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SCALING AI INITIATIVES RESPONSIBLY:

The Critical Role of an Intelligent Data Infrastructure

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The rapid growth of AI, ML, and GenAI is a testament to their immense potential to drive innovation, boost efficiency, and unlock new revenue streams for businesses.

Introduction

The world as we know it is transforming before our eyes. Artificial intelligence (AI) has become a focal point of discussions across companies and government agencies. Organizations are increasingly turning to new advancements in machine learning (ML), natural language processing (NLP), and generative AI (GenAI) to address bottom-line challenges, distinguish themselves in saturated markets, and seize topline opportunities to disrupt and outpace competitors. Businesses are now ushering in the next era of digital transformation: the era of AI transformation. This is the era of AI everywhere, where AI underpins practically every aspect of an organization. From digital personal assistants to AI-led therapeutics discovery in healthcare, these sophisticated systems are shaking up how we live, work, and conduct business.

According to IDC's *Worldwide Artificial Intelligence Systems Spending Guide, V1,* (February 2024) — which tracks artificial intelligence (AI) software, hardware, and services across industries and use cases — enterprises worldwide are expected to invest $232 billion on AI solutions in 2024. This spending is expected to grow to $512 billion at a compound annual growth rate (CAGR) of 31% for 2022–2027. This is more than five times greater than the five-year CAGR of 5.7% for worldwide IT spending over the same period. The rapid growth of AI, ML, and GenAI is a testament to their immense potential to drive innovation, boost efficiency, and unlock new revenue streams for businesses. Organizational leaders often expect that with every subsequent AI use case or application, they will achieve faster speed to market and lower costs. However, many organizations are struggling to maintain this momentum as they embark on scaling their AI efforts. Cost, a lack of skills, a lack of access to high-quality datasets, and data security and privacy concerns are the top impediments to scaling AI responsibly.

Organizations often face significant challenges that lead to longer delivery timelines, higher costs, and unintended negative consequences.

To scale AI initiatives responsibly, organizations need an intelligent data infrastructure that has the flexibility to access any data anywhere; active data management to enable superior data security, protection, and governance; and adaptive operations to maximize the performance and efficiency of their infrastructure and applications while optimizing cost and sustainability. Taken together, these capabilities can maximize AI knowledge worker productivity and propel organizations toward more consistent success as they use AI to achieve more for their business.

Leading organizations that make AI transformation the foundation of their business strategy do so responsibly at scale. They drive operational efficiency, attract new customers, and develop new revenue streams faster than their competitors. IDC refers to these companies as AI Masters.

AI Masters can be found in every vertical.

A few of examples include:

Combilift significantly enhanced its spare parts service efficiency and customer satisfaction by implementing an AI-powered product recommender, reducing order errors by 70% and increasing revenue per transaction by 30%. This strategic move showcases the transformative potential of AI in optimizing operational processes and boosting profitability.

Skoda Auto enhanced its electric vehicle production efficiency by implementing AWS' Magic Eye for predictive maintenance, significantly reducing assembly line disruptions through advanced data analysis and real-time monitoring, showcasing a proactive approach to manufacturing challenges.

Estée Lauder Companies Inc.'s partnership with Google Cloud leverages generative AI to enhance online consumer experiences, offering personalized digital interactions and insights into consumer sentiment and significantly improving operations and consumer satisfaction acros their global brand portfolio.

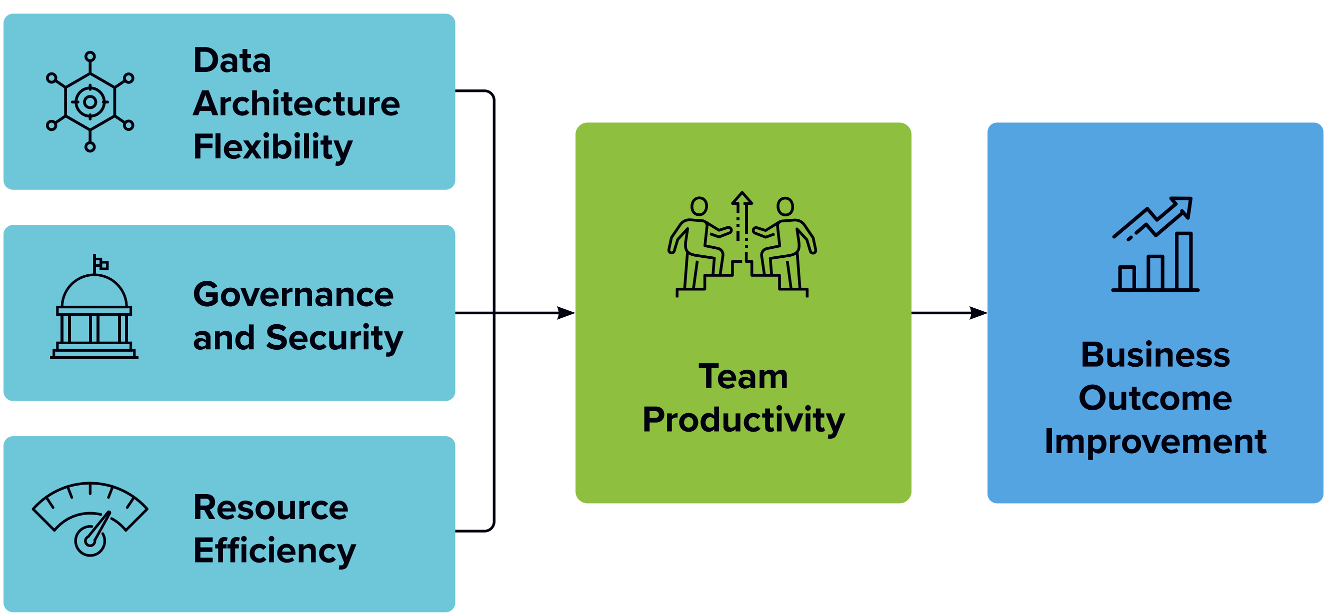
Key Imperatives of Deploying AI Responsibly at Scale

Any organization embarking on an AI transformation journey seeks to use predictive, interpretive, and generative AI to extract deep insights from data by stitching together diverse internal and external data sets, potentially including sensitive and personally identifiable information. The goal for scaling AI initiatives responsibly must be to do so in a seamless manner.

Figure 1 illustrates the three key imperatives that provide the foundation for deploying AI responsibly and at scale. Data architecture flexibility, governance and security, and resource efficiency enable team productivity, which in turn improves business outcomes. An intelligent data infrastructure provides the means necessary to accomplish these imperatives.

