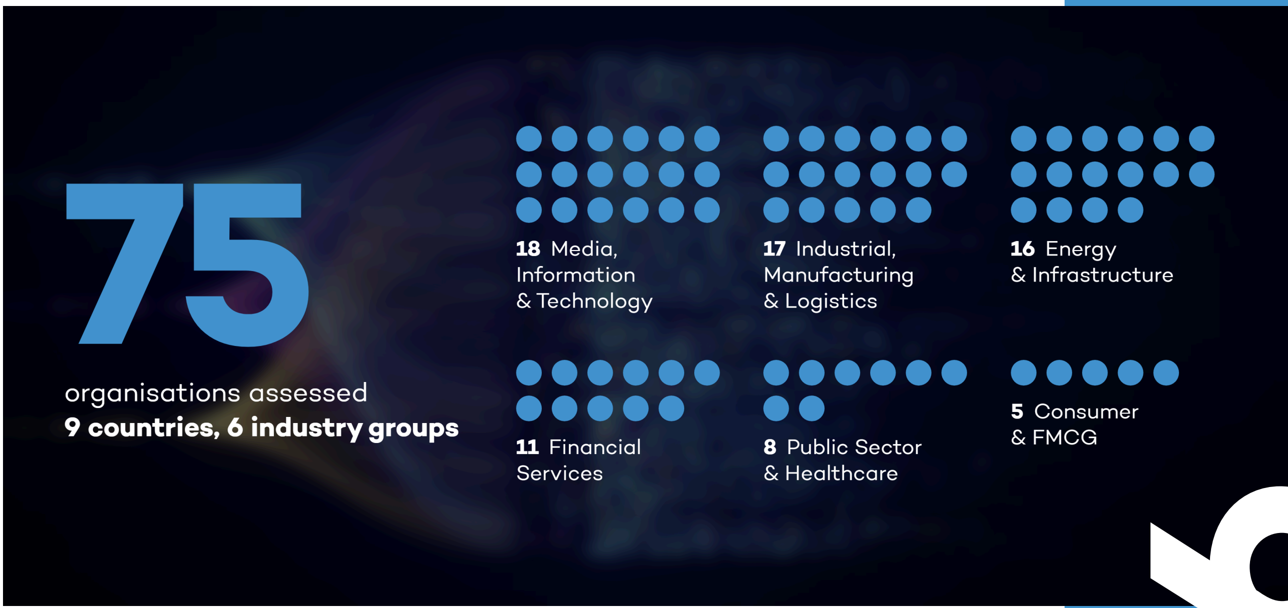
THE AI EXECUTION GAP:
FROM AMBITION TO IMPACT



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SECTION 1: **EXECUTIVE SUMMARY**

Why AI Matters Now

AI ambition is no longer the problem. Execution is.
Investment in artificial intelligence is accelerating at unprecedented levels. This investment, however, is not consistently translating into sustained business value. In several instances, these initiatives are failing to scale beyond isolated use cases, resulting in an ever-widening gap between AI ambition and AI impact.

Our point of view is clear: The next phase of AI advantage will come from organisational maturity, not from tool access.

The Transformation Alliance's (TTA) research across seventy-five organisations spread over several industries shows that a clear execution gap currently exists. Many businesses continue to approach AI as a series of disconnected initiatives, rather than as embedded enterprise activities. These organisations are often trapped in an experimentation cycle, where their AI initiatives are launched before clear ownership or governance has been established.

In the rush to not be left behind by competitors, several businesses have not put in place the necessary frameworks to ensure efficient scaling of the technology. Though there is a clear drive to embed AI into organisational strategy, the execution of this strategy is currently falling short. The strongest organisations are not those with the most pilots. They are the ones who ensure their AI activities are supported by the appropriate operating models, workforce enablement activities, and measurable value tracking frameworks.

What This Report Provides

Whilst new tools, platforms, and use cases are emerging at pace, senior leaders are increasingly facing a more fundamental set of questions which this report is designed to answer:

How mature is our organisation's approach to AI? (See Sections 3 & 6)

- How can organisations assess and benchmark their AI maturity?
- Which organisational capabilities matter most for long-term success?

Why are some organisations scaling AI successfully while others remain stuck in pilot mode? (See Section 4)

- What are the most common barriers preventing AI initiatives from scaling?
- Why are operating models, workforce adoption, and governance becoming more important than technology alone?

How are the most mature organisations creating value from AI, and what can we learn from them? (See Sections 4 & 5)

- What common characteristics exist across higher-maturity organisations?
- How are leading organisations embedding AI into day-to-day operations?
- How do approaches vary across industries and regions?

What capabilities do organisations need to build now? (See Sections 4 & 6)

- What skills, governance structures, and delivery models are becoming critical?
- How should organisations approach workforce adoption and change management?

How can organisations remain adaptable in a rapidly evolving AI landscape? (See Sections 6 & 7)

- How can leaders respond to the pace of technological change?
- What does successful long-term AI scaling look like?

Drawing on our assessments across multiple sectors and regions, including organisations headquartered across the United Kingdom, Germany, France, Italy, Sweden, and several additional international markets, this report examines how organisations are embedding AI in practice and how levels of AI maturity vary across industries and geographies. While most participating organisations were European, the study also incorporates broader international perspectives through selected interviews and cross industry case study analysis.

The findings presented in this report are intended to help leaders identify where their primary capability gaps exist, understand how they interact, and prioritise the actions most likely to unlock sustained value.

Where AI Execution Breaks Down

Our research sample indicates that the barriers to AI adoption are rarely simply due to the technology itself. Instead, these barriers are often a set of systemic organisational challenges. Across the organisations studied, three constraints emerged consistently as the primary barriers to scale:

- **Disconnected Operating Models:** Successful AI pilots are often not designed with scale in mind. AI capability frequently remains concentrated within isolated teams, creating dependency bottlenecks and limiting broader adoption. Without clear ownership and integration into core business processes, use cases remain fragmented and fail to translate into enterprise-wide capability.

- **Limited Workforce Adoption:** Employees are not sufficiently equipped, incentivised, or supported to integrate AI into their day-to-day work. Long standing ways of working often produce a culture which is resistant to change. The potential benefits of AI solutions are not clearly communicated by leadership teams and as a result, tools remain underutilised and potential productivity gains are left on the table.

- **Absence of Value Tracking:** Organisations frequently lack the required mechanisms to reliably measure the impact of the initiatives they introduce. There is often misalignment between whether personal or organisational productivity is being prioritised. Without clearly pre-defined success metrics, it becomes difficult to prioritise investment and consistently demonstrate ROI.

These narratives are emphasised clearly by the scores shown in Figure 1. These constraints reinforce a broader notion that successful AI adoption is less dependent on access to technology, and more dependent on the organisational readiness to operationalise it effectively.

From Fragmentation to Maturity

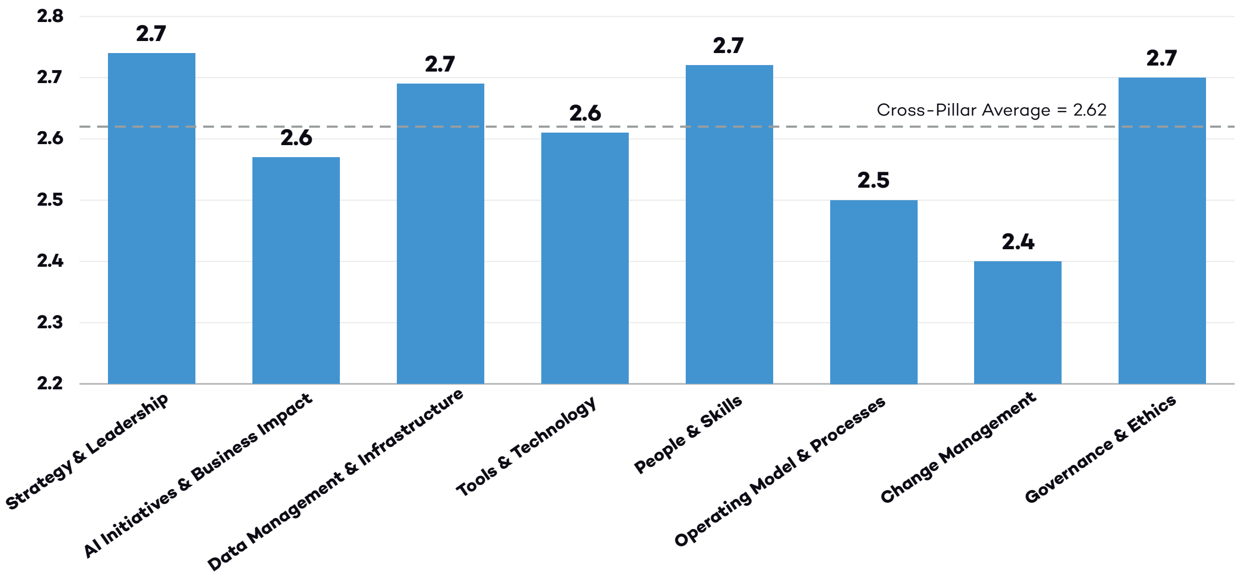

Figure 1: Average Maturity Scores Per Pillar Across All Interviews Conducted

To examine this execution gap more systemically, the report introduces an **AI Maturity Framework built around eight capabilities identified as critical to scaling AI effectively**. Together, these pillars span the enterprise landscape, including strategy, operating model, workforce capability, governance, technology, and value realisation.

Our findings reveal a clear adoption deficit currently exists. Organisations are investing heavily in AI strategy, but comparatively less in the capabilities required to scale delivery. As seen in Figure 1, strategic direction and workforce capability are the areas in which organisations are prioritising at present, however operating model maturity and workforce adoption activities emerge as the most consistent barriers to scale. This is a theme which is echoed across industries, with Figure 2 highlighting that regardless of relative sector strengths, these are the categories which are providing the most persistent challenges. Section 5 of this research explores these industrial trends in more detail.

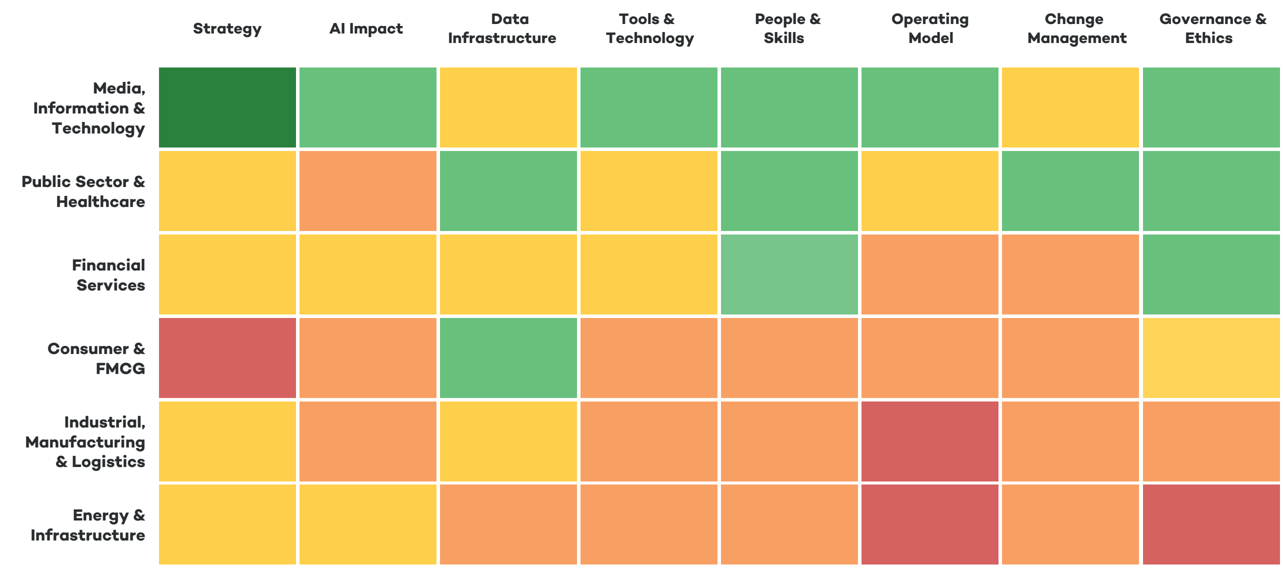

Figure 2: Average AI Maturity Scores per Pillar Across Industries (Green = Higher Maturity, Red = Lower Maturity)

Turning Insight into Action

Alongside our framework, this report introduces an **AI Maturity Toolkit** designed to translate this insight into action. The toolkit enables organisations to assess their current maturity across each pillar, benchmark their position against their peers, and identify the most critical capability gaps limiting progress.

It then provides targeted, practical recommendations aligned to the organisation's existing maturity level, supporting leaders in prioritising and sequencing transformation efforts. This toolkit is designed to be iterative. As the AI landscape continues to rapidly evolve, the toolkit can be consistently revisited over time, enabling organisations to track progress and continuously adapt their approach to ensure that their own maturity grows in tandem with the wider market.

SECTION 2: THE LANDSCAPE OF AI ACROSS ORGANISATIONS

The State of AI Today

Artificial intelligence has rapidly evolved from an emerging capability to a core component of how organisations operate, develop and compete. Adoption is now more widespread than ever, and investment continues to accelerate rapidly, with no indication of slowing. This momentum is reflected in the scale of both private and public sector investment:

- Hyperscalers are projected to invest approximately **$650 billion** in AI-related infrastructure and capabilities by 2026 [1].
- Large-scale initiatives such as Project Stargate (which is backed by OpenAI, SoftBank, Oracle, and MGX) represent planned investment of up to **$500 billion** over four years, including **$100** billion upfront [2].
- Governments are also committing significant capital towards AI development and supporting infrastructure. Recent examples include **France's €109 billion AI investment programme** and the **European Union's €200 billion InvestAI initiative**, alongside major state-backed investment programmes emerging across the Middle East, China, and the United States [3]. In several cases, the scale of announced investment represents a material proportion of national GDP, reflecting the growing strategic importance attached to AI competitiveness.

AI has also increasingly become embedded across a range of business functions for the most technologically mature organisations. Recent studies by Hostinger indicate that nearly 80% of organisations are now using AI in at least one business function, with generative AI adoption in particular rising sharply since 2023 [4].

Whilst investment and experimentation continue to accelerate, organisational maturity is not progressing at the same pace. Many organisations are successfully experimenting with AI and piloting new capabilities, yet comparatively few have translated these efforts into tangible enterprise-wide impact.

Industrial Variations in AI Maturity

AI maturity varies significantly across industries, reflecting differences primarily in the adaptability of business operating models, as well as the differing degrees of regulatory oversight. Data-intensive sectors such as financial services, telecommunications, and technology have generally progressed further in embedding AI into their operations. These industries benefit from large volumes of structured data, established analytical capabilities, and processes that are more easily automated, making business-wide adoption and measurable value realisation far more achievable.

By contrast, organisations which operate with more manual and physical processes, or legacy systems, often face greater challenges. These organisations typically exist within the manufacturing and infrastructure industries, as well as in the public sector. While these sectors may possess significant amounts of data, structural barriers such as outdated systems and entrenched ways of working often limit the ability to scale AI effectively.

Regulation is another major differentiator. In highly regulated sectors such as financial services, healthcare, and the public sector, AI adoption is often more controlled and risk-aware due to requirements around compliance, privacy, and governance. While this can slow deployment, it can also encourage more structured and sustainable scaling approaches.

Less regulated industries, including technology, retail, and media, are often able to move faster and experiment more aggressively with AI use cases. However, this speed can come at the expense of consistency, governance, and long-term scalability. As regulatory frameworks such as the EU AI Act continue to evolve, organisations across all sectors will need to balance innovation with control, transparency, and accountability. Managing this balance effectively is likely to become a defining feature of AI maturity.

The Challenges Presented By AI

While the specific context may differ across industries and geographies, a consistent set of challenges is emerging across organisations. These challenges are not primarily technological in the way they have been previously during the infancy of the AI boom. Many of these are systemic, cultural, and organisational barriers.

