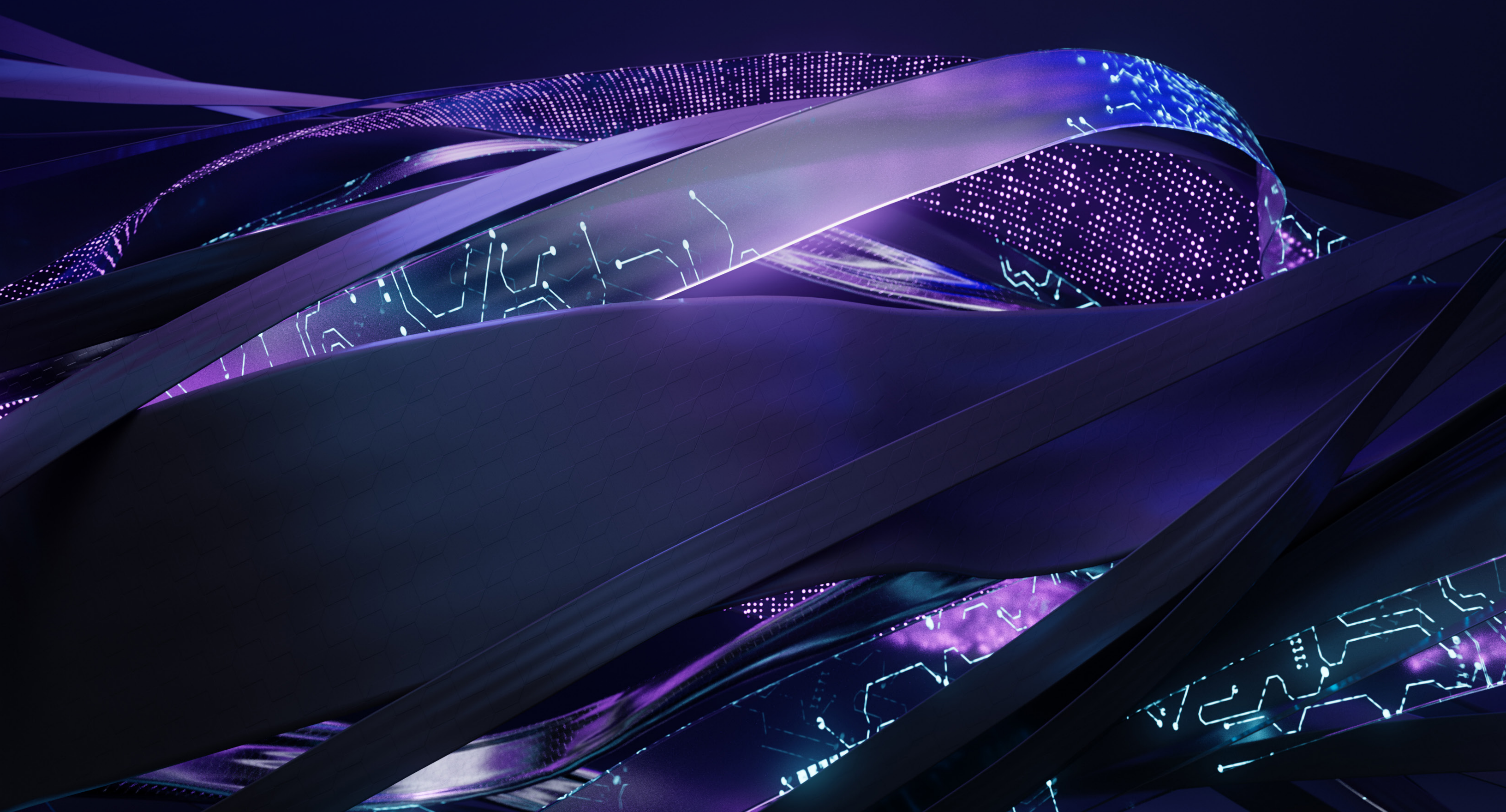
LTIMindtree

Building a Trusted

Data Foundation for Scalable AI

A report by Everest Group



Foreword

Enterprises are accelerating AI adoption, but few understand that data is the foundation. No matter how advanced the models, business outcomes will be constrained if data is inconsistent, fragmented, biased, or inaccessible.

At LTIMindtree, we view a trusted **data foundation** as one of the most critical enablers of enterprise-scale AI. This is not just about fixing pipelines or modernizing platforms. It is about reimagining data as a competitive MOAT governed by accountability, enriched by the business context, and made accessible to the people and systems that use it. When trust is embedded by design, AI systems can operate reliably, deliver outcomes faster, and create measurable business impact.

This Everest Group report provides timely insights into what it truly takes to be AI-ready. It goes beyond the hype to outline the seven pillars of data readiness, share lessons from industry leaders, and present a blueprint for organizations to move from AI experimentation to scaled transformation of business and operations.

Working with global enterprises, LTIMindtree helps leaders build these trusted data foundations so they not only **prepare for AI** but **lead with AI.** This report serves as a practical guide for chief experience officers (CXOs), business leaders, and data and AI leaders seeking to turn AI's potential into enterprise-wide transformation.

Everest Group®

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Building a Trusted Data Foundation for Scalable AI

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Introduction

Enterprise leaders want to scale AI, but questions around data readiness often receive less attention. As enterprises race to embed AI into products, decisions, and operations, one disconnect is increasingly clear: while nearly 90% of enterprises consider AI a boardroom priority, data remains fragmented and underprioritized, often treated as an IT issue rather than a business-critical enabler.

Many enterprises still struggle with legacy data infrastructure, siloed and inconsistent data, weak governance, and talent gaps that hinder AI efforts. Only 28% of enterprises consider themselves advanced in data readiness, the rest remain in early stages, unable to support AI at scale. Without a trusted, high-quality, and accessible data estate, even the most sophisticated AI models will falter.

The timing could not be more critical. Gen AI and agentic AI are driving a sharp rise in enterprise expectations and investment, placing mounting pressure on data systems, teams, and infrastructure. Transformation goals that once sat on multi-year roadmaps have become immediate priorities. Enterprises increasingly recognize that the true bottleneck in “AI readiness” is, in fact, “data readiness.” To explore how enterprises are navigating this shift, Everest Group surveyed executives, senior data and AI leaders, and CDOs at 123 enterprises across industries.