FIGURE 1

Path to Deploying AI Responsibly at Scale



For IT organizations responsible for carrying out an AI transformation strategy, it means implementing a data architecture and supporting infrastructure that:

- Provides one-stop access to corporate data wherever it exists for the myriad AI use cases being implemented across the entire organization
- Enables the comprehensive enforcement of security and governance policies across all data so the organization's reputation remains intact
- Achieves maximum resource efficiency and sustainability objectives across their AI initiatives
- Ensures that all teams involved in AI workflows — IT, data science, data engineers, and developers — are highly collaborative and remain hyperproductive

What Is an Intelligent Data Infrastructure?

Infrastructure that provides the flexibility to access any (structured, unstructured, and semi-structured) data anywhere and offers active data management to enable superior data security, protection, and governance with adaptive operations to maximize the performance and efficiency of infrastructure and applications while optimizing cost and sustainability.

About This Study

In December of 2023 and January of 2024, IDC conducted 24 in-depth interviews and 1,220 quantitative interviews by web survey with global decision makers involved in IT operations, data science, data engineering, and software development for AI initiatives. These interviews revealed in-depth information about the state of AI initiatives today, including the array of challenges, numerous business benefits, and best practices that leading organizations have implemented to achieve success.

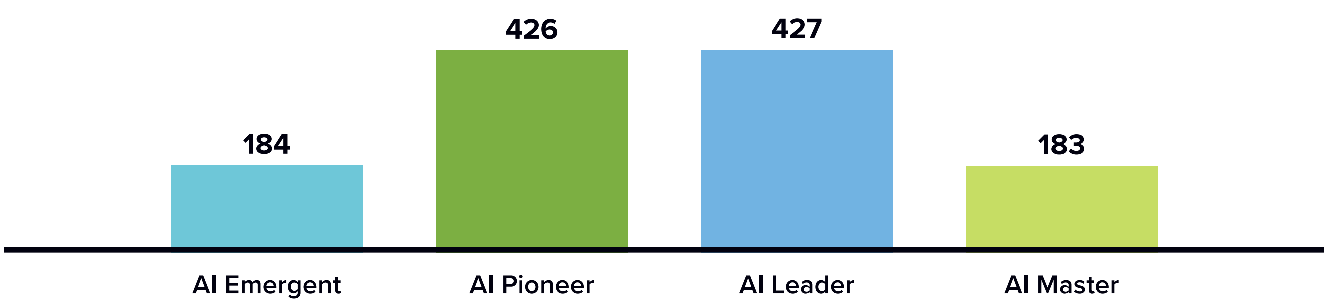
In conducting this analysis, IDC developed an AI maturity model where organizations fall into one of four maturity levels based on their current approach to AI in terms of data and storage infrastructure, data policy and governance, resource efficiency focus, and stakeholder enablement and collaboration. These maturity levels are AI Emergent, AI Pioneer, AI Leader, and AI Master (see **Figure 2**; refer to Appendix 1 for supporting data).

FIGURE 2

AI Maturity Levels

Survey Sample Distribution

(Number of survey respondents)



n = 1,220; Source: IDC's *AI Transformation Study*, January 2024

Through analysis of the organization's experiences using this maturity view, critical areas emerge that organizations need to master to consistently reap the extraordinary business benefits that AI provides.

AI Emergent

These organizations are at the starting point of their awareness of processes and approaches that are critical to AI success (infrastructure, data readiness, governance, security, and stakeholder productivity). Widely disparate data architectures are in use depending on data location and format, with organizations focusing on an array of storage infrastructure improvements, many of which are not directly related to the needs of AI initiatives.

AI Pioneer

These organizations are beginning to execute processes and approaches that are critical to AI success (infrastructure, data readiness, governance, and security, stakeholder productivity). Plans for a more unified data architecture are underway but in the early stages. Storage infrastructure goals are beginning to focus more on AI initiatives, but significant work is necessary on fundamentals such as managing data movement, securing sensitive data, establishing recovery plans, securing endpoints, and establishing a single control plane.

AI Leader

Organizations are midway through implementing many processes and approaches that are critical to AI success (infrastructure, data readiness, governance, security, and stakeholder productivity). A unified data architecture vision is in place, with significant progress made on consistent enterprise-wide data approaches that effectively manage data in all formats and locations. Several data governance objectives have been met, including significant progress on managing auditable copies of data for traceability and managing sensitive data for use in AI training.

AI Master

Organizations employ robust processes and approaches that are critical to AI success (infrastructure, data readiness, governance, security, and stakeholder productivity). A nearly cohesive enterprise-wide data architecture is in place that can support a variety of data formats, structures, and access mechanisms, with data stored and managed in multiple locations that include dedicated (private) and shared (public) cloud environments. Storage infrastructure focuses almost exclusively on optimizing data movement and migration between locations and optimizing access for AI.

Key Findings

Data infrastructure has a foundational role to play in the responsible and scalable implementation of AI. Accordingly, the choices made during the design and planning process can have downstream effects on business outcomes. In other words, the more capable the infrastructure, the more it can help achieve the stated business outcome.

Business Drivers

AI Masters can achieve desired business outcomes faster and more consistently and accurately than AI Emergents (**Figure 3**, next page).

For AI Masters, the importance of AI transformation is reflected in organizational culture. They exploit AI to **increase operational efficiency.** This enables them to **accelerate innovation** turnaround time from order to delivery, upselling and cross-selling products and services, cutting low-margin products and services, and eliminating waste. They use AI to **improve employee productivity,** using AI-aided closed-loop processes in their decision making to increase their chances of better business outcomes. Finally, more AI Masters are leveraging AI to advance enterprise **sustainability goals** than less mature organizations.