Workforce Readiness
While a substantial proportion of knowledge workers are already using AI tools, many are doing so without structured training, clear guidelines, or an understanding of how to apply these tools effectively within their roles. The use of these tools is governed entirely by the individual in many cases. Deloitte have recently reported that less than half of all respondents believe they have been provided with sufficient education or enablement to implement their AI initiatives, with this being a common theme felt across industries [5]. Without workforce readiness, AI adoption cannot be scaled effectively across a business.

Data Readiness
Many organisations possess large volumes of data, but inconsistent data quality and limited governance can severely reduce the ability to deploy AI solutions effectively. A recent Capgemini study indicates that fewer than one in five organisations report high maturity in the data and technology infrastructure required to scale advanced AI capabilities effectively [6]. AI systems rely on high-quality, accessible, and well-governed data to deliver reliable outcomes. The effectiveness of the outputs is almost entirely at the mercy of the quality of the inputs. AI therefore cannot be integrated effectively if this challenge is not addressed as one of the key priorities.

Operating Model and Governance
In many organisations, the accountability for the implementation of AI initiatives remains unclear. Organisational structures have yet to adapt to the significant changes in ways of working which AI is providing, and as a result, there is a split between technology, business, and innovation teams as to who is accountable for what. PwC's recent Global CEO Survey found that only half of organisations have formalised their approach to AI risk, reinforcing how unclear governance and risk structures are limiting the inability of many organisations to scale AI adoption effectively [7].

Sustainability and Environmental Impact Considerations
Alongside the organisational challenges associated with scaling AI, sustainability is becoming an increasingly important consideration for leaders. AI has significant potential to support sustainability outcomes. Organisations are already using AI to optimise energy consumption, as well as to support predictive maintenance to reduce waste. Across sectors such as energy, transport, and manufacturing, AI-enabled applications could contribute meaningfully to reducing emissions and improving operational efficiency.

However, these benefits must be balanced against the environmental impact of AI itself. Training and operating large-scale AI models requires substantial computational power, increasing energy consumption and demand for data centre infrastructure. The International Energy Agency projects that global data centre electricity consumption will rise significantly over the coming years, with AI workloads acting as a major driver of demand [8].

As a result, organisations face a dual challenge of using AI to support sustainability goals while managing the environmental impact of the technology itself. Sustainability considerations will increasingly need to be integrated into governance frameworks, infrastructure decisions, and technology strategy alongside traditional measures of business value.

Why We Undertook This Study

Beneath all the encouraging statistics advocating for the investment into AI solutions, there still lies a sobering reality. This is emphasised by a recent global survey conducted by Hostinger. This study found that while AI adoption itself is widespread, **only 1% of global organisations describe themselves as "mature" in their AI capabilities** [4]. The overwhelming majority describe themselves as early stage, experimental or still developing. This disconnect between adoption and maturity was the catalyst for why we conducted this study.

Across TTA, our partner firms collectively reviewed more than 40 AI-enabled client use cases delivered across a range of sectors. These case studies examined how AI had been implemented in real operational environments. They allowed us to understand what worked, what did not, and what specifically differentiated high-impact deployments from those that struggled to scale. Our analysis helped us to understand where AI is currently delivering value, and what opportunities are currently being missed. We wanted to build on the understanding we obtained from these use cases and speak to the leaders who oversee the implementation of these strategies. Following on from this, we wanted to develop a solution to both diagnose their current state relative to their competition, and to provide actionable recommendations to help them on their journey.

Introducing Our Approach

To further understand, and address the challenges faced by organisations, we have developed a practical **AI Maturity Framework** designed to **help organisations move from intent to impact**. From our analysis of internal use cases, eight recurring organisational categories emerged as the critical enablers of scalable AI adoption. These eight dimensions form the foundation of our AI Maturity Framework, which have been visualised in Figure 3.

Together, these categories provide a comprehensive view of AI maturity across an enterprise. Rather than assessing AI capability in isolation, this framework examines how effectively organisations integrate AI into the core mechanics of how they operate and create value.
By analysing the patterns across organisations, we have identified the common constraints that prevent progress in each pillar to allow us to outline practical actions leaders can take to advance their AI maturity in a structured, sustainable way.

SECTION 3: **INTRODUCING THE AI MATURITY FRAMEWORK**

Research Methodology

The **AI Maturity Framework** has been developed to help organisations assess their readiness to scale AI in a structured and practical way. It focuses on the organisational capabilities that determine whether AI initiatives translate into sustained business impact, rather than remaining isolated experiments or short-term pilots. The framework is grounded in insights from this study, as well as being complemented by our own experience supporting transformation programmes across industries, combining external evidence with practical delivery insight.

Study Overview
The study combined structured interviews with maturity assessments to examine how organisations are embedding AI in practice across industries and geographies.

METRIC	VALUE
Organisations Assessed	75
Countries Represented	9
Industry Groups	6
Interview Period	July 2025 – February 2026
Assessment Model	8 Pillar AI Maturity Framework
Maturity Scale	5 Levels

Geographical Coverage

- United Kingdom
- France
- Italy
- Germany
- Sweden
- Switzerland
- United Arab Emirates
- Saudi Arabia
- United States

Note: Some countries had smaller representation and findings should therefore be interpreted directionally.

Industry Coverage

INDUSTRY GROUP	SAMPLE SIZE
Energy & Infrastructure	16
Financial Services	11
Media, Information & Technology	18
Industrial, Manufacturing & Logistics	17
Public Sector & Healthcare	8
Consumer & FMCG	5

Note: Industries were grouped into broader categories where individual subsectors did not provide sufficient standalone sample size for directional analysis.

Interview Participants
Interviews were conducted with senior business and technology stakeholders, including:

- CEOs
- CIOs and CTOs
- Heads of Data & AI
- Transformation Leaders
- Strategy and Operational Executives

Scoring Methodology
Organisations were assessed across eight pillars of maturity using a five-level scale ranging from ad hoc activity through to embedded enterprise-wide capability. Scoring combined structured qualitative interviews with guided maturity assessment criteria to support consistency. More detail on the research methodology can be found in **Appendix A**.

The Eight Pillars of AI Maturity

The AI Maturity Framework is structured around eight pillars, grouped into four overarching dimensions. Together, these dimensions reflect the organisational capabilities required to translate AI ambition into sustained business value at scale.

DIRECTION

1. **Strategy & Leadership**
   The clarity of organisational ambition for AI, the strength of executive sponsorship, and the extent to which AI is linked to broader business priorities and investment decisions.

2. **AI Initiatives & Business Impact**
   How effectively organisations identify, prioritise, scale, and measure AI use cases, with a clear focus on delivering tangible business value.

FOUNDATIONS

3. **Data Management & Infrastructure**
   The quality, accessibility, ownership, and readiness of data, together with the platforms and architecture required to support AI use cases reliably.

4. **Tools & Technology**
   The maturity of the AI tooling ecosystem, including platforms, integration, scalability, lifecycle management, and the approach to vendors or partners.

EXECUTION

5. **People & Skills**
   The capability of the workforce to use AI effectively, including leadership literacy, specialist expertise, role-based enablement, and continuous learning.

6. **Operating Model & Processes**
   How AI is structured, prioritised, and embedded in operations and pathways, from idea through to deployment.

7. **Change Management**
   The organisation's ability to drive adoption, build confidence, reshape behaviours, and embed AI into day-to-day ways of working.

CONTROL

8. **Governance & Ethics**
   The policies, controls, accountability, and risk management mechanisms that enable AI to scale responsibly, safely, and in line with regulation.

More detail on each of these pillars can be found in **Appendix B**.

		LEVEL 1 **AD HOC**	LEVEL 2 **LOCALISED**
Direction	**Strategy & Leadership**	No articulated AI vision; minimal, ad hoc investment.	C-suite interest emerging; isolated sponsorship of pilots.
Direction	**AI Initiatives & Business Impact**	PoCs and demos only; benefits assumed, not quantified.	Isolated pilots deliver local wins; inconsistent measurement and reporting.
Foundations	**Data Management & Infrastructure**	Fragmented data silos; inconsistent quality; limited compute and access.	Initial cloud platforms and governed data pipelines emerging, but standards and quality controls remain inconsistent across functions.
Foundations	**Tools & Technology**	Ad hoc use of AI tools (e.g. chat interfaces); no integration with enterprise systems.	Teams experiment with AI tools and APIs; limited integration; usage remains fragmented.
Execution	**People & Skills**	Few AI-literate staff; low data literacy.	Small data-science pod; sporadic training for select teams.
Execution	**Operating Model & Processes**	AI projects run in isolation; no standard workflow or funding path.	AI initiatives coordinated within individual functions; ownership and delivery processes remain inconsistent across the organisation.
Execution	**Change Management**	Change efforts are sporadic and unstructured, with ad-hoc comms and no formal strategy.	Basic change activities emerge, but efforts are inconsistent and lack measurement.
Control	**Governance & Ethics**	No AI policies; bias & risk handled reactively.	Initial principles defined; governance applied inconsistently.

Figure 3: The TTA AI Maturity Framework

LEVEL 3 **INTEGRATED**	*LEVEL 4* **SCALED**	*LEVEL 5* **OPTIMISED**
Board-approved AI roadmap linked to OKRs and funded milestones.	AI established as a core strategic lever; governance and executive KPIs track value.	AI shapes corporate strategy and market positioning; scenario planning and investment driven by AI insights.
A cross-function portfolio with baseline KPIs and post-launch value tracking.	Multiple AI solutions deliver significant revenue & cost gains; value dashboard in place.	AI launches new products and revenue streams; material contribution to profit and growth.
Centralised data platform governed pipelines and catalogues enable reuse.	Real-time data availability; domain ownership (data mesh); lineage, quality, and cost transparency embedded.	Autonomous and self-optimising data architecture supports enterprise-scale AI through automated governance and elastic infrastructure.
Standardised AI platform enabling integration of foundation models and APIs; reusable components and basic orchestration in place.	End-to-end AI workflows using orchestration and agent-based systems; integrated into enterprise applications.	Seamless orchestration of agents and models across workflows; rapid deployment of new AI capabilities.
Defined career paths; structured learning programmes; cross-functional squads.	Enterprise-wide enablement (e.g. AI Academy); broad workforce AI literacy.	AI fluency embedded across the workforce; continuous learning and strong ecosystem partnerships support capability growth.
Cross-functional delivery model established; shared standards and workflows enable repeatable AI deployment across business areas.	Hub-and-spoke model; defined lifecycle from idea to production; agile delivery embedded.	AI embedded in core workflows; dynamic resource allocation and continuous optimisation loops.
A structured and tailored change plan with stakeholder engagement beginning to scale.	A formal Change Office drives coordinated activities, leadership coaching, and embedded change practices across AI projects.	Change management is fully embedded, adaptive, data-driven, and seen as a self-sustaining capability.
Defined governance processes; ethics training and documentation in place.	Formal governance structures; automated monitoring (bias, risk); alignment with regulatory frameworks.	Real-time responsible AI governance embedded enterprise-wide and used as a competitive differentiator.

SECTION 4: KEY FINDINGS AND HOW LEADING ORGANISATIONS ARE RESPONDING

Interviews conducted as part of this research revealed several consistent patterns, alongside significant variation across sectors and regions. While many of the core challenges associated with scaling AI are shared, the way they manifest differs depending on industry context, regulatory environment, and organisational maturity.

This section summarises the most significant themes emerging from our analysis, highlighting where organisations are making progress and what differentiates those successfully scaling AI from those still in earlier stages of adoption.

Cross-Industry Summary

Across all seventy-five participants, average scores for the eight pillars of the AI Maturity Framework fall within a narrow range of 2.4 to slightly over 2.7. This suggests that overall organisational maturity remains at the early to mid-stage in most areas.

The highest average scores were recorded in Strategy & Leadership, and People & Skills. This indicates that many organisations recognise the strategic importance of AI and are beginning to match this with investment in workforce capability. The results suggest that these are the pillars which most immature organisations prioritise first. However, this pattern reiterates that the growing awareness and intent are yet to be matched by enterprise-wide execution.

The lowest scores were seen in Operating Model & Processes and Change Management. These are the core capabilities which are critical to embedding AI into day-to-day operations. Lower maturity in these areas highlights a consistent finding across this research:

Organisations are adopting AI faster than they are redesigning the structures, processes, and behaviours required to scale it effectively.

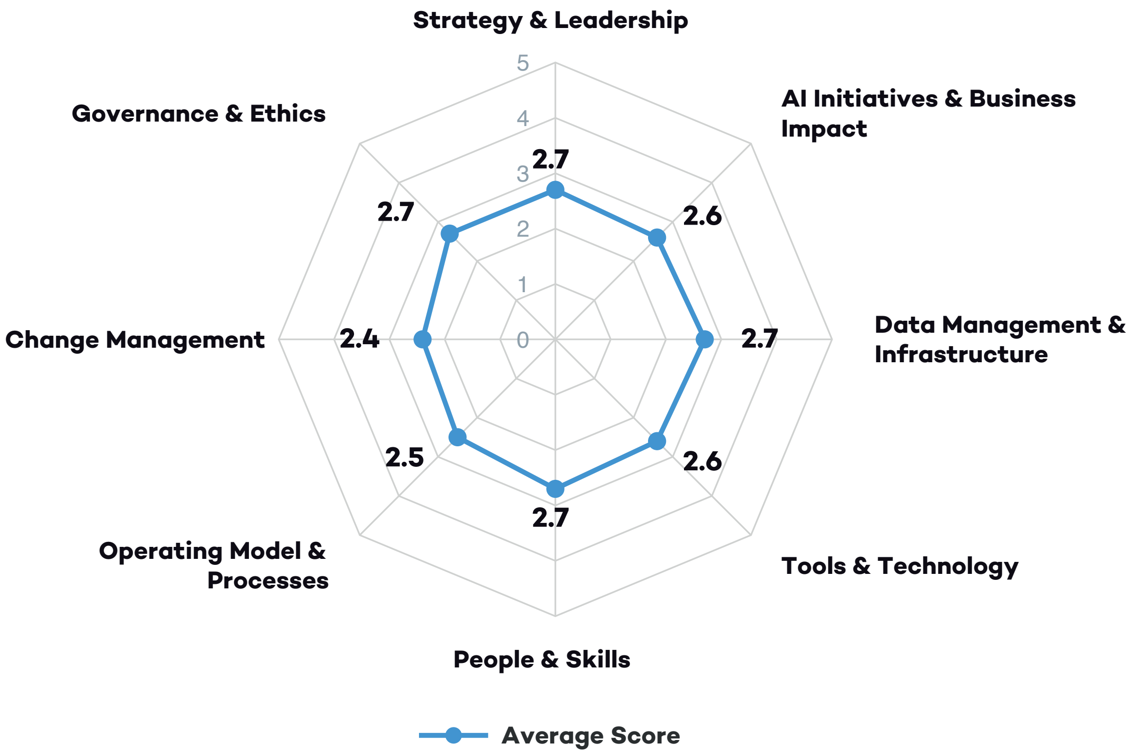

Figure 4: Radar Graph of Average Scores Across Each Pillar of the AI Maturity Framework

The sections that follow examine each area of our maturity framework in more detail, outlining the key trends observed and the drivers behind them. Included in these sections will be commentary from the senior leaders of organisations which are currently at the forefront of the current AI maturity landscape.

Change Management: The Main Barrier to Scale

As discussed, Change Management emerged as the lowest scoring pillar across the dataset, with an average score of 2.4. The box plot in Figure 5 shows that this pillar exhibits one of the smallest degrees of variance in results, highlighting this is a barrier felt by a large proportion of organisations. Around two thirds of participating organisations were assessed at a score of 2 or below. This indicates a pattern of insignificant investment of both time and resources into developing the organisational conditions required to communicate and embed AI tools into day-to-day work.

