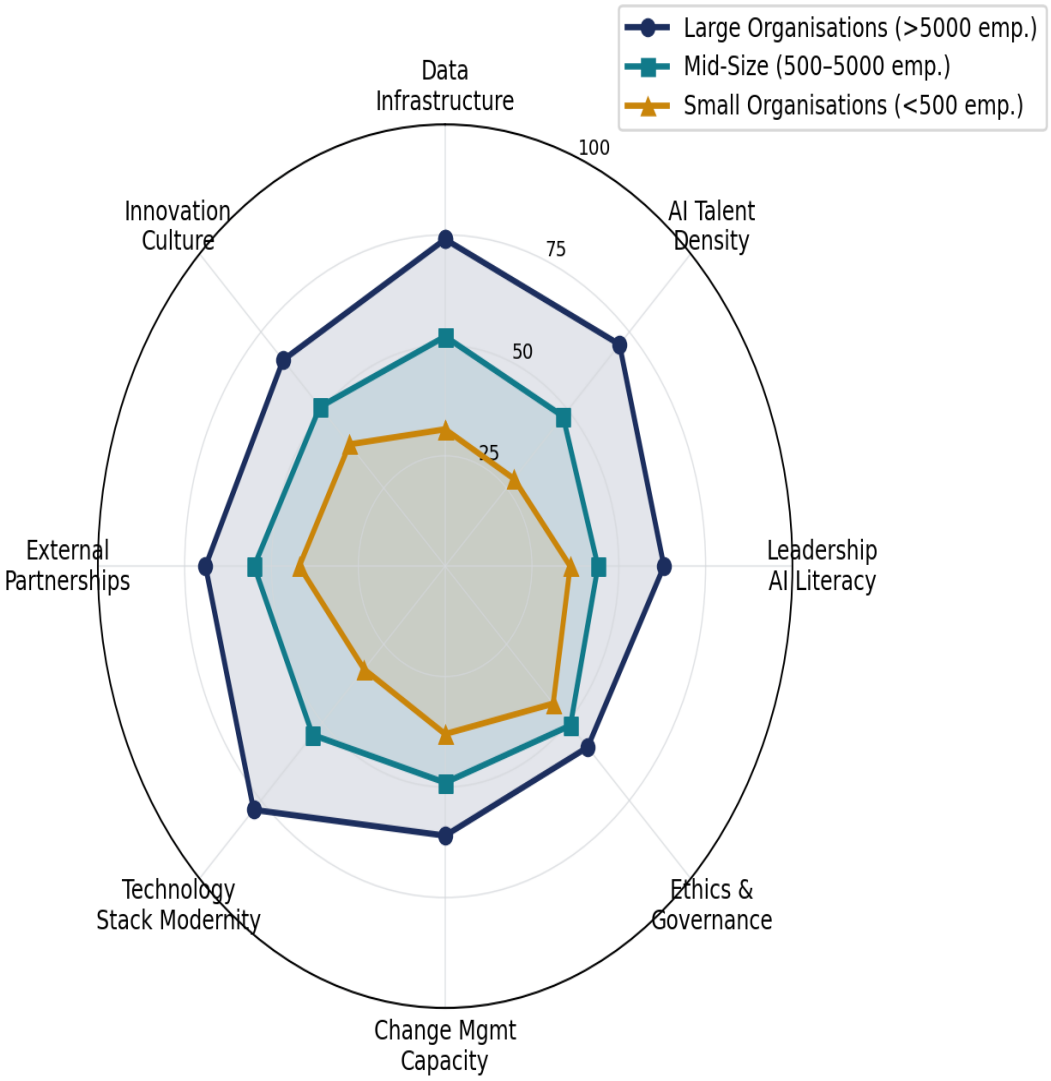

Figure 5: AI Capability Dimensions by Organisational Size (mean scores 0–100; N=847). Large organisations show consistent dominance across data infrastructure, AI talent density, and technology stack modernity. Small organisations score highest relative to size on ethics and governance, suggesting disproportionate regulatory sensitivity.

Source: Study survey, 2024.