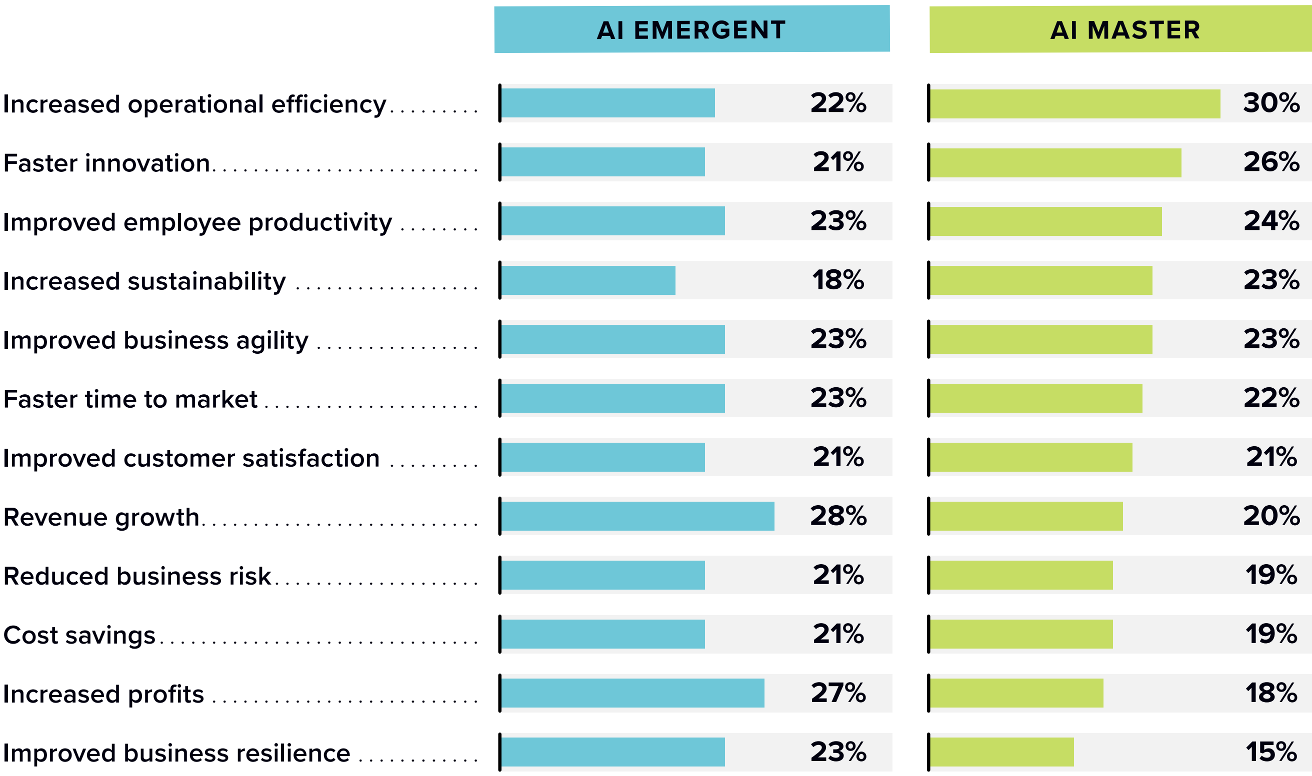
…we do not do a good job of putting this data into a modern architecture, and this is probably our largest challenge… Otherwise, our AI initiatives will likely fail.”

VP of Data Science,
Media and Entertainment, USA

FIGURE 3

Business Drivers of AI

Which of the following were the three most important business outcomes that your organization sought to achieve from its artificial intelligence (AI) initiatives in the past 12 months?
(Percentage of respondents)



n = 1,220; Source: IDC's *AI Transformation Study*, January 2024

AI Initiative Failures

IDC found that not all AI initiatives deliver business outcomes as expected. AI Masters experience a 13% failure rate on average, while AI Emergents see a 20% failure rate on average. However, the reasons for failure are different. AI Masters have more ambitious AI goals, so their reasons for failure are data-related (data access limitations, change management, data expiration, and insufficient data). AI Emergents experience similar challenges but with the added overhead of budget constraints, poor data quality, infrastructure complexity, and large data volumes, for example (see **Figure 4**, next page).

AI INITIATIVES FAILURES:

20% failure rate for organizations at the **AI EMERGENT** maturity level

13% failure rate for organizations at the **AI MASTER** maturity level

FIGURE 4

Reasons for AI Initiative Failures

In your view, what are the main reasons for AI initiatives failing to meet their initial expectations or objectives?

(Percentage of respondents)

	AI EMERGENT	AI MASTER
Inability to access data (infrastructure restrictions)	17%	21%
Inability to access data (business restrictions)	28%	20%
Data sets constantly changing or rapidly expiring	19%	19%
Insufficient data to train models	26%	17%
Privacy or compliance limitations or concerns	20%	16%
Insufficient or lack of initial investments in AI platforms and tools	17%	15%
Data engineering complexity	8%	15%
Data governance requirements	14%	15%
Untrustworthy or poor-quality data sources	19%	14%
Data volumes too large for any meaningful analysis	19%	13%
Lack of C-suite buy-in	17%	13%
IT infrastructure complexity	19%	13%
Insufficient skills in-house	17%	12%
Budget allocation constraints	20%	9%
Lack of organizational buy-in	13%	8%

n = 1,220; Source: IDC's *AI Transformation Study*, January 2024

Improving Business Outcomes

When organizations embark on an AI journey, the incremental benefits they gain from new AI initiatives are enormous. The less mature the organization is with AI, the easier it is to pluck low-hanging fruit and realize immediate and substantial benefits. These benefits include improved business resilience by using AI to reduce points of failure, increased profits from introducing new AI-enabled products and services, greater cost savings by optimizing expenses, and reduced business risk by using AI for if-then analysis. As AI Emergents continue their AI journey, they will begin to realize more sophisticated outcomes through long-term commitment to success, which takes time to evolve, adopt, and master.

This early AI initiative-driven success is confirmed by significant improvements in business outcomes among AI Emergents (see **Figure 5,** next page). For AI Emergents, the 12-month improvement in business outcomes is greater than the improvement realized by their more mature counterparts due to the "low hanging fruit" benefits available to AI Emergents. As the organization matures, the 12-month incremental improvement in business outcomes decreases, but benefits compound throughout the AI journey (see **Table 2 in Appendix 1** for complete 12-month improvement in business outcomes for each AI maturity level).