Several interviewees described early enthusiasm for AI and visible experimentation but limited structured rollout beyond informal enablement. There is reliance on ad hoc, low threshold interventions such as lunch-and-learn sessions, which are in theory designed to build workforce confidence and minimise change resistance. While these activities can be highly effective at building awareness, they are rarely sufficient to deliver long-term behavioural and cultural change across an organisation.

Why does this matter?
Risk and cybersecurity concerns surface repeatedly as factors which hamper adoption. Employee uncertainty around what is and what is not permitted regarding AI usage is also a common pain-point. **Our research therefore suggests that the biggest limiting factor for sustainable AI implementation is the ability to shift behaviours, redesign ways of working, and build the necessary confidence across the workforce.**

The consequence of not prioritising change management activities is a growing gap between technical deployment and realised value. AI initiatives may generate early enthusiasm and isolated productivity gains, but without structured change management they will struggle to scale beyond pockets of experimentation. The implication for leaders is that successful AI transformation depends as much on workforce adoption and organisational readiness as it does on the technology itself.

What are leading organisations doing?
More advanced organisations treat adoption as a coordinated transformation effort rather than a purely bottom-up movement. Ownership for change is clearly defined and there is a drive to ensure that communication is consistent. Support mechanisms are also built around the specific needs of different user groups.

These organisations also move beyond simple awareness campaigns. They anticipate change resistance and respond to it proactively by ensuring a clear communication plan is prepared and that adoption is closely tracked. Managers are equipped to lead change by ensuring they are appropriately coached, and the organisation continuously adapts the change management approach as tools and use cases evolve. AI implementation is treated as an ongoing capability shift rather than a one-off launch.

„We have Change Management Ambassadors who own these activities end-to-end, with appropriate messaging coming from leadership in our regular town halls.“

Development Director, UK Media Organisation

Operating Model Maturity: A Consistent Blocker

Operating Model & Processes was the second lowest scoring pillar across the dataset with an average score of 2.5, and more than half of participating organisations currently operating at Levels 1 or 2. As with the Change Management pillar, the box plot in Figure 5 also shows that this pillar exhibits relatively small variance, strengthening the reliability of the average value. While strategy and experimentation have been advancing, the integration of AI capability into organisational models has not evolved at the same pace.

Interviewees frequently described uncertainty around ownership, prioritisation, and decision-making rights regarding AI development and implementation. In several cases, AI activity was driven either entirely by a central Centre of Excellence, or by enthusiastic individuals within functions. Whilst this approach can in theory lead to clearer ownership, it often results in limited clarity to wider teams as to how initiatives were selected, funded, or integrated end-to-end. The result in many instances is fragmentation and poor collaboration across business functions.

Why does this matter?
The poor collaboration between business functions which was highlighted by several interviewees meant that many promising use cases were often seen to emerge in isolation but lack a consistent delivery mechanism capable of supporting repeatable deployment across the business. The implication for leaders is significant. Without a clearly defined operating model, AI initiatives struggle to transition from successful pilots into repeatable organisational capability. The race for AI maturity is quickly being underpinned by business operating models. Scaling AI therefore depends not only on generating ideas, but on establishing the structures, governance, and cross-functional coordination required to deliver them consistently at enterprise scale.

What are leading organisations doing?
More advanced organisations establish operating models that balance central coordination with business unit ownership. Shared capabilities such as platforms, governance, and specialist expertise are coordinated centrally, while business units often retain accountability for use case demand and adoption.

Clear prioritisation and deployment processes create consistency without slowing innovation. This enables both speed and alignment and ensures that AI initiatives can scale efficiently whilst remaining connected to business priorities.

> *„Our message to all business units is to not let our central AI team slow down your own innovation.“*
>
> *Head of Tech & AI, German Media Organisation*

People & Skills: Uneven Capability Distribution

People & Skills was one of the highest scoring pillars overall, with an average score of over 2.7. Our research indicates that this is the pillar of the execution dimension which many organisations are heavily prioritising. The wider story, however, is that while many organisations report having the relevant AI capability in place, that capability is often concentrated within small specialist teams instead of being distributed across the business.

Interviewees commonly referenced data scientists, automation specialists or innovation teams acting as internal hubs of expertise, alongside informal communities of practice. Conversely, broader workforce enablement remains inconsistent. Several organisations described limited structured training beyond introductory sessions, and varying levels of confidence was often cited amongst employees about how to use AI responsibly and effectively.

Why does this matter?
This concentration of capability creates dependency bottlenecks. Specialist teams become at risk of being overstretched, while the wider organisation underutilises AI's potential and remains reliant on a small number of experts to unlock progress beyond personal use cases.

The key takeaway is that developing AI maturity in this pillar is not simply about hiring multiple experts. It is about **diffusing capability across the business** so that value creation is not constrained by a small number of technical gatekeepers.

What are leading organisations doing?
More advanced organisations are taking a deliberate approach to capability distribution. Specialist expertise is retained and strengthened, but also complemented by structured, organisation-wide enablement programmes which are tailored to different functions, and levels of seniority.

Importantly, capability building is reinforced visibly from the top. Leadership actively participates in training and sets expectations around AI literacy, signalling that adoption is a core organisational priority rather than a niche technical discipline.

„Executive leadership has participated in dedicated AI training and demonstrates basic AI literacy. Mandatory AI awareness training exists for all employees, supplemented by optional prompt-engineering courses.“

Head of AI, German Financial Services Organisation

Organisational direction: Stuck in pilot mode despite strong strategic ambition

The AI Initiatives & Business Impact pillar scores an average of 2.6 across the dataset. Whilst Strategy & Leadership was on average the highest scoring pillar, and nearly all organisations interviewed could point to active use cases and pilots, far fewer demonstrated consistent, value measurement frameworks. Though the differences in the average scores between these two pillars is minimal, the pattern is indicative of value realisation lagging behind ambition at this stage of the AI journey.

References to pilots and proofs of concept were frequent, ranging from internal "Talk to your Data" assistants and GPT-enabled procurement tools, to Copilot trials and supplier scouting applications. These examples illustrate both the creativity and ambition present across organisations. However, interviewees repeatedly highlighted that pilots often remain isolated within individual functions, without a credible route to broader application. A recurring challenge identified through this research is the absence of formal mechanisms to translate early success into long-term impact. Funding models, ownership structures, and value tracking frameworks were frequently stated by interviewees to be underdeveloped.

Why does this matter?
The result is that organisations can appear highly active in AI adoption while still struggling to achieve sustained impact. Promising use cases often remain confined to individual functions, limiting wider operational integration and reducing the long-term return on investment. **Successful AI adoption depends less on idea generation and more on the governance and delivery structures required to scale value.**

What are leading organisations doing?
More advanced organisations treat scaling existing use cases as a deliberate and governed process rather than an informal progression from pilot to production. Use cases are prioritised according to their strategic relevance and measurable value. Success metrics are defined early, and performance is reviewed regularly against these metrics to guide future investment. This ensures that progress never occurs behind closed doors, and the growth of initiatives is constantly aligned to the broader organisational direction.

Clear ownership, disciplined governance, and consistent portfolio management allow successful initiatives to be expanded systemically across the enterprise. In these organisations, AI is managed as a value creation capability rather than a collection of isolated experiments.

> *„We have a monthly AI review board which prioritises our use cases based on their expected business impact. We have set a clear 10% productivity uplift target to steer initiative selection.“*
>
> *CPO, German Shipping Company*

Governance & Ethics: Beginning to Catch Up to Innovation

Governance & Ethics scored 2.70 on average. Many participants described their governance approach as still evolving, reflecting a broader trend of controls developing reactively alongside technological advancement rather than in anticipation of it.

Regulation has predictably become a major catalyst for this change. The EU AI Act was cited repeatedly as shaping internal policy, tool selection, and risk frameworks. This is particularly prevalent among organisations operating within, or trading into, European markets. More broadly, privacy and cybersecurity considerations are increasingly being embedded into AI planning processes, especially in highly regulated industries such as financial services and healthcare.

Why does this matter?

While governance maturity is improving, progress remains uneven across organisations. In lower-scoring organisations, ownership was often fragmented and policies remained at an early stage of development. This frequently created uncertainty around acceptable AI usage and accountability, slowing broader adoption and reducing organisational confidence in scaling AI initiatives.

The findings suggest that **governance is increasingly becoming a prerequisite for sustainable AI adoption** rather than a parallel compliance activity. Organisations that fail to establish clear oversight, risk management, and decision-making structures may struggle to scale AI consistently, particularly as regulatory expectations and operational reliance on AI continue to increase.

What are leading organisations doing?
More mature organisations are moving beyond reactive compliance toward structured and proactive governance. Clear ownership is established, often through dedicated oversight forums or accountable senior leaders. Governance is embedded across the full lifecycle of AI initiatives, influencing how use cases are selected, developed, deployed, and monitored. These organisations also use governance to accelerate adoption by creating clarity, consistency, and trust across the enterprise.

„We quickly established an AI governance board with clear accountability under the Company Secretary. Combined with a strong appetite for new technology, this has enabled a structured and well-governed approach to AI adoption."

Chief Strategy Officer, UK Media Organisation

Tooling & Technology: Integration Challenges and Tool Sprawl Remain Common

Tools & Technology scored an average of 2.6 across the dataset, with significant variation across organisations and industries. This variation is highlighted by the box plot in Figure 5. A common pattern emerges, which is that many organisations have deployed "safe" internal assistants, Copilot-style tools or secured generative AI environments. This suggests convergence around a small set of enterprise grade platforms.

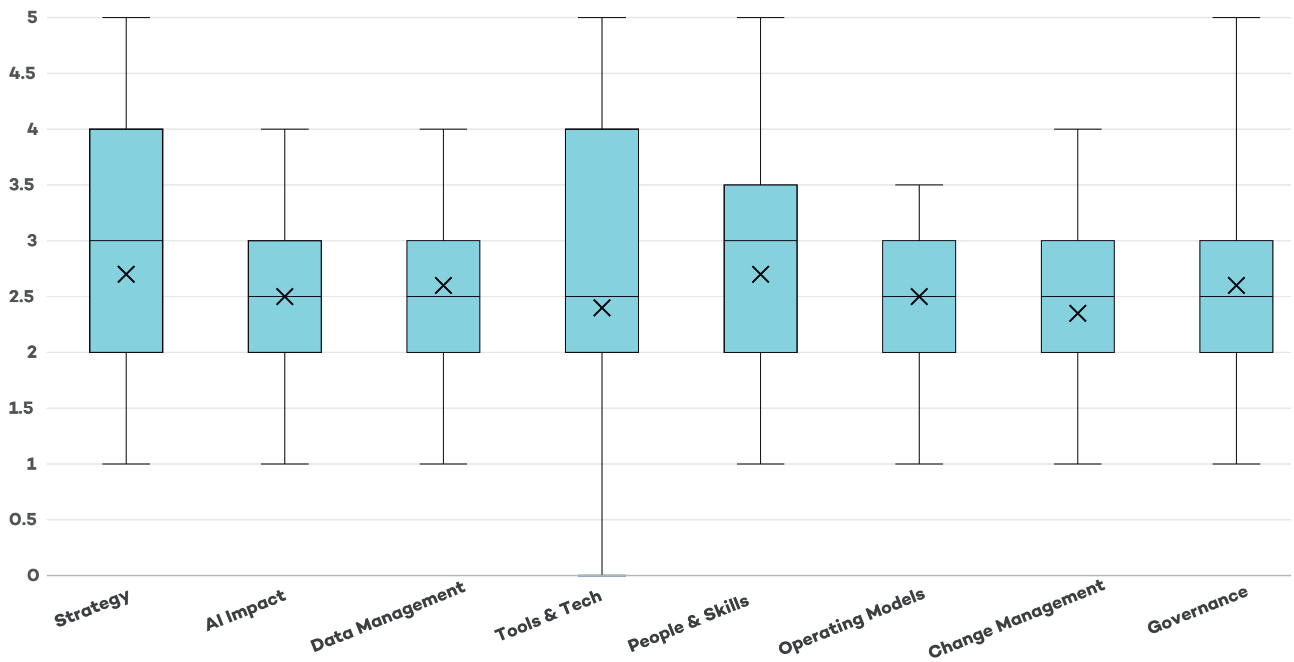

Figure 5: Box Plot of the Variance in Average Maturity Results Across Pillars

However, beneath this surface level convergence, technology landscapes often remain fragmented. Interviewees repeatedly cited legacy systems as one of the main sources of friction. Other shared challenges emerging from our research centred around unclear integration pathways and overlapping toolsets. In some cases, early vendor partnerships did not mature, requiring rework or replacement after pilot stages.

Why does this matter?
These challenges often result in operational inefficiency and increased risk. Without a rationalised and integrated technology stack, AI initiatives become harder to scale, more expensive to maintain, and more difficult to govern. Many organisations are also increasingly exposed to the risk of investing in isolated products or point solutions which generate short-term excitement but fail to integrate effectively into the wider technology ecosystem.

The implication for leaders is that tooling decisions must be made with scalability, interoperability, and long-term integration in mind from the outset. Isolated deployments may generate short-term wins, but sustainable value depends on coherence across the broader technology landscape.

What are leading organisations doing?
More advanced organisations are moving toward integrated, platform-based ecosystems. Rather than relying solely on bespoke builds or isolated point solutions, they combine internal capabilities with selected external platforms to balance speed with flexibility.

Common standards for architecture, security, integration, and vendor management allow new tools to be adopted quickly without creating unnecessary sprawl. In these organisations, technology becomes an accelerator of scale rather than a growing source of complexity.

> *„The organization leverages advanced, continuously improving AI models, combining in-house solutions with premium external tools. This approach reflects high maturity in using technology platforms to drive AI initiatives.“*
>
> *CTO – Saudi Technology Organisation*

Data Management: Both an Enabler and a Constraint

Data Management & Infrastructure scored an average of 2.7, placing it in the mid-to-upper range relative to other pillars. Many organisations have invested in centralised data platforms and improved access mechanisms designed to create more consistent reusable data across the enterprise. Strategically, this enables organisations to make faster decisions and reduce duplication across teams. However, interviewees frequently described these foundations as still being at an early stage of maturity. Ongoing challenges around data quality and governance remain, while fragmented systems and inconsistent data standards were also common themes amongst participants.

This creates a clear cause-and-effect dynamic. In organisations where data foundations are stronger, AI initiatives are more likely to move beyond experimentation into repeatable deployment. Where data is unreliable, poorly structured, or difficult to access, AI remains confined to narrow use cases or requires disproportionate manual effort to scale. This dynamic has become even more important with the rise of generative AI and externally hosted models. In these environments, the value often comes less from the model itself, and more from the quality, accessibility and trustworthiness of the enterprise data connected to it.

Why does this matter?
Data maturity therefore acts as a multiplier or limiter of progress across other pillars. The key implication is that AI success is contingent on treating data as a strategic asset. Sustainable adoption depends not only on access to advanced models and tooling, but on the ability to provide dependable, well-governed, and usable data at scale. Without this foundation, even well-funded AI initiatives are likely to struggle to deliver sustained business impact.

What are leading organisations doing?
More advanced organisations are investing deliberately in data quality and governance. Clear accountability is established for critical datasets, standards are applied consistently, and data is managed as an enterprise asset rather than a by-product of operations.

Dedicated capabilities are also in place to improve access, and ensure that trusted data can be used quickly within AI initiatives. In these organisations, strong data foundations become a platform for scale rather than a recurring barrier to progress.

„We now have large teams dedicated to data cleansing, dashboard development and privacy. This has massively helped us to ensure that data quality and compliance is maintained across the organisation."

International Buyer Director, Global Beauty Retailer

SECTION 5: **INDUSTRY & GEOGRAPHICAL OBSERVATIONS**

While many of the core challenges associated with AI maturity are shared across organisations, the findings also show meaningful variation by sector. These differences are influenced by factors such as:

- Regulatory Pressure
- Digital Maturity
- Data Availability
- Operational Complexity
- Workforce Structure

To support clearer analysis, organisations were grouped into broader industry categories where standalone samples were too small to support robust comparison. For example, the Financial Services category includes organisations from banking, insurance, and fintech. More detail on the grouping of participating organisations into industries can be found in **Appendix C**.