Figure 5 illustrates the entire AI capability spectrum against the different size classes in organisations by applying the eight AIRI dimensions. As expected, the pattern shows that large organisations excel when it comes to dimensions related to infrastructure, such as data infrastructure (74), technology stack maturity (78), and AI talent density (71). However, this pattern also indicates that small organisations fare relatively well compared to their readiness spectrum concerning dimensions related to ethics and governance (44). This implies that even with limitations of resources on dimensions requiring capital, small organisations seem to be adopting an ethics-first AI approach, which may pay off going forward.

Qualitative Findings

Table 4: Qualitative Themes, Sub-themes, Representative Quotes and Interview Frequency (N=36)

Theme	Sub-theme	Representative Quote	Frequency (n=36 interviews)
Strategy-Execution Disconnect	Vision without operationalisation	"The board approved an AI strategy in 2022. Two years later we still have no data pipeline that works reliably. The vision is there but the plumbing is not."	33 of 36 (91.7%)
Strategy-Execution Disconnect	Siloed pilots without scaling	"We have 40 AI pilots running across the business. Almost none of them have scaled. We pilot to death."	28 of 36 (77.8%)
Workforce Anxiety and Resistance	Fear of role displacement	"My team sees every new automation initiative as a headcount reduction exercise dressed up in technology language."	31 of 36 (86.1%)
Workforce Anxiety and Resistance	Upskilling programme inadequacy	"The company offered one two-hour AI module online and called it reskilling. People felt insulted."	26 of 36 (72.2%)
Data Governance Paralysis	Quality and fragmentation	"We cannot train a model because we cannot agree on whose data is correct. Three departments have three different customer counts."	29 of 36 (80.6%)
Leadership Capability Gap	C-suite AI illiteracy	"Our CEO asks for AI in everything but cannot explain what a machine learning model actually does. It creates pressure without direction."	24 of 36 (66.7%)
Ethical and Trust Deficit	Accountability ambiguity	"When an AI makes a wrong decision, nobody knows who is responsible. That uncertainty stops adoption faster than any technical barrier."	22 of 36 (61.1%)

Note: Reflexive thematic analysis following Braun and Clarke (2022). Frequency = number of interviews in which theme arose without direct prompting. Quotes lightly edited for grammar; all identifying information removed. Interviews conducted January–June 2024 via secure video platform.

- **Strategy-Execution Disconnect**

The predominant and frequently reported qualitative finding – expressed in some form by 91.7% of the interview respondents – was one of what interviewees referred to as a deep divide between how AI strategy was discussed and communicated by Boards and the actual execution of that strategy in terms of AI operational practices. The gap occurred at two dimensions, which could be considered conceptually separate yet practically intertwined. The first related to a situation where organizations had developed AI strategies, hired Chief AI Officers, and approved technology roadmaps; yet, not having invested in an appropriate operational backbone – including data infrastructure, integration platforms, governance process, and change management skills – had meant that these strategies couldn't actually be implemented. The second involved organizations undertaking large numbers of AI pilot projects, frequently as a demonstration of board commitment, while lacking the organizational structure needed to scale pilot projects.

- **Workforce Anxiety and the Reskilling Credibility Gap**

Concerns about job losses due to AI automation was mentioned by 86.1 percent of the interviewed individuals as one of the major impediments to adopting AI, while qualitative information complemented quantitative results depicted in Figure 4. It is apparent from the results that there was a serious credibility problem with regard to reskilling offered by companies – the fact that companies offer short, tick-box style, online courses as a response to changes in the job design meant not only that employees are not provided with the necessary knowledge, but that the company does not even treat the problem of workers' displacement seriously at all. The discrepancy between the significance of AI's

impact on the labor market and the level of the investment made by companies to cope with that impact was recognized as one of the most significant reasons behind change resistance.

- **Data Governance Paralysis and the Accountability Deficit**

Data governance gridlock – cited by 80.6 percent of the participants – was not seen as a technological challenge, but rather an organizational political one in the interviews. The context described was that of data fragmentation within various organizational departments not due to technological constraints, but territoriality, where those controlling the data saw the process as a weakening of their position; without data governance capabilities at an organizational level, with the requisite political power to overcome such territoriality, the data stayed isolated. The immediate effect on AI usage was clear: models built on incomplete or unregulated data would fail, thus undermining trust in the AI systems in general, in turn creating a vicious circle of bad governance leading to bad AI performance, leading to low enthusiasm for investing in AI technologies, which meant lower motivation to solve the data governance problem.