This report draws on the survey findings, select in-depth interviews, and Everest Group’s ongoing research and IP on data and AI to provide:

- A breakdown of why the AI imperative has brought data readiness challenges into sharp focus
- An overview of the current data landscape, including enterprise priorities and key gaps
- A deep dive into the seven core pillars of a scalable, trusted data foundation for AI
- Insight into how leading enterprises are operationalizing readiness through technology, talent, organizational, and governance enablers
- Practical lessons and best practices to avoid pitfalls and accelerate enterprise-scale AI adoption

CXOs, business unit heads, and data and AI leaders can leverage this report to understand what enterprise-wide data readiness entails, identify common gaps that hinder AI success, and shape a focused roadmap for strengthening their data foundations. The insights offer practical guidance on where to invest, what to prioritize, and how to align data efforts with broader AI and business outcomes – ensuring that data becomes a catalyst, not a constraint, in the AI journey.

Need for scaling AI and current enterprise readiness

AI’s growing role in enterprise transformation

AI has shifted from the periphery to the core of enterprise transformation. It is redefining how organizations operate, compete, and innovate, shaping everything from customer engagement to product development. By democratizing access to intelligence and automation, AI has accelerated this shift. The conversation is no longer “Why AI?” but “How to scale it?” CXOs are anchoring AI initiatives to enterprise-wide goals by prioritizing scalable infrastructure, cross-functional adoption, and measurable business impact.

Survey findings reflect this strategic pivot. About 68% of enterprises confirm AI as a strategic priority with structured investments, and another 20% report full board-level ownership and an enterprise-wide mandate. In contrast, only 12% indicate that AI is discussed occasionally with limited investment, and none report reprioritization. This overwhelming executive focus confirms that AI has firmly moved beyond the experimental stage and is now institutionalized as a core driver of enterprise value.

What does it mean to be an AI-ready enterprise?

An AI-ready enterprise is one that successfully moves beyond isolated pilots and proofs of concept to scale AI across the business – consistently, securely, and with measurable impact. Achieving this readiness requires a deliberate shift in how data is managed and used. Data must evolve into a strategic asset, directly tied to business goals, and ready for use across diverse AI applications.

AI-ready organizations typically demonstrate the following traits:

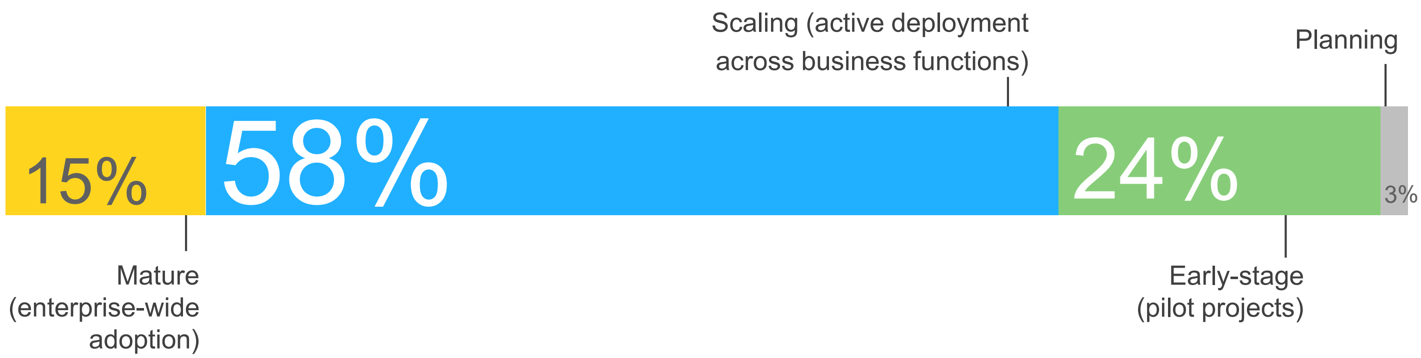
- A well-defined, business-aligned data and AI strategy with executive sponsorship
- Unified governance frameworks that ensure trust, compliance, and agility
- Scalable, cloud-first architecture capable of supporting advanced AI workloads
- Organization-wide data accessibility, enabled by role-based access and self-service platforms
- A workforce that is increasingly AI- and data-literate, supported by structured upskilling and accountability initiatives

However, only a subset of organizations currently meet this bar. While many have moved beyond the planning phase, just 15% report mature, enterprise-wide AI adoption with measurable outcomes, as depicted in Exhibit 1.

Exhibit 1: Enterprise stage in AI adoption

Source: Everest Group (2025)

XX%: percentage of respondents in each stage



This lack of scaled AI adoption highlights structural gaps in enterprise AI readiness, which we will explore in the next section.

What are the underlying challenges?

Most enterprises encounter persistent structural and organizational hurdles when trying to scale AI. These hurdles shift with maturity: early-stage enterprises are typically weighed down by foundational data quality issues, while scaling enterprises face the challenge of maintaining governance and trust as complexity grows.

For early-stage enterprises, the biggest obstacle is poor data quality and availability (85%). Inaccurate, incomplete, or inaccessible data undermines model performance and slows AI deployment. This is closely followed by talent and skill gaps (82%) and budget constraints (79%), which limit the ability to build the infrastructure, processes, and teams needed for scale. Misalignment between IT and business teams (79%) and siloed ecosystems (74%) further delay progress, creating fractured accountability and disconnected pipelines.

For scaling enterprises, the primary barrier shifts to inconsistent data governance (77%). As organizations move toward operationalizing AI at scale, enforcement gaps and unclear ownership begin to erode trust and reliability. Talent shortages (77%) remain a top concern, with greater emphasis on embedding skills across the organization. Other pressing challenges include siloed ecosystems (70%), legacy infrastructure (69%), and IT-business misalignment (69%), all of which undermine agility, integration, and alignment in more complex environments. Exhibit 2 shows how early-stage enterprises and scaling enterprises face different challenges while scaling AI initiatives.

Exhibit 2: Top challenges in scaling AI across enterprises

Source: Everest Group (2025)

XX%: percentage of respondents who ranked each option as high (5-7)

Top challenges for early-stage enterprises		Rank	Top challenges for scaling enterprises	
Poor data quality and availability	85%	1	Inconsistent data governance	77%
Talent and skill gaps	82%	2	Talent and skill gaps	77%
Budget and resource constraints	79%	3	Siloed ecosystems	70%
Misalignment between IT and business teams	79%	4	Legacy infrastructure	69%
Siloed ecosystems	74%	5	Misalignment between IT and business teams	69%

These challenges rarely surface as headline failures. Instead, their impact is cumulative: manifesting as duplicated efforts, disjointed initiatives, and missed opportunities. Across all maturity levels, data-related blockers consistently emerge as the most fundamental constraints to AI success, reinforcing a vital truth: without a trusted, scalable data foundation, AI initiatives will remain limited in scope and impact.