The observations below should be interpreted directionally, particularly where sample sizes are smaller, but they provide useful insight into how AI maturity is developing across different industry contexts.

Media, Information & Technology: Digitally accelerated, but faces familiar constraints

Across the dataset, organisations in Media, Information & Technology consistently scored above the cross-industry average across all pillars, as highlighted below in Figure 6. It can also be seen in the heatmap shown in Figure 7 that the organisations interviewed across this industry scored as "High" or "Very High" in six out of eight pillars according to the score grouping listed in Table 1.

(Note: These scoring bands have been standardised in accordance with the results from our study to get an indicative view of which pillars of the framework tend to score highest relative to one another.)

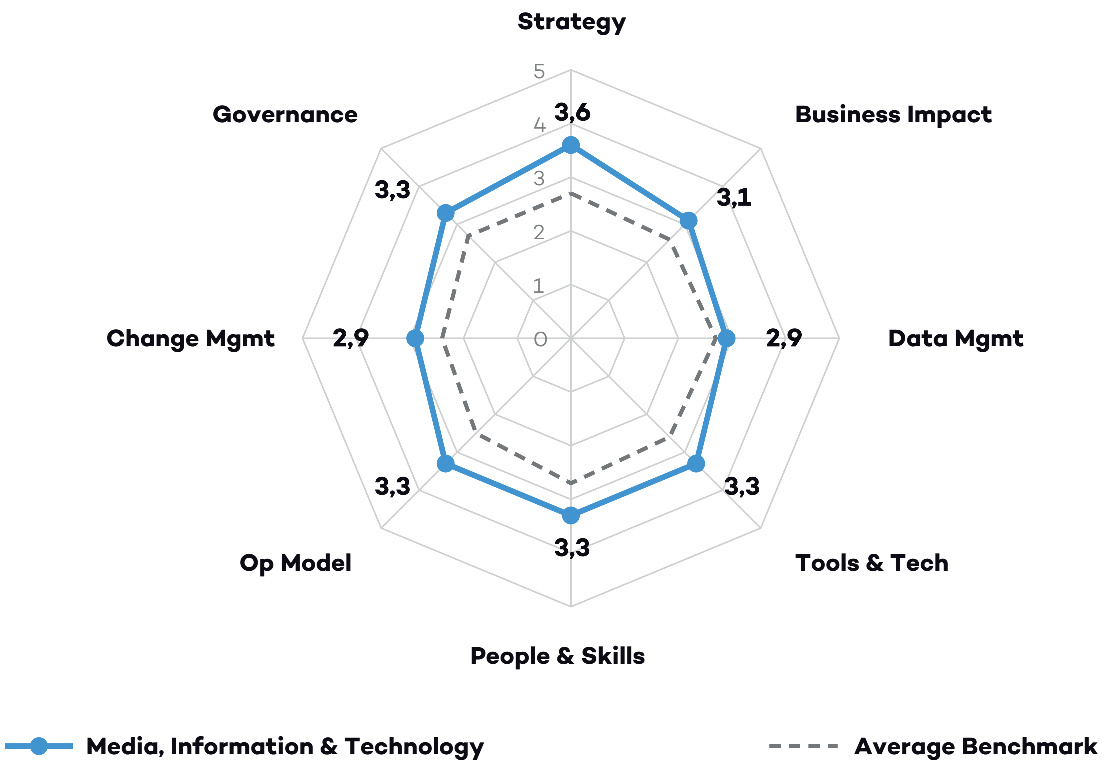

Figure 6: Radar Graph for Media, Information & Technology Organisational AI Maturity

What can be seen from this study is that relative to other sectors, this industry is experiencing digital capability which is already closely tied to commercial success. Several respondents in these sectors described AI as central to competitive positioning and embedded within product decision-making processes.

However, stronger baseline maturity does not remove common scaling barriers. Challenges remain around how to embed new ways of working. Additional challenges exist around applying governance consistently and expanding successful initiatives beyond early adopter teams. In several cases, progress was strongest in isolated areas rather than across the enterprise.

The broader lesson is that sector advantage can accelerate AI maturity, but it does not replace the need for disciplined execution. The organisations making the strongest progress are those moving beyond experimentation and embedding AI systemically into governance structures and operational workflows.

Relative Maturity Grouping	Score Range	Colour
Very Low	1.0 – 1.9	
Low	2.0 – 2.4	
Average	2.5 – 2.9	
High	3.0 – 3.4	
Very High	3.5 – 5.0	

Table 1: Maturity Group Score Range Summary

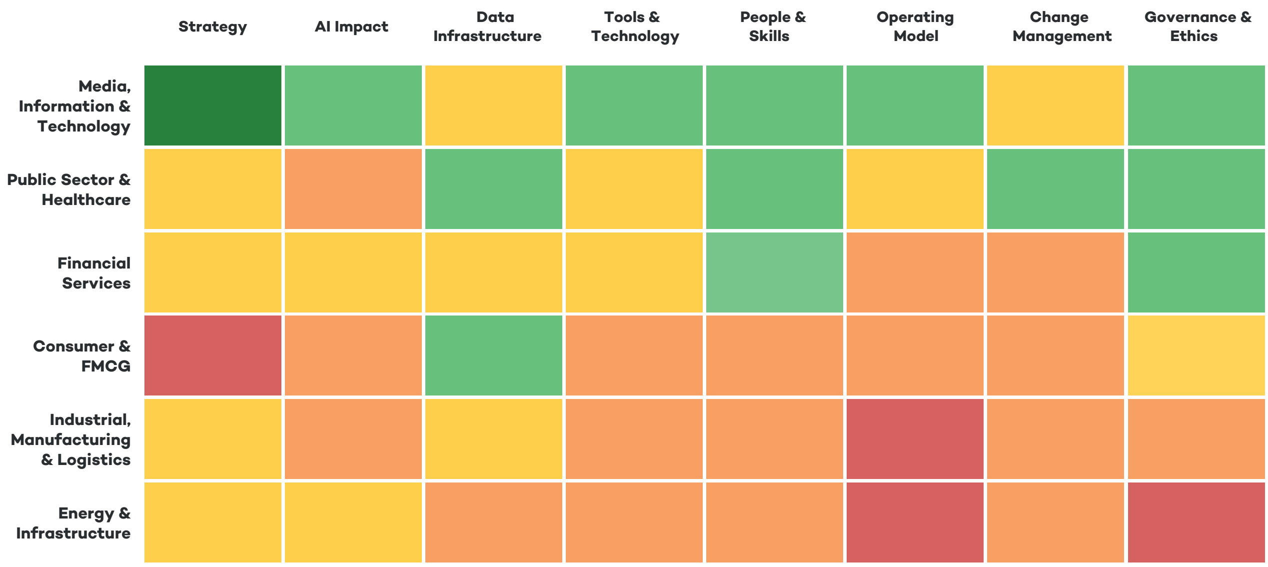

Figure 7: Average AI Maturity Scores per Pillar Across Industries

Consumer & FMCG: Strong data foundations but uneven enterprise execution

Consumer & FMCG was one of the smaller samples in the dataset, so findings should be interpreted with some caution. Within the sample, organisations demonstrated relatively strong scores in Data Management & Infrastructure and Governance & Ethics. This suggests the current landscape within this industry is characterised by increasing investment in customer data environments and a focus on responsible AI controls, but people upskilling and execution is comparatively immature at this stage.

Many interviewees within this industry cited that stronger maturity existed in their customer data compared to their product or trade data. There were also several use cases which primarily centred around demand forecasting and assortment planning. However, the stronger technical base seen across this industry has not yet translated into equally strong enterprise-wide execution. Strategy & Leadership and AI Initiatives & Business Impact scores remain lower, suggesting that in several organisations, AI is still being pursued through local opportunities rather than through a clearly prioritised roadmap.

Many organisations in this sector appear to understand where AI can create value but are still developing the coordination and adoption mechanisms required to scale that value consistently. The organisations progressing most effectively are those integrating AI across both customer and operational workflows, while introducing clearer prioritisation, ownership, and value measurement mechanisms. The implication is that competitive advantage in the sector is likely to depend increasingly on operational integration rather than isolated customer-facing innovation.

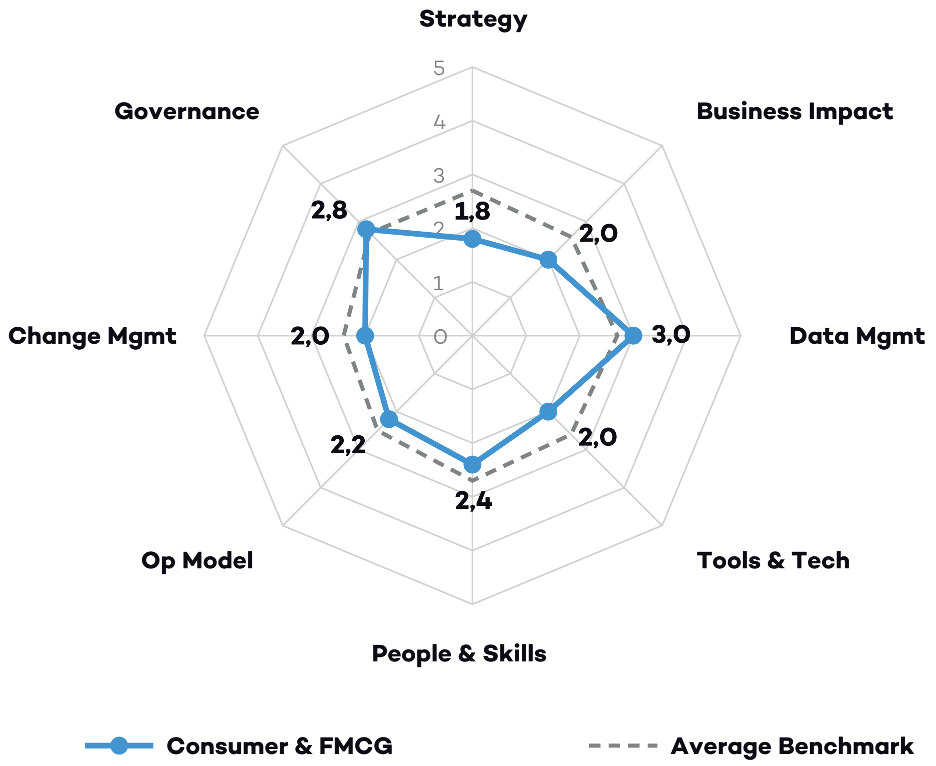

Figure 8: Radar Graph for Consumer & FMCG Organisational AI Maturity

Energy & Infrastructure: Weak Enabling Conditions

Energy & Infrastructure was one of the largest samples in the study and displayed one of the clearest gaps between AI ambition and organisational readiness. Strategy & Leadership and AI Initiatives & Business Impact both scored around 2.6, broadly in line with the cross-industry average. This suggests that many organisations in the sector have identified credible use cases and have begun building momentum around AI adoption.

Interviewees often described practical applications in operational environments, which included scheduling optimisation, document intelligence, tender selection, and risk analysis. However, the enabling conditions required to scale these applications appeared to be materially weaker. Governance & Ethics is the lowest of any industry group at 1.8, while Tools & Technology, Data Management & Infrastructure, People & Skills, and Change Management all sit below their respective cross-industry averages.

The qualitative evidence helps explain this pattern. Many organisations are operating with fragmented data and legacy systems. More than most, this sector currently experiences long-standing ways of working which leads to a workforce which is particularly resistant to change. These organisations also operate in tightly controlled environments where safety and reliability are critical, which reduces the risk appetite for large scale operational changes. As a result, deployment decisions are often slower and subject to greater scrutiny.

There is also visible variation within the sample. Larger energy organisations for example often showed clearer sponsorship and more structured pipelines. Construction and infrastructure organisations however more commonly appeared federated and project-driven in their approach. The implication is that organisations within this sector are not short of relevant AI opportunities. The challenge now is to build the required technical foundations and workforce capability to convert the visible ambition into repeatable advantage.

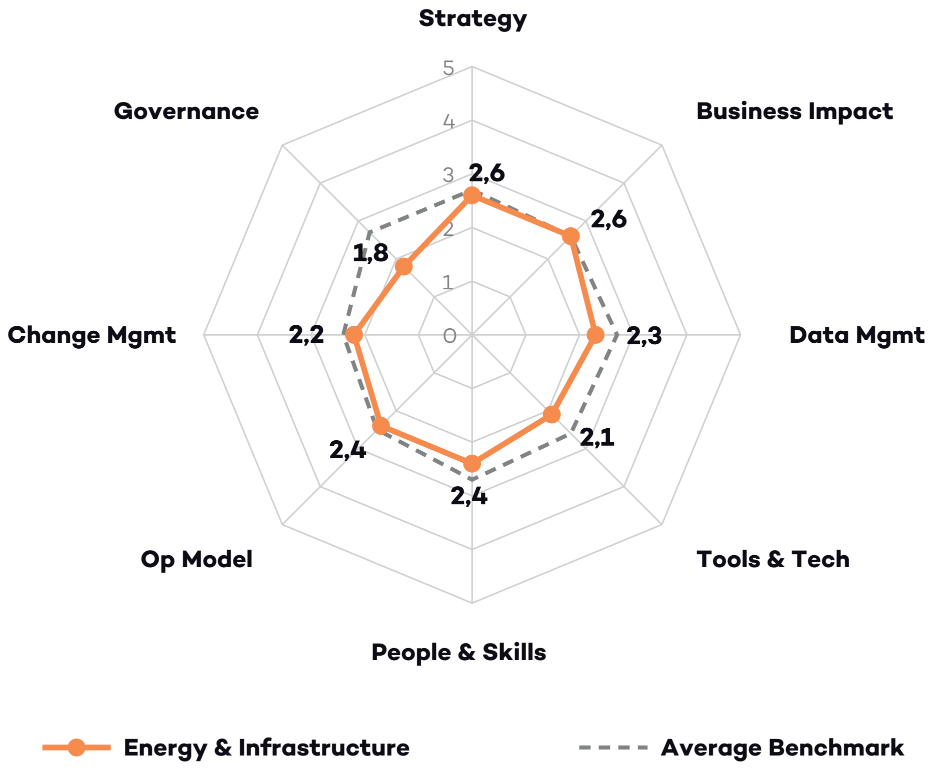

Figure 9: Radar Graph for Energy & Infrastructure Organisational AI Maturity

Financial Services: Governance Led and Comparatively Mature, but Value Realisation Is Slower

Financial Services emerged as one of the more mature sectors in the dataset, particularly regarding their technical foundations and control mechanisms. This reflects the more structured operating environment in which many of these organisations are working in comparison to other industries. Interviewees often described the existence of formal internal AI policies, with many referencing the presence of central AI functions who are closely aligned with external regulatory expectations such as the EU AI Act.

The sector appears further ahead than most in building the controls and capabilities required for responsible adoption. However, that strength does not fully carry through into scaled business impact. With average scores in Operating Model & Processes and Change Management falling below the cross-industry average, execution is the stage in which organisations within this industry are experiencing their biggest challenges. Many interviewees indicated that several use cases remain focused on internal productivity and risk reduction rather than broader commercial transformation. With the foundations of AI maturity currently exceeding the ability to implement, the challenge this industry must now overcome is ensuring that caution does not limit the ability to maximise value creation.

Financial Services may become one of the first industries where governance maturity begins to outpace organisational adaptability. The organisations making the strongest progress are those embedding governance directly into operational delivery rather than treating it as a separate oversight layer. Future leaders are likely to be distinguished by their ability to scale AI efficiently while maintaining regulatory confidence.