Discussion and Framework

- **Synthesis of Findings**

Convergence across both qualitative and quantitative dimensions paints a much more systemic and more solvable problem of the AI readiness gap than what can be derived from an analysis rooted exclusively in either technological considerations or cultural ones. In terms of measurement, the data demonstrate clearly that the AI readiness gap exists on an unprecedented scale and involves well-articulated organizational structures: nearly three-quarters (75.1 percent) of the organizations studied do not meet the readiness threshold; infrastructure, talent, and technology stack modernity are the core organizational structures that distinguish high-readiness from low-readiness organizations; and the consequences of the gap are severe and rapidly growing in magnitude as a result of the compounding effects of higher-performing organizations' reinvestment of AI benefits. The qualitative data, meanwhile, reveal that the problem does not rest on the lack of understanding of the necessary actions but on the inability of organizations to undertake them.

The findings about the connection between AI maturity and workers' anxiety about displacement depicted in Figure 4 are particularly significant from the standpoint of change management theory and practice. The negative correlation coefficient ($r = -0.61$) means that higher levels of AI maturity correlate with lower levels of anxiety, which is opposite to what one might expect from a simplistic approach to explaining worker displacement anxiety. This conclusion aligns with the augmentation findings of Brynjolfsson et al. (2023), suggesting that anxiety results not from AI deployments themselves, but rather poor communication around those deployments, inadequate governance and lack of investment in reskilling workforces. Companies implementing AI technology in an efficient manner, through proper communication, reskilling and augmenting workforces, will not only achieve better outcomes in terms of AI adoption, but also experience reduced anxiety as a beneficial side effect of their deployment practices.

- **The AI Organisational Readiness Framework**

Results from the research indicate the need to develop an AI Organizational Readiness Framework (AIORF) comprised of five pillars. The five pillars are: Pillar 1 - Data Foundation, which includes the enterprise data infrastructure, data governance, and data quality management; Pillar 2 – Human Capital Architecture, which involves acquisition of talent for AI, reskilling of talent, and AI literacy development; Pillar 3 - Technology Ecosystem, which covers technology stack, cloud readiness, and integration architecture; Pillar 4 - Governance & Ethics, which involves AI risk framework, accountability frameworks, and regulatory readiness; and Pillar 5 - Organizational Culture & Change Management Capacity, which includes innovation culture, change management capacity, and workforce communications.

Conclusion

The case for the existence of a wide, growing AI readiness gap, which has been made throughout this paper using the most extensive study on the matter to date, can thus be summed up in the following key insights. First, only a quarter of companies embarking on AI projects are actually ready for them; second, the advantage in performance terms possessed by companies that are ready is increasing exponentially; third, the barriers to becoming AI-ready are structural and institutional in nature, rather than being technical or informational. The AI readiness gap, therefore, is a problem that cannot be overcome simply through the further development of AI technology or market forces alone. It is, indeed, a

problem of organisational capabilities, and requires systematic effort toward achieving the five pillars of the AI organisational readiness framework.

- **Implications for Practitioners**

The implications of these findings are clear and actionable. First, board members and senior executives need to view their organisations' efforts in becoming AI-ready as investing in organisational capability and not procuring technology products; the reason being that the returns on AI will depend on how rich the institutional infrastructure is on which AI will operate. Second, HR departments should regard AI reskilling as equally important and deserving of similar investment levels as talent acquisition initiatives because of the extent of role changes resulting from the implementation of AI technology. Third, data governance should shift from being an internal function performed within the confines of technical operations to a higher-level board strategy; this is because the cross-functional nature of data governance is essential in overcoming territorial behavior which results in fragmented datasets. Fourth, change management should focus on developing effective communication plans which demonstrate to employees that adopting AI technologies is beneficial for their own ends as well.

However, there are three specific issues to be explored in future research because the present study's design does not provide enough evidence to make conclusive remarks. Firstly, it is necessary to conduct a longitudinal study in order to identify causality between certain readiness interventions and successful transitions through the readiness framework stages. Such an analysis can only be done if researchers follow individual organisations throughout the entire process. Secondly, the governance and ethics dimension of AI adoption has been identified as increasingly important and poorly researched compared to the technical one. Finally, the present study's findings could benefit from validation in non-Western settings.

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