Where enterprises stand today

While most enterprises acknowledge that data is foundational to scaling AI, their current focus areas reflect differing maturity levels. Exhibit 3 shows that:

- 47% are focused on enabling AI through scalable platforms and processes, signaling strong intent to build the underlying plumbing for readiness
- 33% are still standardizing data quality, governance, and access, laying the groundwork to build trust and reduce friction
- Only 20% have elevated data to a true strategic asset, capable of driving monetization, ecosystem collaboration, or competitive advantage

Exhibit 3: Enterprises' current strategic focus for data readiness

Source: Everest Group (2025)

XX%: percentage of respondents

Elevate	Standardize	Enable
Reimagine data as a strategic asset for innovation, monetization, and ecosystem collaboration	Establish consistent data quality, governance, and access across the enterprise	Build platforms and processes that support scalable AI deployment
20%	33%	47%

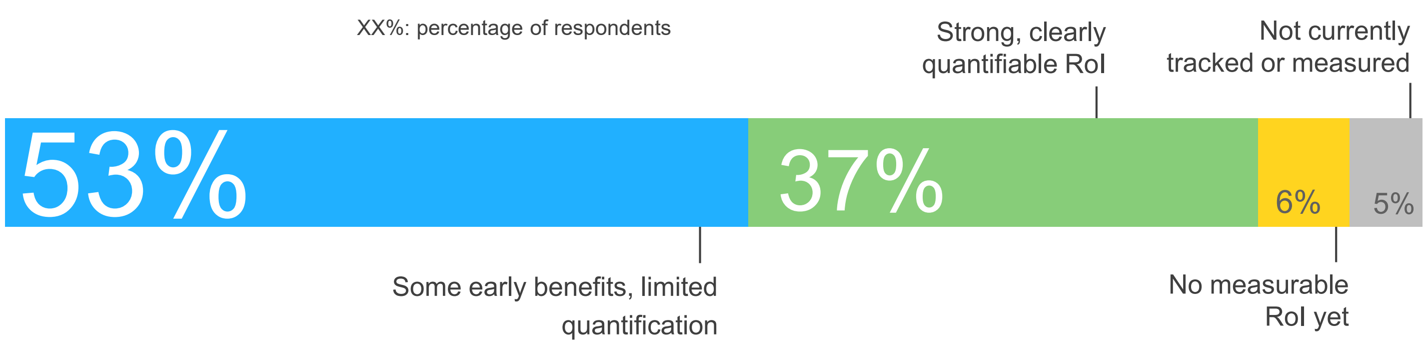
This imbalance highlights an important shift: enterprises are no longer ignoring data, but they are not yet maximizing it. Many still focus on infrastructure and access rather than value realization and differentiation. Even among organizations with defined data strategies, persistent blockers remain – unclear ownership, lack of alignment across teams, and limited support for governance.

The impact of this maturity gap is already visible. Only 35% of enterprises report strong, measurable RoI from their data and AI initiatives. The majority (51%) say they see early benefits but struggle with quantification, while 13% have yet to track impact at all. These figures reveal a consistent pattern: enterprises are investing in AI, but without a scalable, trusted data foundation, value realization remains limited and often delayed, as outlined in Exhibit 4.

Exhibit 4: RoI realization from data and AI investments

Source: Everest Group (2025)

XX%: percentage of respondents



The data imperative for enterprise-grade AI

Dependency on scalable, trusted data foundations

Given the centrality of data-related challenges in scaling AI, it is no surprise that enterprises are reorienting their strategies around data as the foundational enabler. Enterprise-grade AI cannot thrive on fragmented or low-quality data. Scaling requires robust infrastructure that ensures real-time access, cross-functional usage, and governance by design.

Yet only one-third of enterprises report strong alignment between their data and AI strategies. Just 8% describe their data estate as purpose-built for AI, while 25% report having joint roadmaps and funding structures. The remaining 67% continue to operate with partial or ad hoc coordination across teams. This lack of cohesion severely limits the ability to establish scalable data foundations that enable AI at speed and scale.

Executives are increasingly recognizing that trusted, scalable data is no longer a back-end concern, but a board-level priority. These foundations must be designed to support diverse AI workloads, from traditional ML models to Large Language Models (LLMs) and agentic AI, through resilient architectures, embedded governance, and context-rich pipelines. Without this alignment, even the most advanced models will fail to scale effectively.

> "AI does not hallucinate; it tells you what it truly believes to be true. If the data it is using is wrong, it will be confidently wrong."
>
> – Chief Data Officer, FTSE100 defense company

The hidden cost of weak data foundations

Data readiness remains a critical prerequisite for driving meaningful AI outcomes. However, most enterprises still struggle to establish a scalable and well-governed foundation. As depicted in Exhibit 5, when asked about their current state of data readiness, only 28% of enterprises consider themselves advanced, indicating they have scalable, well-governed data systems that may or may not fuel AI aligned to business goals. The remaining 72% fall into typical or nascent categories, suggesting they operate with centralized platforms but inconsistent, siloed data, or minimal accessibility. These organizations often pursue AI initiatives without the foundation needed to support sustained success.

Exhibit 5: Enterprises' current state of data readiness

Source: Everest Group (2025)

XX%: percentage of respondents in each category

Nascent	Typical	Advanced
Siloed systems; limited data access, inconsistent AI/analytics use	Centralized platforms and basic governance in place; inconsistent data and isolated AI pilots	Scalable, well-governed data; real-time, trusted data fueling AI aligned to business goals
3%	68%	29%

The effects of weak data readiness are often subtle but far-reaching. AI use cases stall before reaching scale, leading to inconsistent performance and unclear returns. These gaps slow executive momentum and dampen future investment. The costs are cumulative: every manual override, workaround, or delayed release adds friction to the AI journey. Over time, weak foundations don't just delay value realization, they erode confidence, fragment execution, and limit the scale at which AI can deliver transformation.

The role of data in ensuring AI success

AI performance is inseparable from the quality and readiness of the data it relies on. Poor data results in poor outcomes, from biased predictions and inconsistent model behavior to heightened compliance risks. On the other hand, organizations that invest in strong data foundations consistently achieve faster deployment, broader adoption, and more reliable returns from AI.

Enterprise leaders echo this view. When asked about their top investment priorities in data readiness for scaling AI initiatives, respondents identified the following as most critical: data quality and observability, data governance frameworks, and cloud data platforms and infrastructure. These were followed closely by data talent and literacy, as well as metadata management.

However, recognition is only the first step. To operationalize AI at scale, enterprises must deliberately build these foundations across multiple dimensions. The next section outlines the key data readiness pillars that form the backbone of scalable, trusted AI.