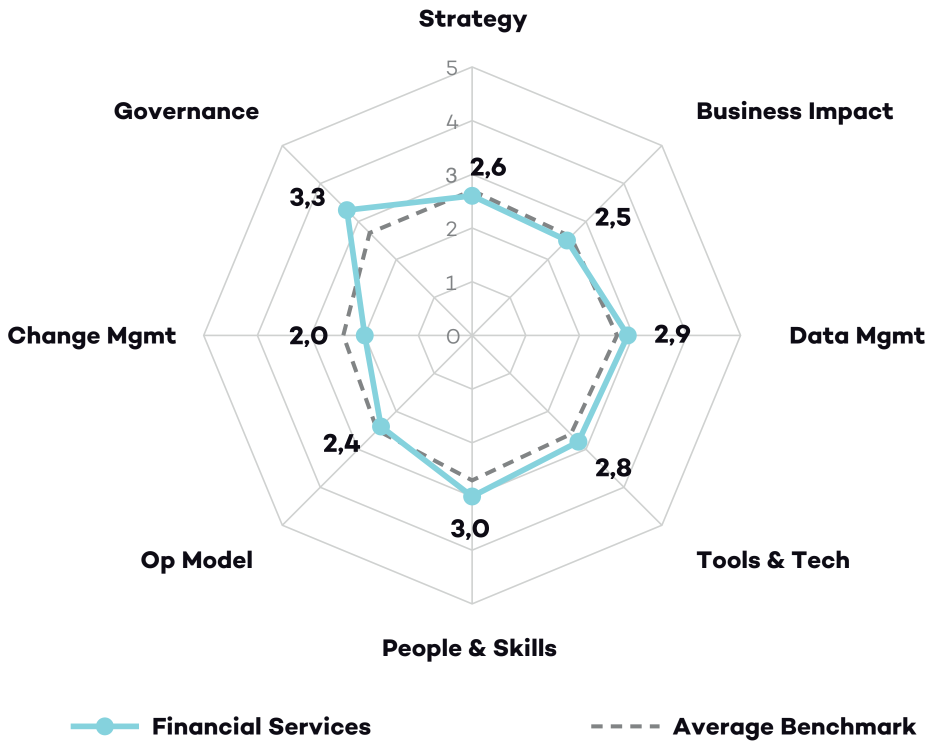

Figure 10: Radar Graph for Financial Services Organisational AI Maturity

Public Sector & Healthcare: Strong Foundations but Impact Remains Uneven

Public Sector & Healthcare presented a more mixed, but in some respects a comparatively mature profile. Data Management & Infrastructure, People & Skills, Governance & Ethics, and Change Management all score well above the cross-industry average, suggesting that several organisations in this group have invested meaningfully in core enabling conditions and central capability.

Interviewees described dedicated data science or analytics teams, as well as internal technology communities. Many also reported broad access to tools and clear policy guardrails. This indicates that organisations within this sector are moving quickly to prioritise their technical capabilities and ensuring the correct foundations are in place for effective execution. However, these strong foundations coexist with comparatively weaker directional maturity, with Strategy & Leadership and AI Initiatives & Business Impact scoring below the cross-industry average. These scores suggest that organisational readiness has not yet translated consistently into scaled outcomes, despite the technical foundations which are in place.

What is also clear from the data collected is the significant spread of data existing in this sector. This is highlighted in Figure 11 below, which illustrates that the largest skew of results was obtained by this collection of interviews. This industry spans across a broad range of different organisational complexities and landscapes, as well as possessing a small sample size of interviewees. Therefore, the results obtained must be interpreted with a degree of caution.

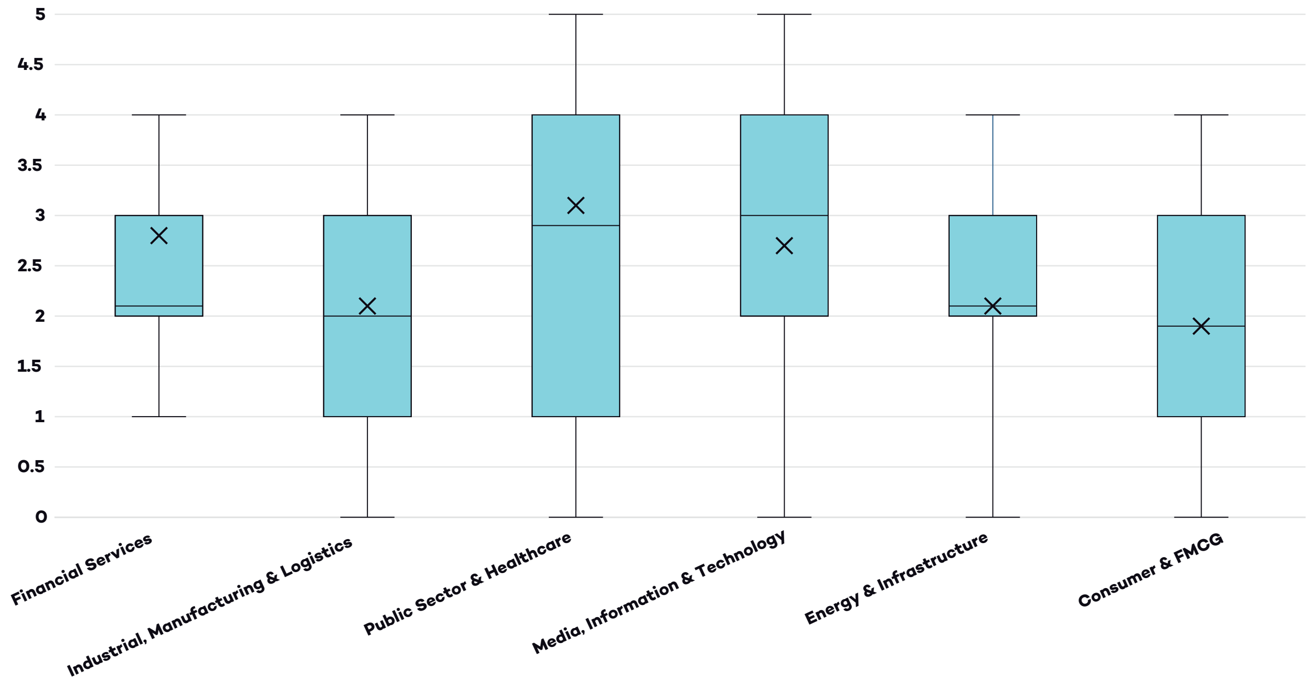

Figure 11: Box Plot of the Variance in Average Maturity Results Across Sectors

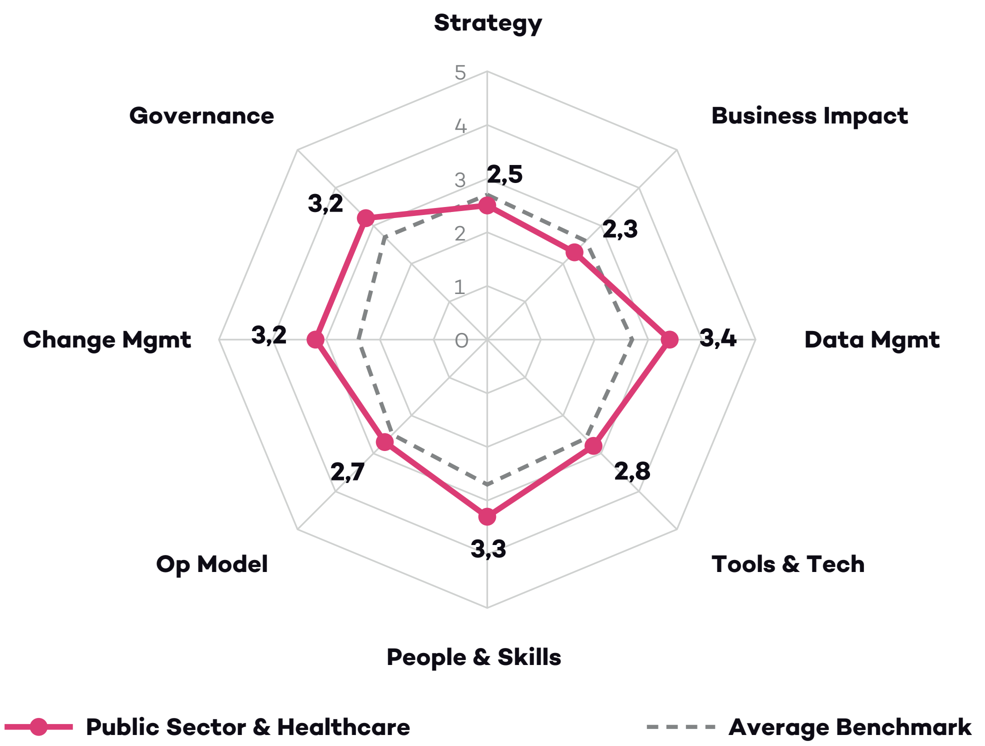

Figure 12: Radar Graph for Public Sector and Healthcare Organisational AI Maturity

Industrial, Manufacturing & Logistics: Weak Organisational Readiness

Industrial, Manufacturing & Logistics is an example of a sector with evident AI potential but weak organisational readiness to realise it. It scores below the cross-industry average on every pillar, with particularly low performances seen in the three execution-based pillars; Operating Model & Processes, People & Skills, and Change Management. Using the scaling described in Table 1, this is the industry in which the highest percentage of organisations are currently scoring “Very Low” as an average across each of the eight pillars of the framework.

Interviewees described a wide range of practical applications, including supplier scouting, document processing, and workforce automation. This indicates that the sector is not lacking in relevant opportunities. Rather, many of the barriers are organisational. AI initiatives are often driven through procurement or operations functions on an ad hoc basis, with limited formal prioritisation and unclear coordination between business teams and IT.

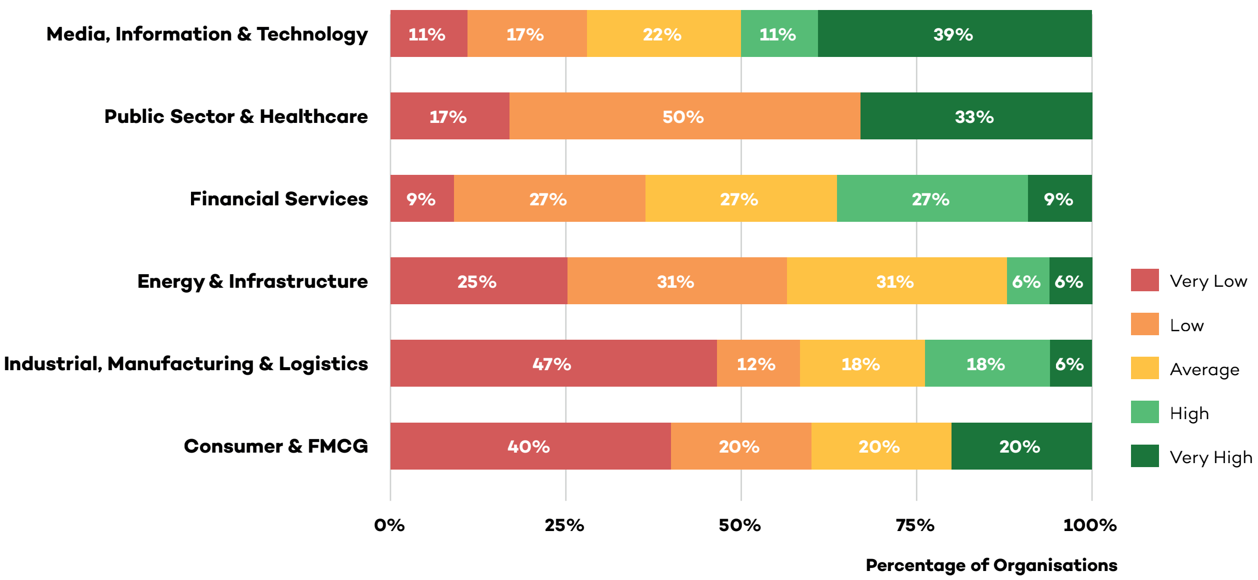

Figure 13: Distribution of Organisations Across AI Maturity by Industry

Data challenges remain prominent in this industry. Many organisations still rely on unstructured documents and fragmented platforms. Like the Energy and Infrastructure industry described previously, legacy systems and workforce capability continue to be one of the biggest challenges to overcome, and they remain one of the key drivers behind the current slow rates of integration.

The result is that many organisations within this industry are beginning to experiment with useful tools, but without the process redesign required to scale adoption effectively. The findings of the research suggest that this sector’s AI challenge is primarily about execution discipline. There is significant room to create value, but only if organisations strengthen the operating model and workforce foundations that sit beneath the technology.

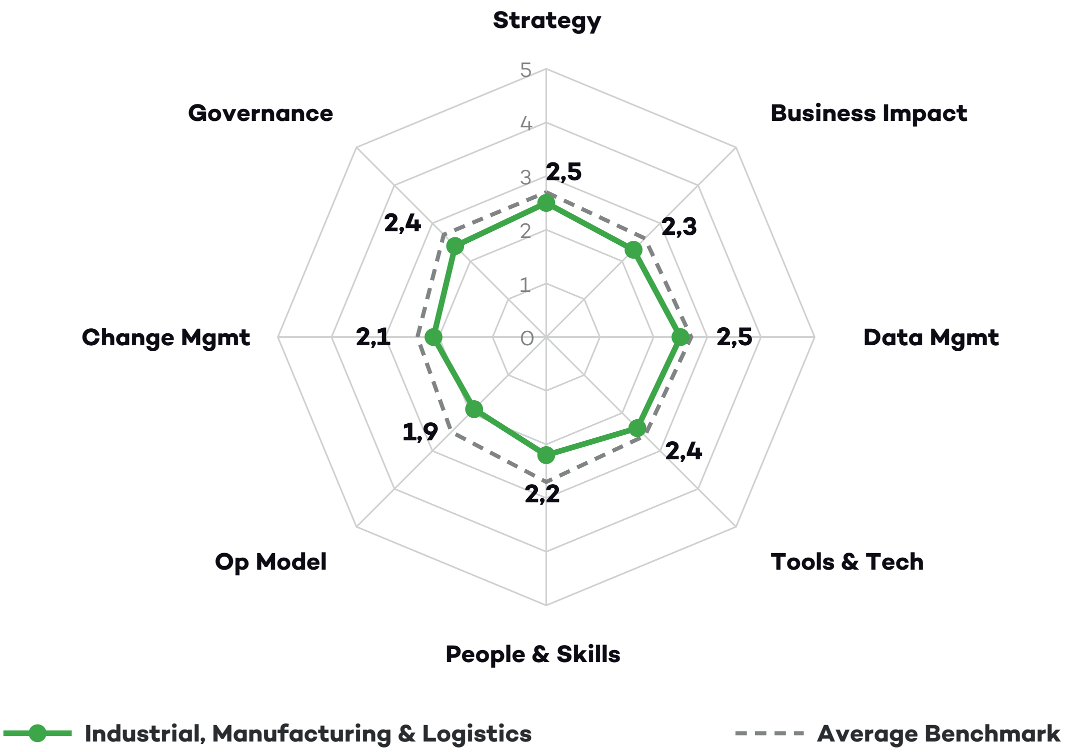

Figure 14: Radar Graph for Industrial, Manufacturing & Logistics Organisational AI Maturity

Country-Specific Observations

While common themes emerge across the organisations included in this study, the results also indicate meaningful variation between countries. These differences are likely influenced by a combination of regulatory environment and organisational readiness rather than any single national factor. As such, the scores should be interpreted as directional indicators based on participating organisations, rather than as definitive rankings.

The chart in Figure 15 focuses on countries where the number of participating organisations was sufficient to support more meaningful comparison. Interviews were also conducted with organisations headquartered in the United States, United Arab Emirates, Switzerland, and Saudi Arabia. However, the number of participants from these markets was comparatively small, and results have therefore not been shown separately to avoid overstating conclusions from limited samples.