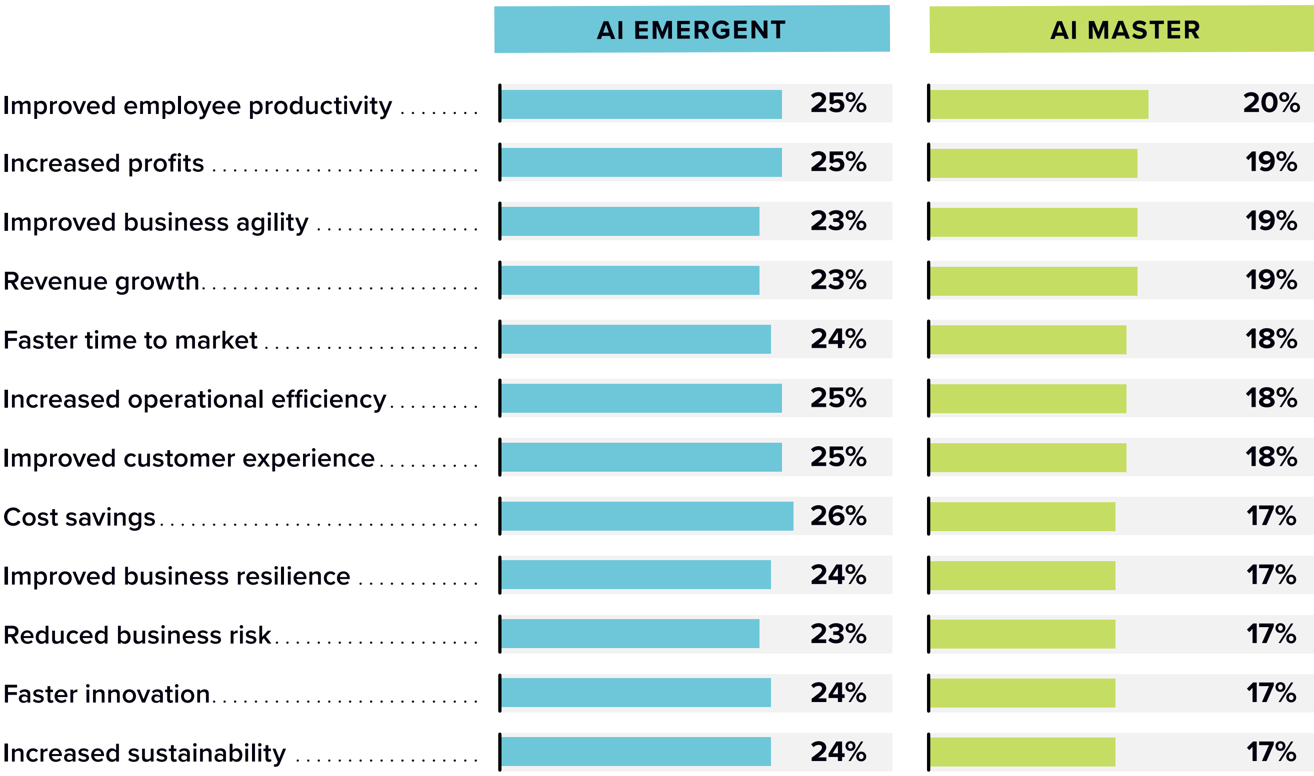
As Emergents continue their AI journey, they will begin to realize more sophisticated outcomes through long-term commitment to AI success, which takes time to evolve, adopt, and master.

FIGURE 5

Business Outcomes Improvement Due to AI

What annual percentage change in the past 12 months did your organization experience in each of the following as a direct consequence of these AI initiatives?

(Percentage of respondents)



n = 1,220; Source: IDC's *AI Transformation Study*, January 2024

"...what we need to improve within our data architecture is the ability to handle multi-modal data..."

VP of Data Science,
Telecommunications, Canada

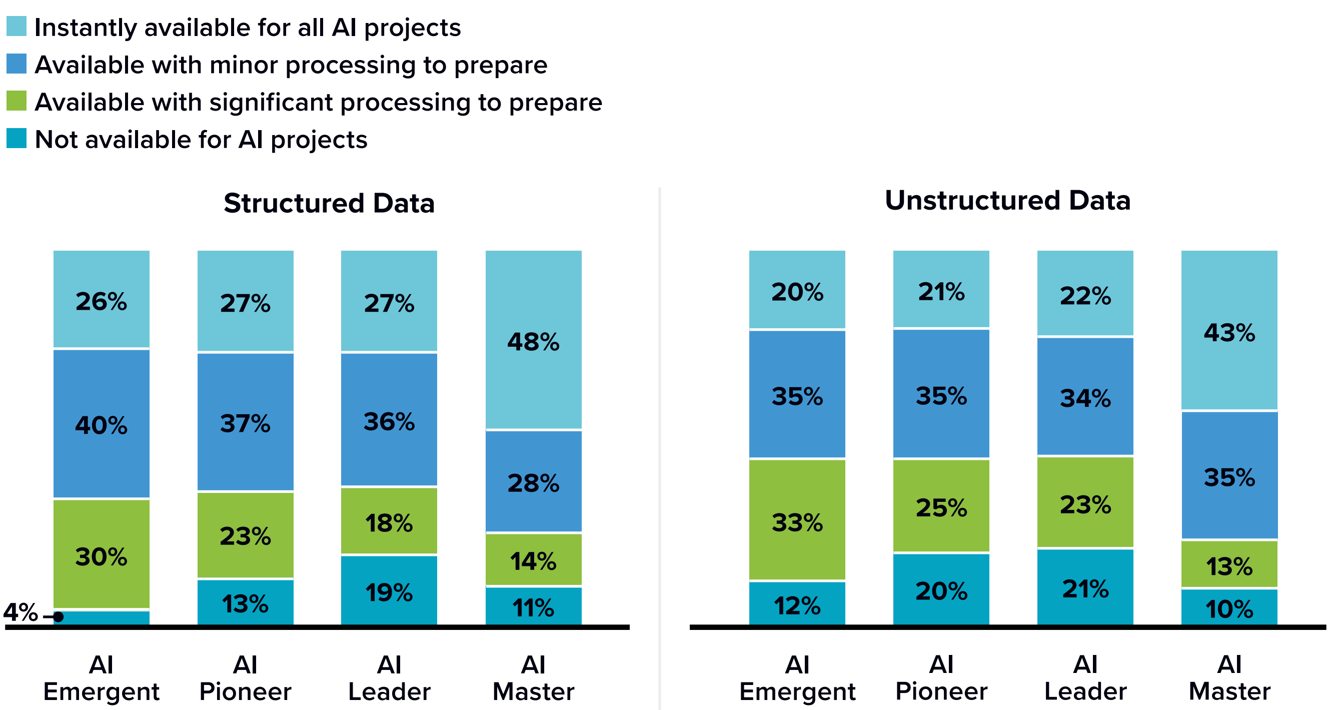
Increasing Data Availability with Infrastructure Flexibility

Infrastructure decisions during the design and planning process must factor in flexibility. AI workflows are complex and vary across stages, requiring ultrahigh performance, massive scale, and high input/output operations per second. Parts of these workflows will ultimately reside both in the public cloud and on-premises cloud and non-cloud environments for the most mature organizations. The dynamic nature of data inputs to AI and GenAI workstreams means ready access to multimodal data (i.e., a combined repository comprising structured and unstructured datasets and data types with varying characteristics) is critical. This dynamic nature also demands the use of a common control plane and management tools; governance, security, and data protection capabilities; and frictionless integrations with dedicated and shared cloud environments and service providers.

FIGURE 6

Data Availability for AI

How available are each of the following types of organizational data for use in projects using AI?
(Percentage of respondents)



Note: Totals may not add up to 100% due to rounding. n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

For an accessible version of the data in this figure, see Figure 6 Supplemental Data in Appendix 2.

AI Masters know that their data infrastructure deployments for transformational AI initiatives offer instant access to corporate data sets or are available with minor preparation or preprocessing (see **Figure 6,** previous page). They design a unified, hybrid, multicloud operating environment that can support multiple data types and access methods.

AI Masters also know that this is not a “one-and-done” decision and design their environment in such a way that it can easily adapt to future performance, capacity, and data services requirements (see **Figure 7,** next page).