Key pillars of data readiness to enable AI at scale

What makes a strong foundation for enterprise-scale AI? A strong foundation for AI at scale is not the result of a single investment in infrastructure or tools, but rather a connected set of capabilities that ensure data is available, trusted, accessible, and aligned to business outcomes. These capabilities must span both technical systems and organizational readiness. Everest Group's research identifies seven essential pillars that together define true data readiness for scalable AI.

Exhibit 6 illustrates how enterprises are progressing across these pillars, highlighting where most are concentrated today and where gaps in scaled AI persist.

Exhibit 6: Enterprise maturity across key data readiness pillars for AI

Source: Everest Group (2025)

Low	Medium	High
Data culture	Data accessibility	Data strategy
Data products	Data governance	Data quality
	Data foundation	

While each enterprise follows its own path, survey findings highlight clear maturity patterns and persistent gaps:

- **Data strategy and data quality** show relatively higher maturity. Enterprises typically focus on these first, establishing structure, prioritization, and baseline trust in AI outputs
- **Data culture and data products** remain underinvested despite being essential for reusability, adoption, and scale. These suffer from limited executive attention and accountability
- **Achieving data readiness requires balanced progress across all seven pillars** is necessary. Maturity journeys may differ, but these pillars are not designed to follow a fixed order; they can be built sequentially or in parallel based on enterprise priorities. Ultimately, it is the collective strength across all pillars that defines readiness and unlocks the ability to scale AI confidently and consistently

The sections below unpack each pillar in detail: what it entails, why it matters, and where enterprises are gaining traction or facing challenges.

Data strategy

A strong data strategy anchors investments in both business and AI objectives. Without it, downstream readiness efforts often lack direction or executive buy-in.

More than 60% of C-suite respondents say their data strategy remains in early or mid-stages, where efforts are fragmented, inconsistently prioritized, and disconnected from decision-making. Without a clear strategic anchor, enterprises risk investing time and money with limited returns.

Leading organizations go beyond vision documents, directly linking strategy to business priorities, quantifying risks and opportunities, and funding initiatives accordingly.

> "Without a data strategy, efforts around quality, platforms, and governance risk consume time and effort without a clear purpose. The data strategy must tie to the business mission."
>
> – Chief Data Officer, global telecom provider

Data quality

AI is only as strong as the data it learns from. Poor quality often reveals itself too late – through rework, delays, or eroded trust in outputs. Nearly 40% of enterprises report enterprise-scale maturity in data quality, with structured processes across functions. The next challenge is moving from oversight to continuous refinement, which includes defining standards by data type, building feedback loops, and holding stewards accountable for outcomes, not just access.

Leaders embed quality into daily operations, starting with high-visibility domains, ensuring that accountability is clear and ongoing.

Data accessibility

Even the best data loses value if it is difficult to find, access, or use. Accessibility converts data into a usable asset through self-service platforms, role-based permissions, and centralized discovery. Nearly 80% of enterprises have reached or surpassed the standardized stage, where access is documented, repeatable, and aligned with AI goals. More than one in three have scaled further, embedding access mechanisms across teams and workflows.

The leaders are investing in platform-based discovery, streamlined access management, and guided support to ensure data is not only available but also usable at scale.

Data governance

AI cannot scale without trust, and trust depends on robust governance. As AI systems become more autonomous, weak governance carries higher risks. More than 50% of enterprises report having only basic governance frameworks. Policies exist but remain uneven, often treated as an afterthought rather than a built-in safeguard. This creates exposure, especially in regulated environments or high-stakes AI use cases.

Leaders are embedding governance into daily workflows, automating rules, defining escalation paths, and aligning with regulatory and sector-specific requirements to reduce exposure and build trust.

Data foundation

A scalable data foundation underpins modern AI workloads. It includes the infrastructure – pipelines, platforms, storage, and architecture – that enables data to move reliably and efficiently across systems.

While many enterprises have foundational elements in place, progress remains uneven. More than half (54%) cite poor integration across cloud and data platforms as a top constraint. Latency in retrieval systems (50%) and real-time pipeline gaps (33%) continue to slow high-volume gen AI use cases.

At the same time, enterprises are adopting new infrastructure technologies such as lakehouse platforms, vector databases, and gen AI-ready metadata management systems. These reflect a shift toward modular, AI-optimized foundations designed for real-time, multimodal, and increasingly autonomous workloads. Leading enterprises are not just modernizing infrastructure – they are reshaping it for the demands of next-generation AI.

Data culture

Talent and culture are not endpoints; they are ongoing enablers that must evolve alongside every stage of data and AI readiness. Without shared understanding, clearly defined roles, and the right mindset, even the best-designed strategies and platforms struggle to take hold. Everest Group's survey shows that one-third of enterprises remain in the early stages – building awareness and running basic upskilling programs but still lacking formal roles and accountability.

Enterprises advancing in maturity are investing in structured training programs, defining enterprise-wide data roles, and formally recognizing internal stewards. They focus on shaping culture intentionally from the very beginning.

Whether built step by step or developed in parallel, these pillars form the groundwork enterprises need to embed AI at scale with trust, speed, and impact. Together, they determine whether data becomes a bottleneck or a catalyst in the AI journey. Leading organizations are prioritizing areas that accelerate value realization. In particular, data products, governance, and culture are increasingly activated in parallel – not only to improve reusability and control but also to drive faster adoption and RoI across business functions.

Data products

Data products transform raw data into clean, reusable, and governed assets that accelerate AI development. Unlike ad hoc pipelines, they are designed for discoverability, integration, and consistent use across teams by operationalizing data into modular, governed units. Importantly, most data products are domain-specific, built and maintained around the unique needs of business functions such as marketing, finance, or supply chain. This domain alignment shifts the model from pipeline ownership to product thinking, embedding accountability and usability closer to where value is created.

Nearly all enterprises (98%) now recognize data products as part of their data strategy, highlighting a strong shift toward product thinking. However, maturity levels vary significantly. Fewer than half (42%) of enterprises describe data products as a formal strategic pillar or enterprise-wide mandate. The rest are still in early phases; either treating it as a moderate focus (41%) or an emerging topic (15%). This suggests that while interest is high, most organizations are still exploring how to define, embed, and scale the concept effectively. One reason maturity remains limited is that data products are typically designed for use by business teams, not just technical users. Making this model work requires more than technical implementation – it demands clear ownership, strong governance, and a foundation of data literacy.

While not a new concept, data products are gaining renewed prominence as enterprises scale AI. Some organizations are even starting to treat them as monetizable assets – clear evidence that trusted, well-managed data has evolved from a back-end concern into a core business enabler.

Exhibit 7 illustrates early-stage momentum in the types of data products enterprises are prioritizing today, with a preference for use cases that deliver immediate business value or demonstrate quick wins.