Among the countries with larger representation, Sweden recorded the strongest and most balanced performance across the dataset. Scores were consistently high across Strategy & Leadership, People & Skills, and Governance & Ethics, suggesting that many participating organisations in Sweden are beginning to combine strategic intent with workforce readiness and mature governance structures.

Italy displayed one of the most polarised profiles. Participating organisations scored strongly in Data Infrastructure, Tools & Technology, and Governance & Ethics, while scoring materially lower in Operating Model and Change Management. This suggests that technical and control foundations may be developing faster than enterprise-wide adoption and execution capability.

Germany and the United Kingdom both showed balanced mid-range results across most pillars. Neither market produced the highest overall scores, but both demonstrated broad based progress without severe weaknesses. This may indicate steady maturity development across multiple organisational dimensions rather than concentration in a small number of capabilities. France recorded lower average scores across several pillars, particularly People & Skills and Governance & Ethics. This may suggest earlier stage organisational maturity among participating organisations, or a more cautious pace of adoption beyond initial experimentation.

Overall, the findings reinforce that AI maturity does not progress uniformly across markets. Different countries are advancing through different pathways, with some placing greater emphasis on governance and leadership, while others are progressing more strongly in technical foundations or workforce capability. Geography alone does not determine maturity. The more important differentiator is how effectively organisations align strategy, operating model, skills, data, and governance within their own context.

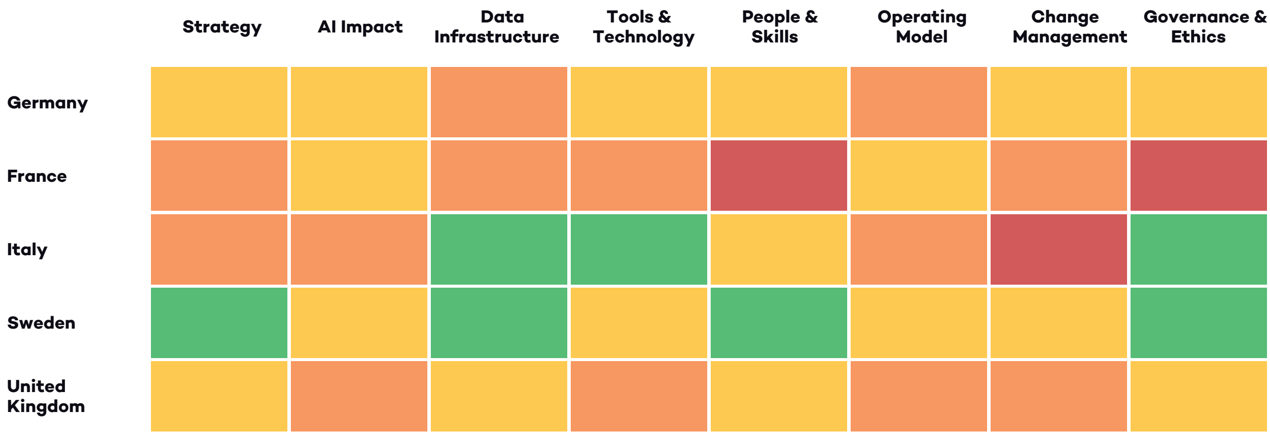

Figure 15: Average AI Maturity Scores Per Pillar Across European Countries

Critical Reflections

While the findings of this research highlight many consistent patterns, they should be interpreted with an understanding of the underlying limitations of the data, and the context in which this data was collected. The results are intended to provide directional insight into relative maturity, rather than precise or absolute measures of performance.

Data Limitations and Interpretations

The maturity scores presented in this report are based on facilitated self-assessments with interviewees and should therefore be interpreted with the necessary amount of caution. Responses have been shaped by individual perspective and organisational context. Interviewees were also assessing their organisations without a defined external benchmark, which introduces further subjectivity. In some cases, scores may reflect perceived capability rather than consistently demonstrated practice.

The distribution of scores also suggests there is some central tendency bias, where respondents avoid selecting the highest or lowest ends of the scale and instead cluster around the midpoint scores. This can be seen in Figure 16, where Levels 2 and 3 account for most responses across all pillars, with comparatively few organisations providing scores of either Level 1 or Level 5. This may compress differences between organisations, industries and geographies and underrepresent the true variance at the upper and lower ends of the maturity scale. As shown in Figure 1, only 0.3 points exist between the highest scoring pillar, Strategy & Leadership (2.7), from the lowest scoring pillar, Change Management (2.4). These differences are still useful in identifying directional patterns, but they should not be treated as precise statistical gaps.

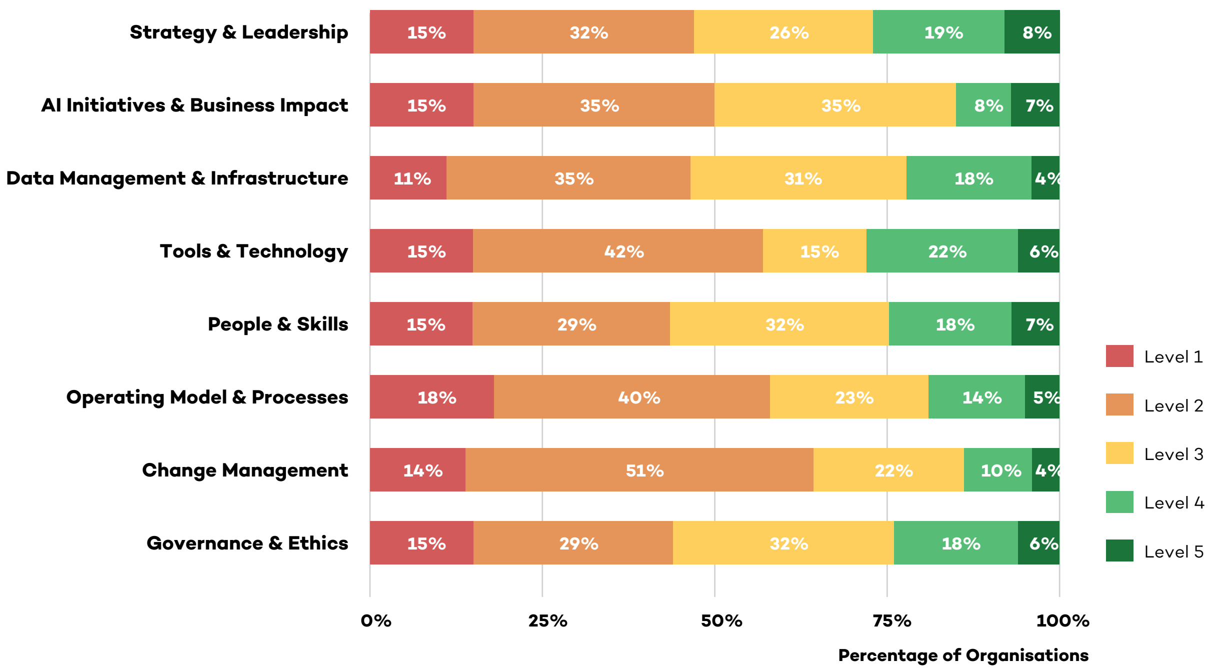

Figure 16: Distribution of Scores Per Pillar of the AI Maturity Framework

Variability and Representation

The sample size of organisations for this research provides broad coverage across industries and geographies, however representation is not perfectly uniform. Some sectors and geographies are more heavily represented than others, which may influence cross-industry comparisons and the ability to draw definite conclusions. Figure 17 below shows the degree of deviation seen across each industry, highlighting that some of the industries which scored comparatively highly against our framework showed large variances in their results.

Furthermore, organisational maturity is dynamic, and scores reflect a point in time assessment within a rapidly evolving AI landscape. This further highlights the importance of interpreting the outputs of this research as directional indicators only.

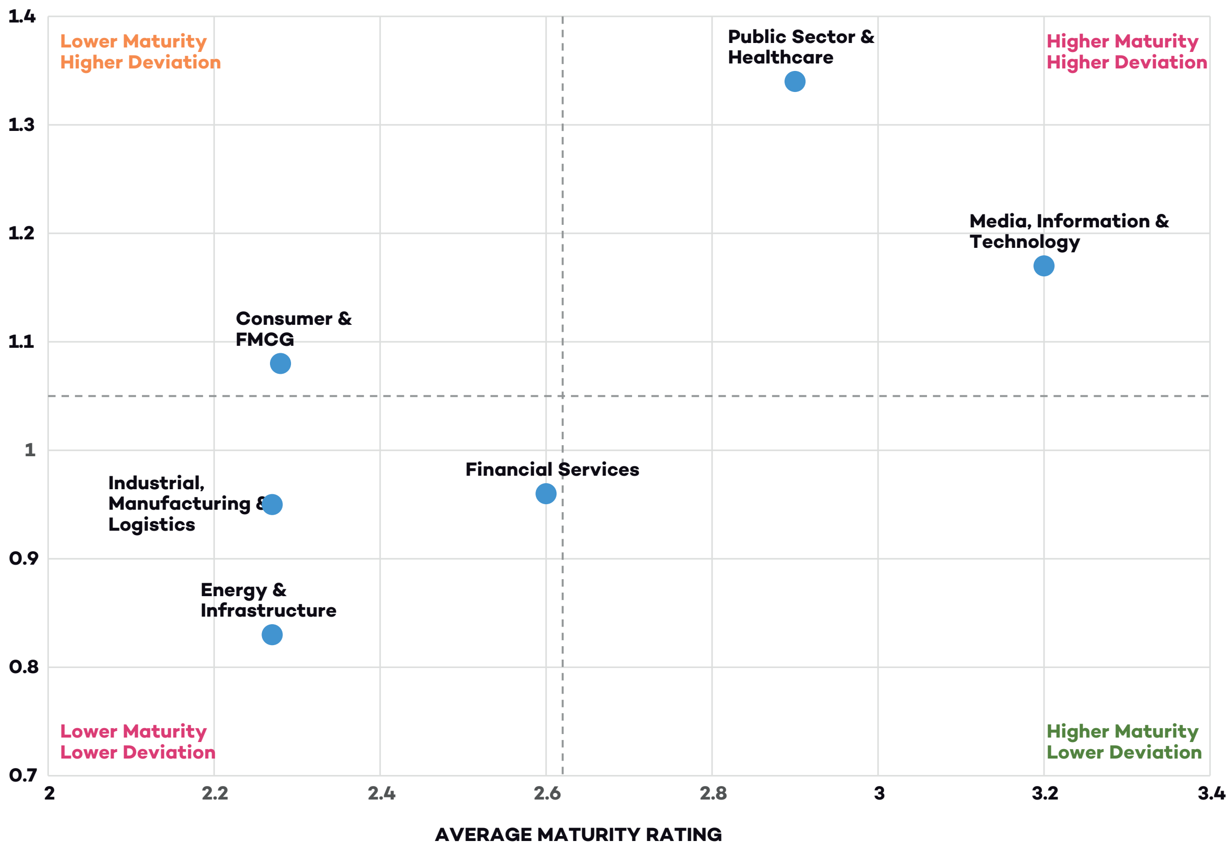

Figure 17: Standard Deviation of Average Maturity Rating Across Industries

Interdependencies Across Capabilities

One of the more notable observations is the degree of alignment between pillar scores within individual organisations. Capabilities within the framework do not tend to develop in isolation. Organisations that score highly in areas such as strategy and leadership are also more likely to demonstrate stronger performance in areas such as data, operating model, and governance. Conversely, lower maturity in one capability is often associated with broader structural gaps. Figure 16 illustrates this point visibly. Though the distribution of scores across every level by each pillar is not exactly uniform, the indicative trends are strikingly similar. This strongly suggests that AI maturity is systemic in nature. Progress is rarely driven by isolated strengths, and constraints in one area can limit advancement across others. The implication is that improving a single capability in isolation is unlikely to translate into meaningful progress without coordinated development across the broader operating environment. As such, the recommendations which are provided by this report and our associated toolkit are ones whilst being aligned to a specific pillar of the framework by label, must be applied in conjunction with activities across other pillars in a connected effort to improve overall maturity.

How Our Findings Challenge Expectations

The Pearson correlation analysis in Figure 18 highlights several areas where our findings diverge from common assumptions about how AI maturity develops. This graph illustrates the strength of the relationship between each pillar of the AI Maturity Framework. The closer the value is to 1, the more positive the relationship (i.e. both variables show a tendency to increase together). An example of this is that Strategy and leadership show weaker relationships with foundational capabilities such as Data Management and Governance than might be expected. While many organisations articulate a clear ambition for AI, this ambition is not consistently grounded in the underlying frameworks required to support it.

A similar pattern is observed when data is considered specifically. Despite being widely recognised as a critical enabler of AI, data maturity appears less connected to execution than anticipated. The low correlation between data and both change management and operating model indicates that strong data foundations do not automatically translate into successful adoption or scale. In practice, organisations can invest significantly in data without seeing a clear impact on how AI is embedded into day-to-day operations.

	Strategy & Leadership	Business Impact	Data Management	Tools & Technology	People & Skills	Operating Model	Change Management	Governance & Ethics
Strategy & Leadership		0.84	0.45	0.64	0.69	0.74	0.63	0.51
Business Impact	0.84		0.52	0.70	0.70	0.76	0.61	0.50
Data Management	0.45	0.52		0.71	0.59	0.48	0.40	0.56
Tools & Technology	0.64	0.70	0.71		0.77	0.72	0.66	0.68
People & Skills	0.69	0.70	0.59	0.77		0.69	0.67	0.59
Operating Model	0.74	0.76	0.48	0.72	0.69		0.74	0.51
Change Management	0.63	0.61	0.40	0.66	0.67	0.74		0.53
Governance & Ethics	0.51	0.50	0.56	0.68	0.59	0.51	0.53	

Figure 18: Pearson Correlation Analysis (r values) of the Pillars of the AI Maturity Framework

By contrast, the Tools and Technology pillar shows consistently strong relationships across almost all other pillars. This suggests that tooling often acts as the central enabler, connecting technical capability with practical application. However, this also highlights a potential imbalance. Organisations may be more effective at deploying tools than embedding the organisational conditions required to use them effectively, leading to environments where capability exists but is not fully realised.

The correlation analysis also highlights the importance of operating model maturity as a key enabler of successful AI transformation. Strong relationships between the Operating Model pillar and several other dimensions suggest that organisations are significantly more likely to realise value from AI when initiatives are supported by clear ownership, coordinated delivery structures, and integrated ways of working.

Governance presents a more nuanced picture. Its comparatively moderate correlation with other pillars may initially suggest that it is less integrated. However, this may reflect the nature of governance itself. Unlike other capabilities, governance often operates as an overarching layer that cuts across strategy, data, technology, and operations, rather than developing as a discrete capability in parallel. As a result, its impact may not be fully captured through direct correlation with individual pillars. In many organisations, governance frameworks are introduced progressively, often in response to regulatory requirements or emerging risks, which can further contribute to this pattern.

Taken together, these findings indicate that AI maturity does not progress in a linear or evenly distributed way. Strength in strategy or technology does not guarantee execution, and investment in individual capabilities does not automatically translate into broader organisational maturity. Progress instead reflects how effectively organisations align and develop these capabilities as an interconnected system, with governance acting as a cross-cutting enabler rather than a standalone pillar.

SECTION 6: **OUR RECOMMENDATIONS & THE AI TOOLKIT**

As indicated by the findings of this report, the most significant barriers to enhancing AI maturity lie in how organisations operationalise, govern, and embed their technical capabilities into their day-to-day ways of working. As established, Operating Model & Processes and Change Management have emerged as the weakest scoring pillars of our framework, with Governance & Ethics also presenting a growing challenge as regulatory expectations evolve and AI is applied in more critical contexts.

At the same time, organisations are operating within an environment where AI innovation is advancing at unprecedented speed. New models, tools, and capabilities are emerging faster than organisations can adapt their structures, skills, and controls. Therefore, it is in these areas that maturity is at greatest risk of diminishing over time due to innovation progressing at a rate which awareness and adaptation can rarely keep up with.