AI Masters excel at three key data-related approaches more than their less mature peers:

- Taking advantage of first-party integration of enterprise storage systems and services with native AI services offered by public cloud service providers (e.g., managed generative AI services, hosted MLOps platforms, and native data pipeline services)
- Seamlessly and securely integrating the organization’s private data with cloud AI services, allowing the organization to fine-tune GenAI model responses with private data using methods such as retrieval-augmented generation (RAG)
- Leveraging existing data through newer techniques that are becoming more prevalent in mature organizations, such as “in-place ingest”, which eliminates the cost and complexity of moving data or creating new data silos solely to use the data for generative AI model training

> We’ve realized that we need a multi-(public) cloud environment to take advantage of some of the unique services and capabilities that each cloud has to offer to maximize the benefits of our AI models and strategy.”

VP of Data Science,
Telecommunications, Canada

FIGURE 7

Data Architecture Readiness for AI

Does your organization's current data architecture allow you to do the following?
(Percentage responding "yes")

	AI EMERGENT	AI MASTER
Allow the organization's networks to seamlessly adapt to growth in data use arising from AI projects	65%	67%
Use validated solutions from AI vendors to provision your organization's data architecture on demand when needed	59%	59%
Safely integrate the organization's private data with AI Cloudservices	56%	73%
Seamlessly integrate the organization's private data with AI Cloudservices (fine-tune GenAI models using RAG)	35%	65%
Take advantage of first-party integration of enterprise storage with native AI services from public cloud service providers	46%	67%

n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

Effective Data Governance and Security

The kinds of data that are typically used for AI training and inferencing include some of the most sensitive datasets of an organization. When these data are combined (i.e., unified) in an AI initiative, the exposure of an organization to accidents or potential bad actors significantly increases compared with other corporate data workflows. AI is all about innovation. Governance for AI provides guardrails for that innovation. Without data lineage tracking, organizations can be exposed to data and model poisoning, Personally Identifiable Information (PII) theft, or biased results and hallucinations. Similarly, filtering and excluding intellectual property or Private and Personal Information (PPI) data from model training data sets and limiting (or eliminating) exposure of this data through GenAI algorithms are critical governance and security requirements. Preventing malicious data access from bad actors is an area of ongoing concern. The fear of these types of exposures in itself is likely to slow or even halt innovation. Governance guardrails enable the organization to accelerate innovation knowing that their data remains safe.

“

Anticipate but don’t assume! This proactive approach is vital for safeguarding sensitive commercial and operational data in an increasingly digital and interconnected world.”

VP of Data Science, Education, U.K.

Depending on local cultural norms, businesses in certain geographies can lose the confidence of customers if, in their role as stewards of sensitive data, they handle it inappropriately — even if such data is free of legal or regulatory limitations.

Governance and security enforcements are therefore critical markers of maturity within an organization. Managing data responsibly and securely is an ongoing issue for enterprises, where one or multiple AI stakeholders may try to shortcut the process to accelerate development and deployment; organizations should be ready for potential resistance from these stakeholders that may value agility and time to value over security and governance. With AI and GenAI, this approach cannot be the norm: disregarding internal governance, the ethical use of data, privacy concerns, and bias can destroy the value of AI initiatives.

Security, data sovereignty, and regulatory compliance failures can drastically increase the risk of serious financial, civil, or even criminal penalties. The proliferation of data sources, repositories, and access means increased threat profiles for organizations, while cyber events continue to increase in scale, scope, speed, and sophistication. As a result, companies must prioritize governance and security investment requirements when embarking on any AI initiative.

AI Masters take a deliberate and consistent approach to ensuring governance and security. Here is how they display organizational maturity vis-à-vis their less mature peers:

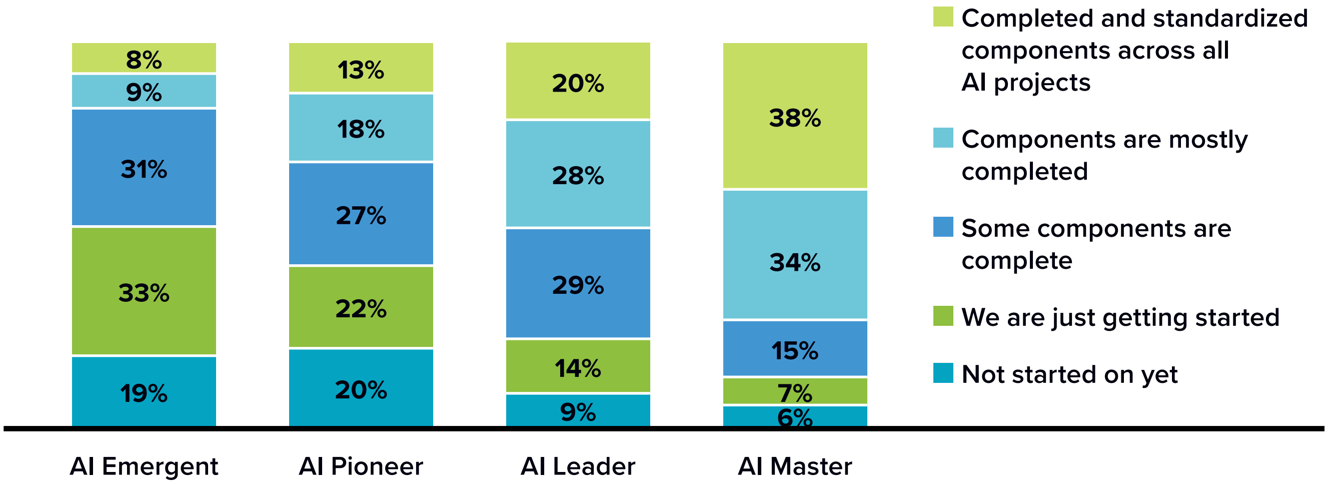
- They ensure that **established AI governance policies and procedures** are fully or mostly completed and standardized across all AI projects (see **Figure 8**, next page).
- They are able to enlist the **services of an independent, internal governing body** to rigorously enforce the usage of AI responsibly and safely (see **Figure 9**, next page). In other words, they make it transparent.
- They have **specific protocols and procedures** to address bias and/or data sovereignty issues across all AI projects (see **Figure 10**, page 19).
- Finally, they have **specific policies and procedures enforced by a central but independent team** to address data security and privacy issues (see **Figure 11**, page 19).

FIGURE 8

AI Governance Policies and Procedures

An AI strategy will have many components. How do established AI governance policies and procedures contribute to the overall AI strategy?