Exhibit 7: Most commonly prioritized types of data products

Source: Everest Group (2025)

XX%: percentage of respondents who selected this data product as a current priority

- 56% Customer segmentation or personalization models
- 52% Operational decision-making datasets
- 41% Internal analytics and reporting accelerators
- 38% Risk-scoring or fraud-detection models
- 33% Monetizable external data offerings

Yet, transforming data into strategic assets requires more than intent – it requires operational rigor. Leading enterprises define clear criteria for what constitutes a data product, including ownership, business value, and essential metadata such as quality scores and schemas. They embed data contracts and access controls directly into product design, ensuring each product is modular, discoverable, and governed by design. This disciplined, product-oriented approach transforms raw data into scalable, trustworthy building blocks that deliver far greater impact than isolated pipelines ever could.

The data readiness pillars are not designed to follow a fixed order; they can be built sequentially or in parallel, based on where the greatest need or opportunity lies.

However, understanding the pillars is not enough. Enterprises must bring them to life across teams, systems, and workflows. The next section explores how enterprises are moving from principles to practice, operationalizing data readiness to scale AI effectively.

Operationalizing data readiness: What drives AI success?

It is one thing to define the pillars of readiness; it is another to make them work. Many enterprises understand what they need to do to become data-ready for AI, but far fewer have figured out how to operationalize those capabilities at scale.

Doing so requires more than technology upgrades. It demands a coordinated approach that spans architecture, processes, roles, culture, and governance.

From pillars to practice: activating readiness

Data readiness is an evolving practice that requires continuous operational focus. It involves building modern infrastructure, embedding governance into operational pipelines, and aligning organizational ownership so data consistently supports AI outcomes.

Exhibit 8 shows where enterprises report the highest levels of maturity across both technology and organizational enablers.

Exhibit 8: Top technology and organizational enablers driving data readiness

Source: Everest Group (2025)

XX%: percentage of respondents who ranked each option as high (5-7)

Technology enablers		Rank	Organizational enablers	
Data governance, quality assurance, and observability	65%	1	C-suite sponsorship and advocacy	75%
Enterprise metadata management	59%	2	Clear ownership and accountability across data domains	66%
Automation of data preparation and cleaning	59%	3	Cross-functional operating models involving IT and business	64%
Self-service data platforms or data marketplaces	56%	4	Alignment of data goals with business KPIs	63%
Data integration and orchestration capabilities	55%	5	Formal data councils or governance boards	61%

The findings reveal that while tooling continues to advance, leadership alignment and ownership are equally critical, and in some cases even further ahead. The following sections explore the technology and organizational enablers shaping readiness today.

Technology enablers

Data and AI leaders consistently converge on a core set of technical enablers essential for readiness at scale. These are not abstract design principles but operational capabilities that determine how efficiently enterprises ingest, manage, and activate data across their life cycle.

Enterprise leaders highlight a few standouts:

- **Governance, observability, and quality management** – 65% report maturity in these areas, enabling early issue detection and risks before they impact models or decisions
- **Automation and metadata management** – 59% report advanced automation for data preparation and cleaning, while 59% also highlight enterprise metadata management as a priority for lineage, reuse, and governance
- **Self-service data platforms/marketplaces** – 56% report maturity here, vital for democratizing access to trusted data, reducing reliance on central teams, and accelerating business-driven innovation

In more advanced organizations, these enablers operate as a shared trust layer. Metadata, governance, and observability are integrated to create self-reinforcing ecosystems that deliver explainable, repeatable, and high-quality AI. The shift is clear: from disconnected tools to interconnected systems built to scale AI confidently and continuously.

Organizational enablers

Technology may lay the groundwork, but true data readiness depends on how effectively ownership, decision-making, and execution are embedded across the organization. Enterprises increasingly recognize that structure and accountability are just as critical as tools. Data and AI leaders consistently highlight organizational enablers as make-or-break for readiness, and the strongest signals are coming from the top:

- **C-suite sponsorship and advocacy** stand out as the most widely cited enabler, with 75% of leaders noting strong executive involvement. This elevates data and AI from side initiatives to enterprise imperatives
- **Clear domain ownership and accountability** follow closely, with 66% highlighting strong stewardship models where data responsibilities are formally defined and funded
- **Business alignment** is another differentiator, with 63% reporting that data goals are tightly tied to business KPIs, helping translate platform investments into measurable impact

However, maturity remains uneven. Only 52% of enterprises report having dedicated data or AI enablement teams. This highlights a persistent execution gap, especially in translating strategy into sustained support.

While structural enablers such as sponsorship and accountability provide the foundation, two areas are proving especially pivotal in translating strategy and execution: talent and culture, and governance. These dimensions are embedded elements of organizational readiness that ultimately determine how consistently and confidently enterprises can scale AI.

Talent and culture

Operationalizing readiness depends not only on technology but also on how well the broader workforce is equipped to adopt, apply, and evolve with data and AI. This is not just about building technical talent; it is about embedding data fluency across functions, fostering ownership, and creating a culture that supports experimentation and accountability.

Exhibit 9 illustrates where enterprises currently stand in their talent journey, ranging from early-stage efforts to scaling and maturity.

Exhibit 9: Enterprise talent readiness for AI

Source: Everest Group (2025)

XX%: percentage of respondents at each stage of talent readiness

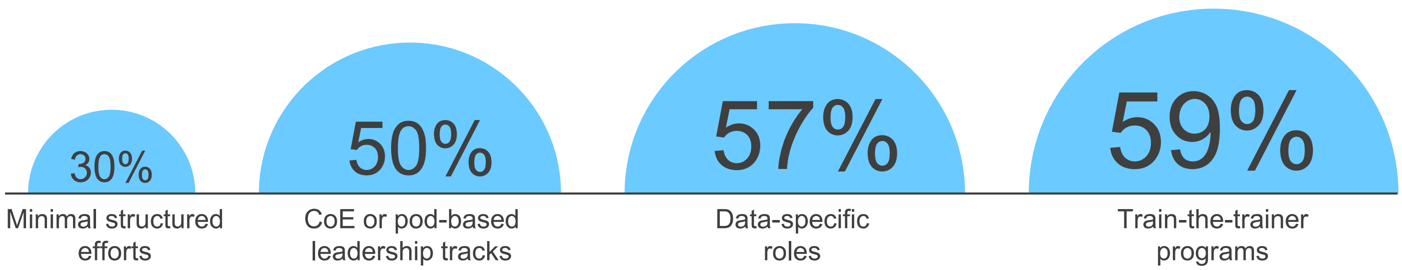
Scaling	Foundational	Emerging	Mature
Growing pool of AI/data-literate talent across business and IT	Adequate skills in isolated teams/functions	Limited internal expertise, external dependencies	Enterprise-wide fluency and skill depth
47%	28%	15%	9%

The distribution reveals that while progress is underway, consistent enterprise-wide readiness remains a work in progress. To accelerate the shift, enterprises are doubling down on enablement programs – from dedicated roles and leadership tracks to capability-building models that can scale across teams – as reflected in Exhibit 10.