This creates a fundamental tension. Leaders must balance the need to keep pace with sustainable innovation, while building the stability required to scale existing technology effectively. Those that fail to manage this balance risk continued investment without meaningful return.

What Organisations Must Do Next

To move from experimentation to sustained value, organisations must prioritise the capabilities that most directly enable execution at scale. We are now in a phase where the organisational systems around the technology are what require strengthening to maximise value realisation.

Operating Model: Building Around AI Delivery, Not Experimentation

To address the most significant barrier to value realisation, AI needs to be deeply embedded into the core operating model for the organisations of tomorrow. This means clearly defining ownership, establishing consistent pathways from idea to deployment, and ensuring alignment between business priorities and technical delivery.

Rather than managing AI as a series of isolated initiatives, organisations must treat it as an integrated capability that is embedded within business processes. Without this shift, progress will remain fragmented and impact will be limited.

Change Management: A Core Capability for Mature Organisations

AI adoption is a people challenge as much as it is a technological one. While organisations continue to invest heavily in tools and platforms and introduce new AI initiatives as part of their long-term strategic direction, many underestimate the scale of behavioural change required. Employees are increasingly expected to incorporate AI into their roles, yet often lack the clarity, support, and confidence to do so effectively. This results in inconsistent adoption and unrealised value.

As this report has established, leading organisations tend to begin with practical pain points that employees already recognise. This may include repetitive administration, slow approval processes, or time spent on low value manual activity. They then demonstrate how AI can remove friction, improve quality, or create time for higher value work. Training is practical and clearly linked to real workflows rather than abstract theory. Adoption should also be measured over time. Low usage and inconsistent behaviours are the most common signals that additional support may be required for this change to be adequately embedded.

Governance: Creating the Conditions for Responsible Scale

As AI becomes further embedded in decision-making and operations, governance is no longer optional. It is now a prerequisite for sustainable scaling. Many organisations are still in the initial stages of defining their approach, often relying on high-level principles. However, as regulatory expectations increase and AI is applied in more business-critical contexts, this approach becomes increasingly difficult to sustain.

More mature organisations are embedding governance directly into how AI is developed and deployed. Accountability is clearly defined, risks are actively managed, and mechanisms are in place to monitor performance and compliance on an ongoing basis. This is not about constraining innovation. It is about creating the conditions under which innovation can scale safely, responsibly, and consistently.

Value Discipline: Measure What Matters

Several AI initiatives fail because success is never clearly defined. Activity increases, but value remains uncertain, making it difficult for leaders to know where further investment should go. Before investment decisions are made, organisations should define how success will be measured. The right KPI depends on the specific use case and the value being targeted. Productivity initiatives may focus on time saved or faster throughput. Cost focused use cases may track reduced manual effort or lower external spend. Customer initiatives may measure satisfaction, conversion, or response times. Revenue use cases may focus on growth or pricing performance. Whatever the specific performance indicator may be, the key consideration is tying this to broader organisation objectives. Measures should be tracked consistently and communicated frequently to allow leaders to compare the impact of initiatives and prioritise the highest value activities.

Selectivity Around AI Application

A key consideration for every senior leader is that not every process is suitable for AI. It cannot be assumed to be the solution for all business needs. Many organisations waste effort by pursuing use cases that appear interesting on the surface but are structurally weak. Use cases are more likely to succeed where demand is frequent and the ownership around delivery is clear. The availability of reliable data should be the primary consideration when deciding which use case to proceed with, while the expected value should be measurable from the outset. Existing processes with high manual effort and long turnaround times for example, are some of the strongest candidates as it is immediately clear what outcome is desired.

Use cases are far less likely to scale where data quality and availability is poor, responsibilities are unclear, or benefits are too small to justify change. Mature organisations are selective about which AI use cases they pursue. They focus resources where value, feasibility, and readiness align.

Building for Adaptability in a Rapidly Evolving Landscape

Underlying all these priorities is a broader challenge. AI innovation is advancing at a pace that traditional organisational models are not designed to accommodate. Many organisations respond by accelerating experimentation and adopting new tools as they emerge. However, without the right foundations, this often leads to fragmentation rather than progress.

The organisations that are making the most progress are taking a different approach. Rather than attempting to keep up with every new development, they are building the capability to continuously absorb and deploy change. This requires more flexible operating models, governance frameworks that evolve alongside technology, and a workforce that is equipped to continuously learn and adapt. In this context, the objective is not to reach a fixed end state of maturity, but to develop the ability to evolve at the same pace as the technology itself.

A Structured Development Pathway: The AI Maturity Toolkit

Many organisations now recognise the importance of AI maturity, but far fewer have a clear understanding of where they currently stand, which organisational gaps matter most, or how to prioritise action effectively. While the immediate actions required to strengthen AI maturity have been explored throughout this report, the challenge for many leaders is determining what practical steps their organisation specifically needs to take to progress.

To address this, we have developed the AI Maturity Toolkit, designed to provide a practical pathway from ambition to execution.

The toolkit converts the framework presented in this report into a decision support tool for leadership teams. It enables organisations to assess current maturity, benchmark performance, identify the constraints limiting scale, and prioritise the actions most likely to improve outcomes.

This report provides the what and why of AI maturity. The toolkit provides the how. Typical outputs of using the tool include:

- **Executive Maturity Dashboard:** A consolidated view of overall maturity across the eight pillars, highlighting areas of relative strength and the capabilities most likely to constrain progress. This is shown in Figure 19.
- **Peer Benchmarking:** Comparison against organisations of comparable size, industry, or geography, helping leaders understand where they are ahead of peers and where gaps may be emerging.
- **Priority Gap Analysis:** Identification of the capability constraints most likely to be limiting scale, adoption, or value realisation. This helps focus leadership attention on the issues that matter most.
- **Targeted Recommendations:** Practical actions aligned to the organisation's maturity level across each pillar, enabling a sequenced improvement plan.
- **Progress Tracking:** The toolkit can be revisited over time to measure improvement, reassess priorities, and track progress as organisational capability develops.

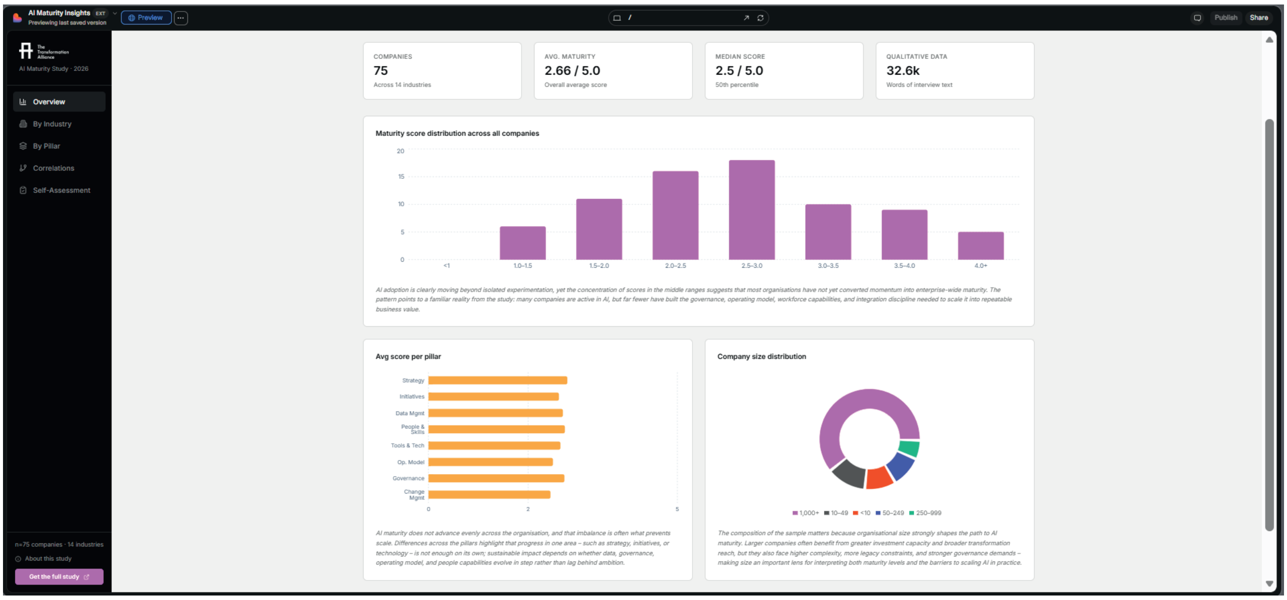

Figure 19: TTA AI Maturity Toolkit Dashboard

Applying the Toolkit in Practice

The toolkit is most effective when used to support structured leadership discussion and focused decision making by applying the following six steps.

Step 1: Establish Your Baseline

Begin by assessing your organisation's current maturity across each of the eight pillars of the framework using our assessment criteria. This creates a shared, evidence-based view of where you are today. It also highlights differences in perception across leadership teams, which are often a barrier to alignment and progress.

Step 2: Benchmark Your Position

Once the assessment is complete, results are benchmarked against organisations within your industry. This provides important context. It helps identify where your organisation is ahead, where it is behind, and where gaps may be limiting your ability to scale AI effectively.

Step 3: Identify the Critical Gaps

The next step is to focus on the areas that are most constraining progress. For many organisations, this will highlight weaknesses in operating model, change management, or governance. These are often the factors preventing successful initiatives from scaling, rather than a lack of ideas or technology. This step ensures that effort is directed towards the areas that will unlock the greatest impact.

Step 4: Define Targeted Actions

Based on the identified gaps, the toolkit provides a set of tailored recommendations aligned to your current level of maturity. These recommendations are designed to be practical and actionable, helping organisations to move from insight to implementation. The focus is on building the capabilities required to scale AI, rather than launching additional isolated initiatives.

Step 5: Implement and Embed

Organisations then move into execution, implementing the required changes across operating model, workforce enablement, technology foundations, or operational governance. At this stage, the focus should be on embedding AI into core business processes and ways of working, rather than treating it as a standalone transformation programme.

Step 6: Reassess and Evolve

AI maturity is not static. As capabilities develop and the external landscape continues to evolve, organisations should revisit the assessment on a regular basis. This allows progress to be tracked, priorities to be refined, and new opportunities to be identified. It also ensures that the organisation continues to adapt in line with the pace of innovation.

Taken together, these steps create a continuous cycle of assessment, action, and reassessment. This approach reflects the reality that AI transformation is not a one-time initiative, but an ongoing capability. Organisations that adopt this mindset will be better positioned to scale AI effectively, sustain value over time and respond confidently as the market evolves.

If you are interested in applying the framework, participating in benchmarking activities, or using the AI Maturity Toolkit to support internal transformation discussions, please do engage directly with authors of this report, or directly with The Transformation Alliance following publication of this research.

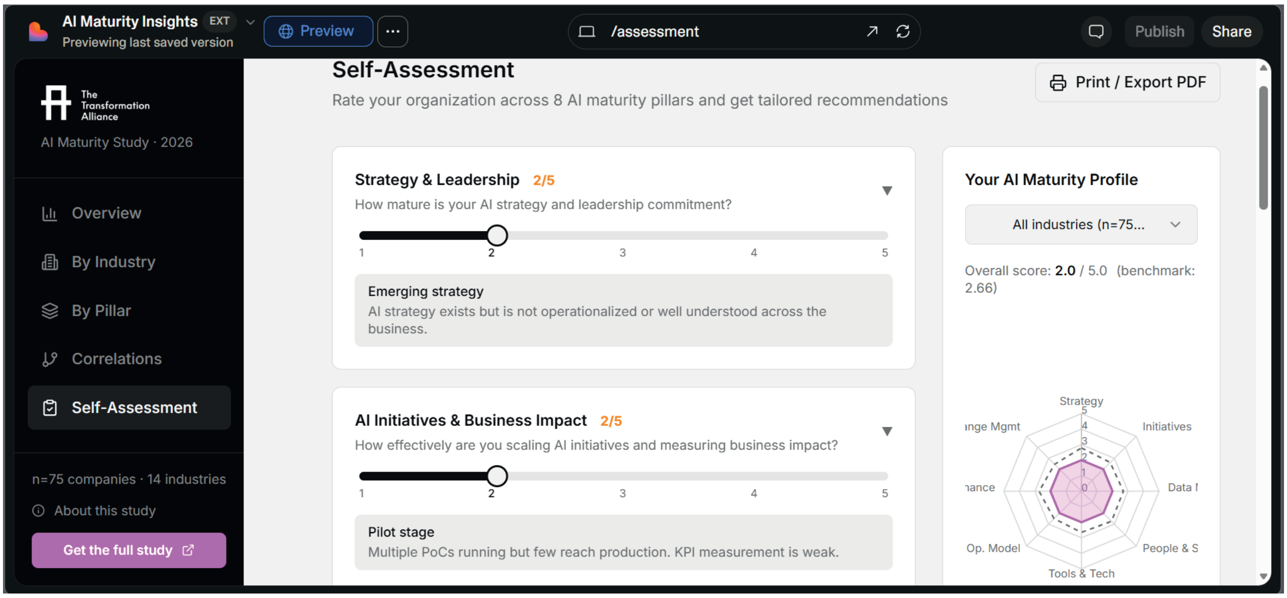

Figure 20: TTA AI Maturity Self-Assessment

SECTION 7: **CLOSING PERSPECTIVE**

For leaders, the AI agenda has fundamentally changed. The question is no longer whether artificial intelligence matters, or whether the organisation should begin experimenting with it. In most sectors, that debate has already passed. AI is now present in some form across products, internal processes, customer service, analytics, or employee workflows. The more pressing question is whether the organisation is equipped to convert growing AI activity into sustained business value.

This report suggests that many organisations are entering a new phase of competition. Access to technology is becoming less of a differentiator as tools, models, and platforms become more widely available. What remains harder to replicate is the organisational capability to deploy AI effectively, govern it responsibly, and adapt continuously as the market evolves.

For leaders, this requires a shift in focus. AI should no longer be treated as a side initiative owned solely by innovation or technology teams. It needs to be managed as an enterprise capability that cuts across operating model, workforce strategy, governance, investment decisions, and performance management.

Leadership teams should frequently be asking themselves several practical questions:

- Do we have clear ownership for AI priorities and delivery?
- Are we investing in the use cases most likely to create measurable value?
- Is our workforce equipped and motivated to adopt new ways of working?
- Do our governance frameworks build confidence without creating unnecessary delay?
- Can our organisation adapt as capabilities and market expectations continue to change?

The findings also highlight two common leadership risks. The first is underreaction, where organisations move too slowly and allow competitors to build structural advantage through faster productivity gains or better decision making. The second is overreaction, where organisations chase every new development without the discipline required to scale effectively, creating fragmentation, duplication, and wasted investment.

The organisations most likely to succeed are those that balance ambition with execution. They remain alert to new opportunities but are selective in where they invest. They build flexible foundations rather than committing too heavily to short term trends. They treat adoption, governance, and value realisation as leadership priorities rather than downstream operational issues.

AI maturity is becoming a reflection of leadership maturity. The winners are unlikely to be those with the most pilots or the loudest ambition. They will be those whose leaders can align the organisation, make disciplined choices, and repeatedly turn technological change into commercial impact.

SECTION 8: **ACKNOWLEDGEMENTS**

We would like to thank the senior leaders and subject matter experts who contributed their time, insight, and experience to this research. Their openness and practical perspectives were invaluable in shaping the findings of this report.

We are also grateful to the organisations that participated in interviews and maturity assessments across multiple sectors and geographies. Their contributions helped create a broader and more representative view of how AI maturity is evolving in practice.

Finally, we would like to recognise the internal teams and reviewers whose expertise supported the development of the AI Maturity Framework and Toolkit.