(Percentage of respondents)



Note: Totals may not add up to 100% due to rounding. n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

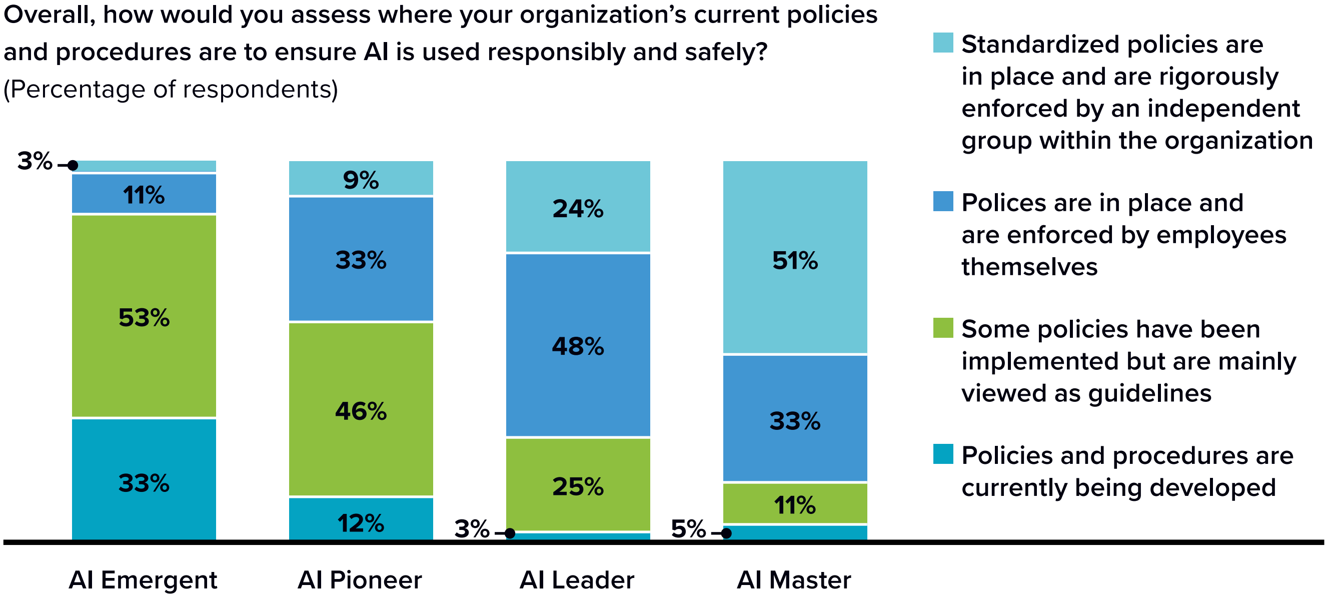
For an accessible version of the data in this figure, see Figure 8 Supplemental Data in Appendix 2.

FIGURE 9

Policies to Ensure AI is Used Responsibly and Safely

Overall, how would you assess where your organization's current policies and procedures are to ensure AI is used responsibly and safely?

(Percentage of respondents)



n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

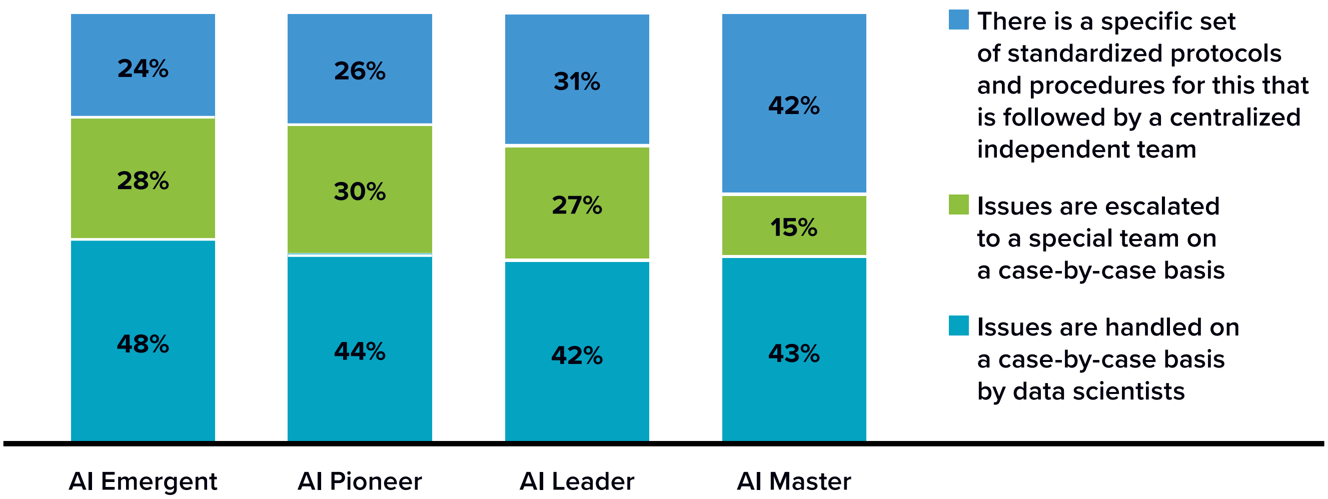
For an accessible version of the data in this figure, see Figure 9 Supplemental Data in Appendix 2.

FIGURE 10

Policies in Place to Address Bias or Data Sovereignty

What policies and procedures does your organization have in place to address data issues arising from bias or data sovereignty concerns in using AI?

(Percentage of respondents)



n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

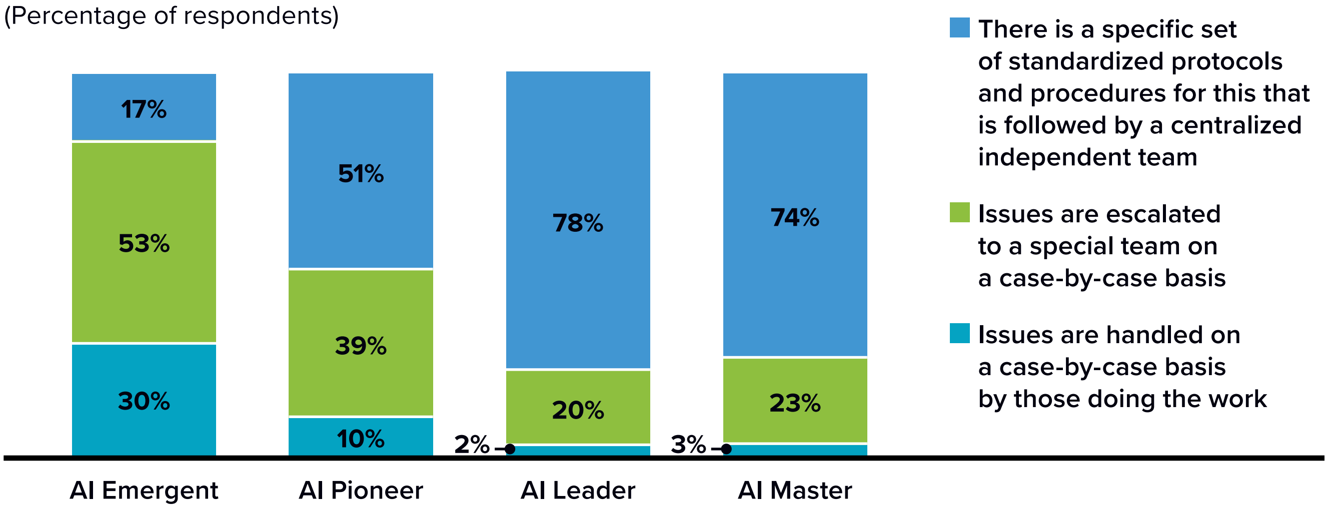
For an accessible version of the data in this figure, see Figure 10 Supplemental Data in Appendix 2.