Exhibit 10: Enterprise investments in developing data and AI talent

Source: Everest Group (2025)

XX%: percentage of respondents investing in each program



Still, almost one in three enterprises report that their efforts remain minimally structured, highlighting the need for stronger internal scaffolding. The most effective organizations treat enablement as a system: they formalize roles, build communities, celebrate internal champions, and invest in long-term skill-building initiatives that shift both mindset and capability.

Governance

Enterprises are increasingly moving beyond intuition to adopt formal governance mechanisms that enforce and monitor data readiness for AI. These mechanisms do more than track progress – they shape behavior, ensure accountability, and embed trust into how data is accessed, used, and scaled.

Exhibit 11 shows that the most widely adopted mechanism is centralized dashboards, used by nearly two-thirds of enterprises, which track data availability, accuracy, and use.

Exhibit 11: Mechanisms enterprises use to govern and measure data readiness

Source: Everest Group (2025)

XX%: percentage of respondents investing in each program

1. 63% Centralized dashboards to monitor data availability, accuracy, and use
2. 51% Data readiness maturity models or frameworks
3. 51% Regular audits and compliance assessments
4. 50% Scorecards aligned with AI goals
5. 36% Business unit-level data health checks or reporting routines

Ranked highest in governance effectiveness, these dashboards provide real-time visibility into data health and enable proactive intervention when issues arise. Data maturity models and frameworks are the second-most adopted mechanism, offering a structured way to benchmark progress, diagnose gaps, and align teams around common readiness goals. These frameworks help enterprises move beyond one-off diagnostics to continuous readiness evolution.

Also gaining traction are regular audits and compliance assessments, especially as AI expands into regulated or high-stakes domains. Scorecards tied to AI objectives (for example, adoption metrics or value realized) and business unit-level data health checks are also used, though less consistently. Notably, 8% of enterprises still report having no formal measurement or governance system in place, a risky blind spot as AI moves deeper into production environments.

> "Without governance, it is a wild, wild west. You need a board that combines technical people who understand AI with businesspeople who understand the risks."
>
> – Michael Trostle, Director, Global Automation and Manufacturing Analytics, Viatris

Leading organizations treat governance not as a one-time compliance activity but as an operating discipline. They combine quantitative metrics (for example, cost-to-serve, model adoption, and data latency) with qualitative signals (for example, data literacy and usage behavior) to create a 360-degree view of data readiness – measured, enforced, and continuously improved.

The next section highlights the best practices adopted by enterprises that are more advanced in operationalizing data readiness for AI.

Best practices for operationalizing readiness

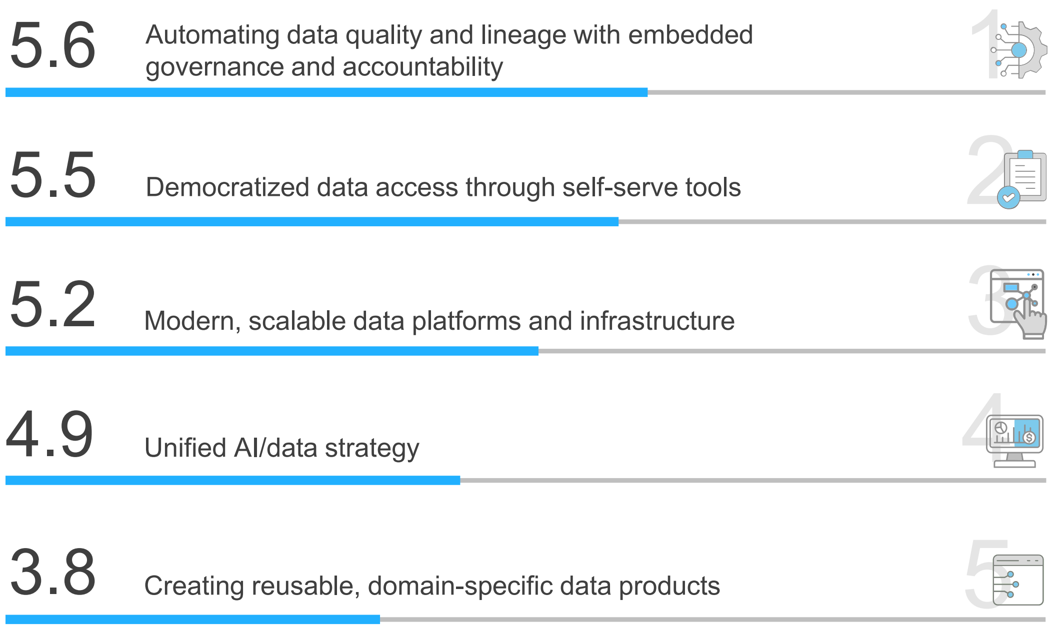
As enterprises move from AI ambition to AI execution, a consistent theme is emerging: data readiness must be operationalized through repeatable, embedded practices. According to Everest Group's survey, a few best practices have proven particularly effective in helping enterprises scale AI with both trust and speed.

Exhibit 12 illustrates the best practices most commonly adopted by enterprises that are advanced in their data readiness for AI.

Exhibit 12: Top best practices adopted by enterprises for AI success

Source: Everest Group (2025)

X.X: weighted average score on a 7-point scale



At the top of the list are automated quality and lineage controls, which reduce manual oversight and embed trust directly into data pipelines. Closely following is the adoption of modern, scalable data platforms and infrastructure – the foundational enablers that support ingestion, movement, and activation of data across enterprise use cases.

Enterprises are also investing in unified AI/data strategies and self-serve data access models to ensure cross-functional alignment and reduce dependence on centralized data teams. These efforts aim to make data not only available but also usable and governed across business functions. Notably, reusable data products are gaining traction, signaling a shift from isolated pipelines to scalable, governed building blocks for AI.

Getting the approach right, however, is only half the battle. The next section examines where many initiatives falter, and why even well-intentioned efforts often run into trouble.