APPENDIX A: **DETAILED RESEARCH METHODOLOGY**

This report is based on structured interviews and maturity assessments conducted across seventy-five organisations operating across multiple industries and geographies. Participating organisations included businesses headquartered in the United Kingdom, Germany, Italy, France, Sweden, and several additional international markets. While most participating organisations were European, the study also incorporated broader international perspectives through selected interviews and case study inputs.

The objective of the research was to understand how organisations are embedding AI in practice, identify the organisational capabilities required to scale AI effectively, and examine how levels of AI maturity vary across sectors, geographies, and organisational contexts.

The research combined quantitative maturity assessment scoring with qualitative interview analysis. Interviews were conducted with senior business, technology, data, and transformation leaders, including CIOs, CTOs, Heads of AI, transformation directors, operational leaders, and strategy executives. Discussions focused on organisational readiness, adoption challenges, governance maturity, workforce capability, operational integration, and value realisation.
The findings presented in this report are based on directional analysis rather than statistically representative sampling. The intention of the study was not to produce definitive market benchmarking, but to identify consistent patterns, emerging themes, and common capability constraints observed across organisations.

Each of the eight pillars was assessed against a five-level maturity scale ranging from fragmented and ad hoc activity through to embedded, enterprise-wide capability.

At lower maturity levels, AI activity is typically characterised by isolated experimentation, inconsistent ownership, limited governance, and unclear links to measurable business value.
As organisations mature, AI initiatives become more coordinated, supported by improved data foundations, clearer operating structures, stronger governance mechanisms, and broader workforce enablement.

At higher maturity levels, AI becomes embedded within core organisational processes and decision making. Activity is supported by scalable platforms, enterprise-wide capability, integrated governance, and systemic measurement of business impact.

The maturity assessment process combined structured interview responses with guided assessment criteria to support consistency across organisations. Scores were intended to provide directional insight into organisational capability rather than precise quantitative measurement.
Organisations rarely mature evenly across all pillars. In practice, progress is often constrained by weaker organisational capabilities rather than accelerated by isolated areas of strength.
The framework therefore assumes that successful AI adoption depends on coordinated development across multiple dimensions.

APPENDIX B: **FULL PILLAR DEFINITIONS**

Strategy & Leadership

Organisational strategy and leadership form the guardrails of AI maturity, providing the starting point for a business' AI journey. While many organisations are actively experimenting with AI, far fewer have established a clear and aligned view of how it supports long-term strategic objectives. Without this clarity, initiatives often remain fragmented. Investment remains difficult to prioritise, and momentum is hard to sustain beyond initial use cases.

This pillar assesses the extent to which AI is embedded within enterprise strategy and actively championed by senior leadership. It considers whether AI is positioned as a core capability shaping competitive advantage or treated as a collection of isolated initiatives driven by individual teams. It also evaluates how clearly the organisation's ambition for AI is defined, how consistently it is communicated more broadly, and whether employees understand how AI relates to their roles and day-to-day decision-making.

Leadership alignment is often the defining factor between isolated experimentation and scaled adoption. Organisations with higher maturity tend to demonstrate a clearly articulated ambition for AI, supported by strong executive sponsorship and consistent messaging across the business. AI is integrated into strategic planning cycles, reflected in investment decisions, and reinforced through governance and performance management. Accountability for delivery is clearly defined at a senior level, ensuring that initiatives are prioritised, coordinated, and aligned to measurable business outcomes.

In contrast, organisations at earlier stages of maturity often lack a unified direction. While leadership may recognise the importance of AI, the absence of a clearly defined strategy is likely to lead to inconsistent prioritisation. This may then result in the prevailing initiatives being disconnected, and a limited ability to scale successful use cases. Efforts are frequently driven bottom-up, with limited coordination or visibility across the enterprise.

Strategy and leadership anchor AI maturity. Progress across areas such as operating model, data, and workforce capability accelerates significantly when organisations establish a clear strategic direction for AI and align leadership behind it.

AI Initiatives & Business Impact

While strategic ambition defines the direction for AI adoption, organisations must translate that ambition into tangible outcomes to realise value. Pilot activity is widespread in the current AI climate, yet progression beyond proof-of-concept remains a persistent challenge across industries.

This pillar assesses how effectively organisations identify, prioritise, and scale AI initiatives that deliver financial and operational impact. It considers the extent to which use cases are aligned to core business priorities, how success is defined and measured, and whether value is realised consistently across the organisation. While strategy defines the "what" of an organisation's wider direction, this pillar focuses on the "so what," which can be summarised as the delivery of measurable outcomes.

A common pattern observed across organisations is the considerable number of pilots without a clear pathway to scale. Initiatives are often driven by technological curiosity rather than a specific business need, resulting in cycles of experimentation that fail to translate into sustained impact. Without clearly defined success metrics and accountability, even promising use cases struggle to progress beyond initial deployment.

Organisations with higher maturity in this space tend to approach AI initiatives with the same rigour as other strategic investments. Use cases are prioritised based on clear business value, aligned to existing business inefficiencies or growth opportunities, and supported by robust success metrics. Performance is tracked consistently, which in turn enables leadership to evaluate outcomes and reallocate investment toward the highest-impact initiatives. Successful solutions are then scaled systemically as necessary, across the enterprise.

Conversely, less mature organisations tend to adopt a more opportunistic approach, launching initiatives in response to emerging technologies rather than clearly defined business requirements. This leads to fragmented efforts and most significantly, limited return on investment. This pillar reflects an organisation's ability to convert AI ambition into measurable impact. Without structured prioritisation and clear success metrics, AI initiatives are unlikely to progress beyond experimentation. Organisations must ensure that they are evaluating use cases against concise business-wide objectives to ensure maximum value is realised.

Data Management & Infrastructure

AI systems are only as effective as the data on which they are built and integrated. As such, data management and infrastructure form the critical foundation for scalable AI adoption. This pillar assesses the extent to which organisations have established the data capabilities required to support AI initiatives, including data quality, accessibility, governance, and the ability to integrate and process data effectively across the business.

While many organisations possess large volumes of data, comparatively few have the infrastructure and governance required to use it effectively at scale. A common challenge is the gap between data availability and usability. A challenge many organisations are currently experiencing is that data is often distributed across multiple systems and stored in inconsistent formats. Significant effort is then spent on data preparation, limiting the ability to develop and scale AI solutions efficiently and effectively.

The increasing adoption of pre-trained and foundational models further amplifies the importance of strong data foundations. As organisations rely more on external models, the quality and structure of their data become critical in determining the reliability and relevance of outputs.

Organisations with higher maturity in this pillar tend to treat data as a strategic asset rather than a by-product of operations. Data is integrated into well-governed platforms, with clear standards for quality, accessibility, and security. It is structured to support operability across internal systems as well as external models, enabling teams to access trusted datasets and deploy solutions efficiently.

By contrast, less mature organisations operate with fragmented data environments, where information is siloed and difficult to access. Governance is often reactive rather than proactive, and data quality issues are only addressed once they begin to impact AI outcomes. Without accessible, reliable, and well-governed data, organisations will not be able to scale AI effectively, regardless of their investment in tools or models.

Tools & Technology

AI adoption is in large part enabled by the tools and technologies used to develop, deploy, and scale solutions. Without a structured and integrated technology environment, AI initiatives often rely on fragmented tooling and manual processes, further limiting their ability to scale. This pillar therefore assesses the extent to which organisations have established the platforms required to support AI across its lifecycle, from experimentation through to deployment and ongoing operations.

The technology landscape for AI is evolving rapidly. Historically, organisations have focused on building bespoke machine learning models, supported by dedicated data science teams and custom infrastructure. While this remains relevant for certain organisations and specialised use cases, the emergence of large-scale and foundational models has significantly shifted the approach to AI development.

Organisations are increasingly realising value by integrating and adapting pre-trained models rather than building solutions from the ground up. This enables faster deployment and often significantly reduced cost, as well as providing easy access to continuously improving capabilities. As a result, leading organisations are rapidly adopting platform-based approaches that combine internal capabilities with external tools and services, forming part of a broader AI ecosystem.

Organisations with higher maturity establish standardised, scalable platforms that support the full AI lifecycle. These platforms enable rapid experimentation and allow for smooth integration into systems across the business. Tooling is selected based on specific business needs, rather than technical novelty, and is always supported by clear standards and governance.

Less mature organisations, however, often rely on fragmented or overly bespoke tooling, increasing development time, complexity, and cost. In some cases, perceived technological sophistication becomes a barrier to progress, limiting the ability to scale when desired.

The value of AI tools is therefore determined not by their sophistication in isolation, but by how effectively they are integrated into the broader operating environment and aligned to business needs.

People & Skills

While the preceding pillars focus on the technical and strategic foundations of AI, the ability to realise value and execute effectively ultimately depends on people. This pillar assesses whether organisations have the workforce capabilities and training opportunities required to effectively adopt and scale AI. This includes both deep technical expertise and the broader ability of employees to understand and apply AI in their roles.

The nature of required skills is evolving as the implementation of AI technology changes. Historically, organisations prioritised specialist roles such as data scientists and machine learning engineers. While these capabilities remain critical, the emergence of foundation models and AI-powered tools has expanded usage across business functions. Employees in a wide range of roles are now interacting directly with AI to analyse information, support decision-making, and automate tasks.

As a result, organisations must build capability at two levels. Firstly, they require deep technical expertise to design, deploy, and maintain AI systems. Second, they must develop broad AI literacy across the workforce, ensuring employees understand how to use AI effectively, where its limitations lie, and when human judgement remains vital.

Organisations with higher maturity in this space tend to adopt a structured approach to workforce enablement. This includes formal training programmes, as well as clear expectations around AI usage. Continuous learning is embedded across teams, recognising that the technological capabilities evolve rapidly and therefore require ongoing development of internal skills. Critically, leadership plays an active role in setting the tone, reinforcing the importance of AI capability, and ensuring adoption is driven consistently across the organisation.

In contrast, less mature organisations rely on ad hoc skill development, with limited training and unclear expectations. This leads to inconsistent adoption, underutilisation of tools, and a lack of confidence in applying AI effectively.

To summarise, this pillar reflects an organisation's ability to translate technological capability into workforce capability. Without the skills, confidence, and cultural readiness to use AI effectively, even the most advanced technologies will fail to deliver meaningful impact.

Operating Model & Processes

Workforce capability enables AI experimentation, but it does not guarantee that value will be realised at scale. This will also depend on how effectively organisations structure responsibilities, workflows, and decision-making. This pillar assesses how AI initiatives move beyond isolated pilots and become embedded within core business operations and functions.

The Operating Model pillar evaluates how effectively organisations connect strategy, technical development, and business execution. This includes how initiatives are prioritised, how ownership is defined, and how solutions are integrated into day-to-day processes. Organisations with higher maturity in this area adopt operating models which balance scale and flexibility, enabling both coordination and local responsiveness.

A common approach seen across businesses is the establishment of centralised capabilities, such as AI Centres of Excellence or platform teams, combined with decentralised ownership within business units. Central teams provide standards, governance, and shared capabilities, while business units are responsible for identifying use cases and embedding solutions within their domains. This model can often enable both consistency and speed, supporting more effective scaling of AI across the enterprise.

The organisations which are less mature in this area often lack clearly defined ownership and coordination. Initiatives emerge in silos, with limited alignment to business priorities and weak integration into existing processes. Without structures that enable collaboration across business, technology, and data teams, organisations struggle to move beyond experimentation.

This pillar reflects an organisation's ability to translate AI initiatives into operational reality. Without a clear operating model, defined ownership, and integrated processes, AI will remain disconnected from core business activity and fail to deliver enterprise-wide impact.

Change Management

Successful AI adoption depends not only on technology, training, and structure, but also on an organisation's ability to adapt how its people work. This pillar assesses how effectively organisations support workforce adoption by their ability to manage cultural change and embed new ways of working as AI capabilities scale across the enterprise.

Many organisations deploy AI tools rapidly but fail to support employees in adapting their behaviours. Resistance is rarely driven by opposition to the technology itself, but more often it stems from a lack of clarity around roles, expectations, and impact. Employees may be uncertain how AI affects their responsibilities, how to interpret its outputs, or how it should be integrated into existing processes.

Organisations with higher change management maturity take a structured and proactive approach in this area. They clearly communicate the purpose of AI initiatives, link them to strategic objectives, and demonstrate tangible value early in the adoption process. Expectations are well defined, and leadership once again plays an active role in reinforcing consistent messaging. New ways of working are embedded through practical examples, enabling employees to clearly understand how AI supports their roles. Change is treated as an ongoing process rather than a one-off activity. Leading organisations implement formal change management practices, including stakeholder engagement and mechanisms to capture feedback and continuously improve adoption and the wider employee experience.

By contrast, less mature organisations treat change management as an afterthought, prioritising this pillar significantly less compared to other areas. AI tools are introduced without sufficient communication or support. Without a clear understanding of what this means for them, this amplifies resistance within the workforce, and consequently underutilisation across the business.

Governance & Ethics

Effective governance is essential for scaling AI responsibly and sustainably. This pillar assesses how organisations establish the policies, controls, and accountability required to ensure AI is deployed securely, and in line with regulatory expectations.

Governance spans all aspects of AI maturity, influencing how data is managed, how models are developed and deployed, how decisions are made, and how risks are identified and mitigated. As AI adoption increases, the absence of clear governance becomes a critical barrier, introducing risk and undermining trust in AI-driven outcomes.

Many organisations are still developing their approach. In early stages, oversight is often fragmented and reactive, with limited visibility over how AI systems are used. As a result, risks related to bias, data privacy, model reliability, and regulatory compliance may not be fully understood or managed. The evolving regulatory landscape, including frameworks such as the EU AI Act, further increases the need for structured and proactive governance.

Regulatory context plays a key role in shaping how governance is established. In highly regulated industries, such as financial services and healthcare, governance frameworks are typically more mature and formalised, supported by existing risk and compliance structures. In less regulated industries, governance often develops more gradually. While this can enable faster experimentation, it also increases the risk of inconsistent and unmanaged ethical considerations, requiring organisations to take a more deliberate and hands-on approach to defining governance frameworks.

Organisations with higher maturity in this space generally adopt a comprehensive and integrated approach. Clear policies define how AI is developed, deployed, and monitored, with accountability established at both central and business unit levels. Governance is embedded across the full lifecycle of AI initiatives, and ethical considerations are integrated into decision-making rather than treated as a standalone compliance activity.

In contrast, less mature organisations treat governance as an afterthought. Controls are applied inconsistently and responsibilities in terms of who is owning what is often unclear. The limited oversight which exists greatly restricts the ability to scale AI with confidence.

To summarise, this pillar reflects an organisation's ability to balance innovation with control, enabling responsible deployment, effective risk management, and sustained trust in AI outcomes.

APPENDIX C: INDUSTRIAL CLASSIFICATION AND GROUPING

To support meaningful comparison while protecting confidentiality, participating organisations were grouped into broader industry categories for analysis. In several cases, individual subsectors did not provide a sufficiently large sample size to support robust standalone conclusions. Related sectors were therefore combined where they shared similar operating models, regulatory dynamics, customer characteristics, or technology environments. This approach improves comparability across the dataset while recognising that variation may still exist within each category.

These groupings were created to support directional analysis rather than imply that all organisations within a category are identical. In practice, maturity levels can vary significantly within each sector based on organisational size, leadership priorities, regulatory exposure, legacy systems, and investment levels.

Where smaller samples existed, findings in the main report should be interpreted with appropriate caution.

REPORT CATEGORY	EXAMPLE SUBSECTORS INCLUDED
Financial Services	Banking, Insurance, Professional Services
Media, Information & Technology	Media, Entertainment, Telecommunications, IT Services
Consumer & FMCG	Consumer Goods, Retail, Food & Beverage
Industrial Manufacturing & Logistics	Transportation, Logistics, Automotive, Supply Chain
Energy & Infrastructure	Energy, Utilities, Construction, Real Estate, Engineering
Public Sector & Healthcare	Healthcare, Pharmaceuticals, Government, Public Bodies

Table 2: Grouping of Subsectors

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