FIGURE 11

Policies in Place to Address Data Security and Privacy

What policies and procedures does your organization have in place to address data security and privacy issues in using AI?

(Percentage of respondents)



n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

For an accessible version of the data in this figure, see Figure 11 Supplemental Data in Appendix 2.

Resource Efficiency

How can AI transforming organizations better manage the infrastructure needed to support AI and GenAI while achieving timely business outcomes with an eye on cost, performance, energy utilization, and GPU scarcity? This section of the paper addresses how to consider the most resource-efficient solution and make pragmatic choices.

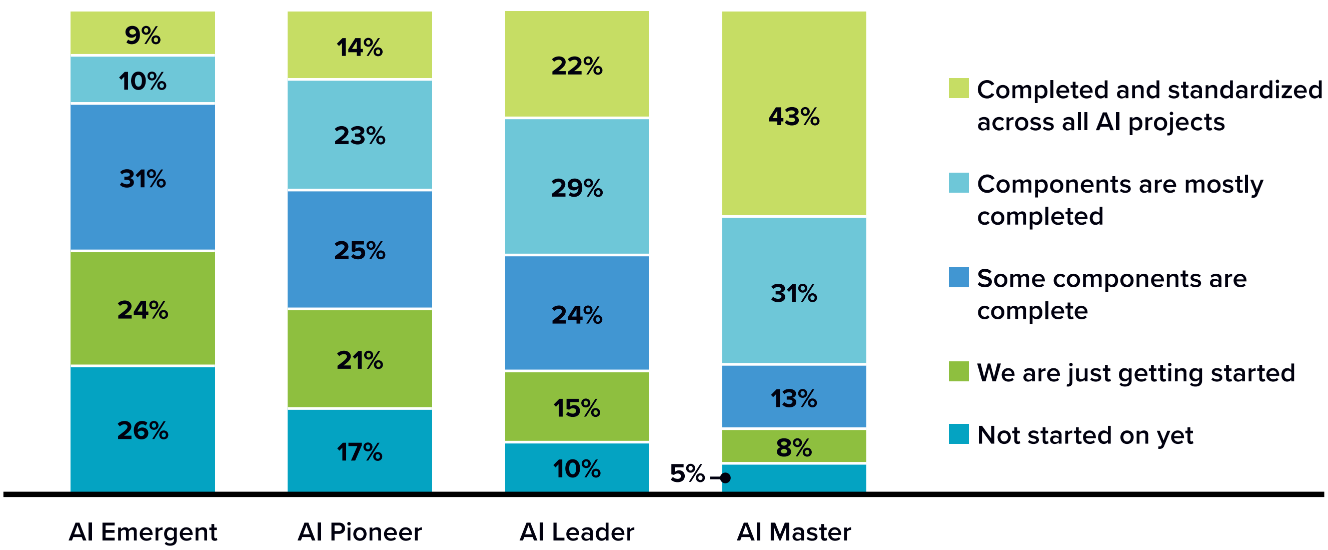
One of the most critical measures of AI maturity is defining and implementing metrics for assessing the efficiency of resource utilization when developing AI models (see **Figure 12**).

FIGURE 12

Assessing the Efficiency of Resource Use

How developed are clearly defined metrics for assessing the efficiency of resource use when developing AI models?

(Percentage of respondents)



n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

For an accessible version of the data in this figure, see Figure 12 Supplemental Data in Appendix 2.

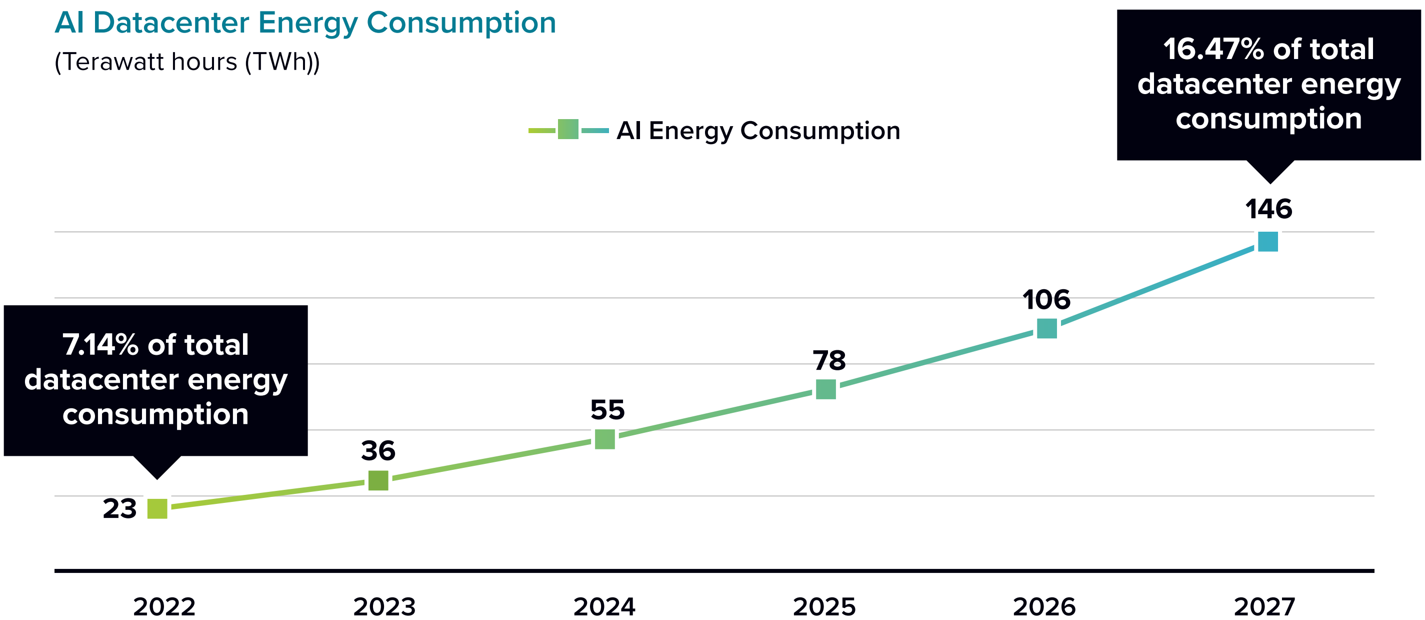
As AI workflows become increasingly integral to various industries, it is important to acknowledge their implications on compute and storage infrastructure, data and energy resources, and their associated costs.