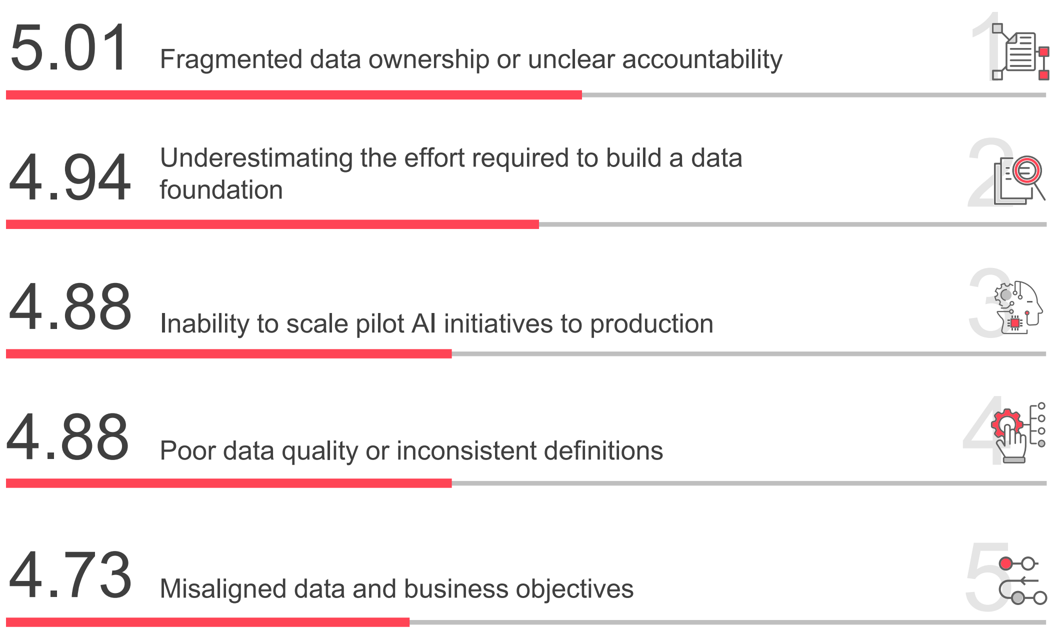
Common execution pitfalls to avoid

Enterprises may have the right strategy, tools, and intentions, but still fall short in execution. Failures are rarely the result of a single factor. More often, they stem from compounding gaps in coordination, timing, and foundational planning. The execution challenges shown in Exhibit 13 are among the most frequently observed across enterprises.

Exhibit 13: Top execution pitfalls in the data and AI journey

Source: Everest Group (2025)

XX: average score for the level of importance on a scale of 1 to 7, 7 being the most important



These challenges reflect structural weaknesses in how organizations coordinate, prioritize, and operationalize their data efforts. What sets more successful enterprises apart is their ability to anticipate and counter these risks with focused, repeatable actions built into their operating rhythm, such as:

- Establishing a board-sponsored steering group with clear escalation paths to align decisions across data, AI, and business teams
- Investing in the data foundation first, ensuring core infrastructure and trust mechanisms are in place before scaling AI use cases

- Defining formal ownership and stewardship models, with accountability tied to funding and decision rights, rather than isolated in central teams
- Prioritizing small, high-visibility wins to generate early momentum and demonstrate value
- Embedding feedback loops and continuous tagging cycles into workflows to surface data issues early and reduce downstream rework
- Tracking both soft and hard metrics, including use, adoption, revenue impact, and cost efficiency, to stay aligned with business outcomes
- Aligning timelines and goals across technical and business teams to avoid duplicated effort and missed outcomes

While many enterprises are actively addressing these challenges today, a new wave of risks is already emerging. This is shaped by shaped by shifting regulations, evolving talent pressures, and the growing complexity of scaling AI.

Emerging risks

Looking ahead, enterprises anticipate a new set of risks that could undermine their data readiness and AI scaling efforts. Everest Group's research highlights where many expect challenges to surface over the next 12-24 months:

- **Regulatory scrutiny** is the top-ranked risk, reflecting uncertainty around evolving compliance demands and their potential to stall or reshape AI initiatives
- **Data governance lagging behind innovation** is nearly tied for first, highlighting the speed mismatch between new AI capabilities and the guardrails needed to support them
- **Inability to operationalize reusable data assets** ranks close behind, reflecting ongoing struggles to scale what has already been built
- **Shifting leadership priorities and talent attrition** feature prominently, signaling that internal alignment and retention remain weak spots
- **Integration challenges** across legacy and modern systems persist, remaining unresolved for many enterprises

It is clear that pitfalls span the entire stack – from technical friction to structural misalignment. Success depends on treating data readiness not as a one-time milestone but as a continuous, enterprise-wide capability that matures alongside AI ambition.

Case study: Scaling AI through strong data foundations at Viatris

Company background and business objectives Viatris is a global pharmaceutical company headquartered in the US, operating in over 165 countries with a workforce of approximately 32,000 employees. The company offers a broad portfolio of medicines, including branded, generic, and complex products, spanning therapeutic areas such as infectious diseases, cardiovascular health, and oncology.

As part of its broader automation and digital transformation agenda, Viatris launched an AI program to modernize legacy workflows, improve operational efficiency, and reduce costs by embedding AI-based automation across manufacturing and commercial operations. Focus areas included streamlining repetitive tasks, accelerating access to SOPs, and other vital documents through chatbots. Efforts also focused on optimizing manufacturing processes, and building a consistent, centralized data foundation to support scalable AI deployments across multiple sites.

Challenges As a highly regulated pharmaceutical company, Viatris encountered several challenges that slowed AI adoption:

- Fragmented data landscapes from acquisitions and siloed systems, making it difficult to centralize, clean, and qualify datasets for AI models
- Inconsistent taxonomy across systems, complicating integration and increasing model training complexity
- Limited explainability and compliance mechanisms, especially for use cases involving regulated pharmaceutical data
- Cross-functional misalignment and internal resistance, particularly from quality and compliance functions

These challenges highlighted the need for a foundational reset across governance, architecture, and organizational structure to scale AI responsibly and securely.

The solution Viatris adopted a phased approach to operationalizing AI, with strong emphasis on governance and platform readiness. It established a cross-functional AI governance board and an IT-led Center of Excellence (CoE) to review use cases, support training, and guide adoption. AI solutions were classified based on data sensitivity: non-confidential, low-risk data was deployed on cloud or enterprise tools; confidential/regulated data was deployed on-premises. To ensure compliance, data loss prevention and security controls were embedded directly into AI systems in collaboration with cybersecurity and data retention teams.

In parallel, Viatris built foundational data enablers vital for scaling AI adoption:

- Standardized taxonomy to create consistent naming and references
- Implemented graph databases to map equivalent terms across systems
- Centralized data within a secure warehouse with built-in access controls
- Applied data segmentation and classification to ensure users accessed only relevant information

Outcomes achieved By addressing foundational issues up front and embedding AI within a governed, scalable model, Viatris achieved notable outcomes:

- **Cost savings:** Reduced document translation time and cost by about 80% through machine translation, eliminating external provider dependency and accelerating multilingual communications
- **Productivity and operational efficiency:**
  - Achieved approximately 10% productivity improvement in functions using AI for document summarization, IT ticket resolution, translation, and internal search
  - Initiated manufacturing AI pilots, such as fluid bed dryer optimization, with projected annual savings of up to US$200,000 per site through improved energy use and runtime
- **Governance and safeguards:** Established enterprise-wide AI governance mechanisms to guide deployment, manage risk, and maintain oversight across functions

Future outlook Viatris plans to continue scaling AI by focusing on repeatable use cases such as predictive maintenance and equipment optimization that can be deployed across global manufacturing sites. To support this, the company is building consistent data models and strengthening instrumentation. Business teams are also taking greater ownership of data assets, developing reusable dashboards and reports, while the AI CoE continues to drive adoption through training and cross-functional engagement.

“Our biggest challenge in scaling AI has been data: cleaning, qualifying, and centralizing it.”

– Michael Trostle, Director, Global Automation and Manufacturing Analytics, Viatris

Conclusion

AI's transformative potential is no longer in question – but its scalability and enterprise-wide impact still are. For many organizations, the critical roadblock is not the algorithm or architecture but the lack of a trusted, scalable, and well-governed data foundation. As enterprise AI adoption matures, one truth is becoming evident: AI readiness is, at its core, a data readiness problem.

While a majority of enterprises have high ambition and strong executive sponsorship for AI, only one in three report strong alignment between their data and AI strategies, and fewer than 30% describe their data estate as mature. Most continue to grapple with fragmented ownership, uneven governance, siloed infrastructure, and limited cultural readiness – factors that quietly but significantly constrain their ability to scale AI with confidence.

The good news is that the blueprint for change is clear. Leading enterprises are operationalizing data readiness across seven key pillars – from strategy and foundation to governance, products, and culture. They are embedding readiness into how teams work, how decisions are made, and how value is realized – not as one-time projects but as repeatable, scalable disciplines.

Ultimately, data readiness is not a checkbox. It is an enterprise capability that must evolve in parallel with AI ambition. For CXOs and data leaders, the priority now is not simply to invest in AI, but to build the data readiness muscle that transforms AI potential into scalable, measurable impact.

Appendix

Everest Group surveyed executives across 123 enterprises as part of this research. The charts below provide demographic details of the respondents.

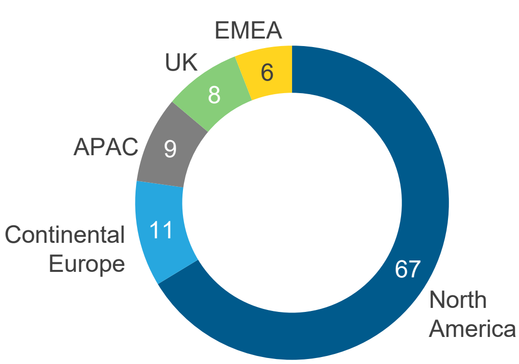
Exhibit 14: Respondent demographics

Source: Everest Group (2025)

XX%: percentage of respondents

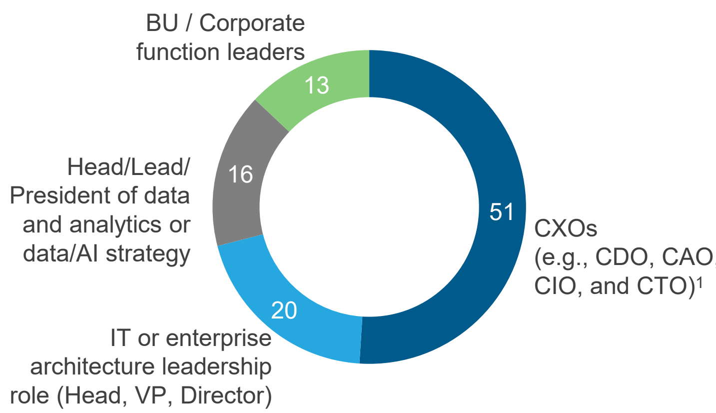
Respondent profile by enterprise geography
Share of respondents

100% = 123



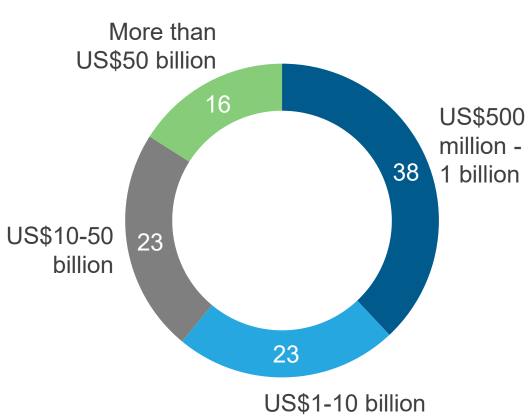
Respondent profile by role
Share of respondents

100% = 123

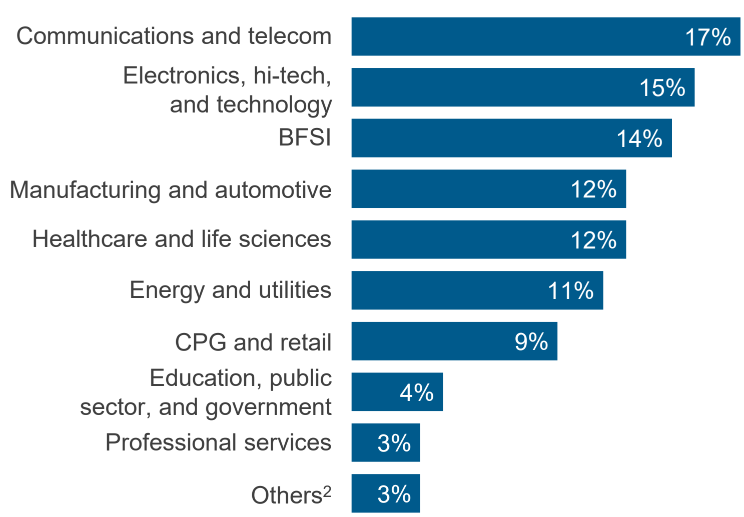


Respondent profile by enterprise revenue
Share of respondents

100% = 123



Respondent profile by enterprise industry
Share of respondents



1 CDO: Chief Data Officer, CAO: Chief Analytics Officer, CIO: Chief Information Officer, CTO: Chief Technology Officer
2 Others include travel, transportation, logistics, and aerospace and defense
Source: Everest Group 2025

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