With AI, the energy consumption of data centers is exploding. According to the International Energy Agency (IEA), training a single AI model consumes more power than 100 households do in one year. Per another source (Epoch), the amount of computing power necessary for AI training is doubling every 6 months. IDC has forecasted that AI Datacenter Energy consumption will grow at a 44.8% CAGR from 23 Terawatt hours (TWh) in 2022 to 146 TWh in 2027 (see **Figure 13**).

FIGURE 13

AI Datacenter Energy Consumption

(Terawatt hours (TWh))



Source: IDC *Datacenter Trends - Sustainable Datacenter Builds and CO2 Emissions* (Lead Analyst: Sean Graham)

For an accessible version of the data in this figure, see Figure 13 Supplemental Data in Appendix 2.

In our AI initiatives, goals related to cost optimization and efficient resource utilization, including computing and storage, are critical. These goals ensure that our AI solutions are effective, economical, and operationally sustainable."

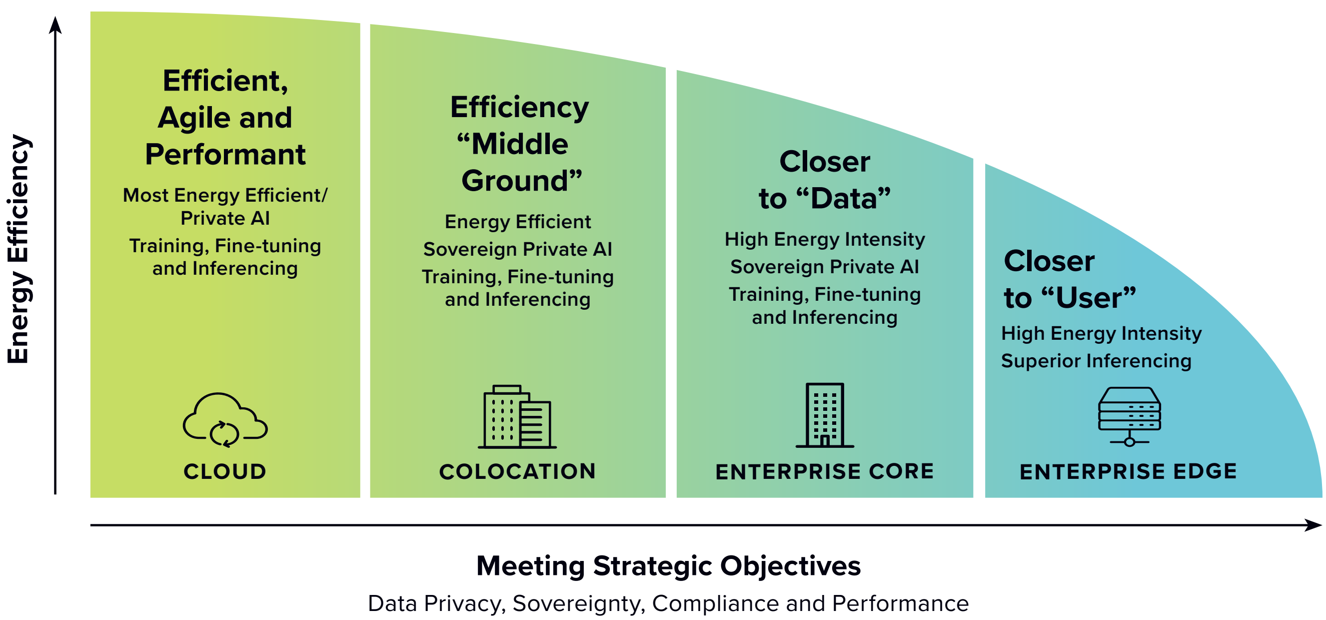
VP of IT Operations, Manufacturing, USA

This growth in energy consumption illustrates that AI can be a double-edged sword. It can be a powerful tool for climate action, improving the efficiency of the energy grid, modeling climate change predictions, or monitoring climate treaties. At the same time, the compute and storage infrastructure necessary to run AI is energy- and resource-intensive. Training or fine-tuning a large language model requires significant infrastructure, which can increase data center energy consumption which in turn requires large amounts of water for cooling its processors. To mitigate data center emissions, industry players have pursued various strategies, including investing in renewable energy and using carbon credits. While these initiatives have yielded some progress, the escalating adoption of AI requires additional measures to responsibly manage energy use and CO2 emissions.

An effective strategy to manage cost and energy use is to consider where the training, fine-tuning, and inferencing are done. Organizations must strike an appropriate balance between locations that offer the greatest energy efficiency with those that offer data privacy, sovereignty and performance benefits (see **Figure 14**).

FIGURE 14

Striking a Balance — Energy Efficiency Amidst Trade-Offs in Data Sovereignty, Compliance, and Performance



n = 599 (total), n = 188 (North America), n = 203 (Asia Pacific), n = 177 (Western Europe). Data weighted by IT spend; Source: IDC *GenAI ARC Survey*, August 2023

While companies have traditionally chosen build over buy a third category is emerging for enterprises pursuing generative AI initiatives: tuning or customizing models.

Build, Buy, or Tune

Another critical factor impacting resource efficiency will be the decision to build, buy, or tune (or all of the above) AI models for each use case. While companies have traditionally chosen build over buy, a third category is emerging for enterprises pursuing generative AI initiatives: tuning or customizing pre-existing models.

Each of the three approaches has their advantages and disadvantages, in terms of TCO and ROI, the time and skilled resources required, and ensuring company IP, corporate and customer data all meet data protection, security, privacy, compliance and governance requirements.

For use cases where an organization has a significant competitive advantage and the necessary skills, data, and budget, it may opt for parameter-efficient fine-tuning and/or grounding using RAG techniques. Taking this approach emphasizes optimized infrastructure and supports resource efficiencies. Conversely, for many use cases, the organization can use off-the-shelf solutions and mitigate additional resource overheads.

Small Language Models Increase Efficiency

Another trend that aims to improve efficiency — especially in enterprises — is using smaller, pre-built GenAI models: small language models (SLMs). SLMs are RAG-ed or tuned before the model itself is shifted to a runtime environment. SLMs can be confined to the bits of the LLMs relevant to the particular use case for which the model is being developed. This contextualization and the elimination of non-useful model elements improves performance and reduces the GPU and infrastructure footprint necessary to deliver the target outcome.

Storage Optimization

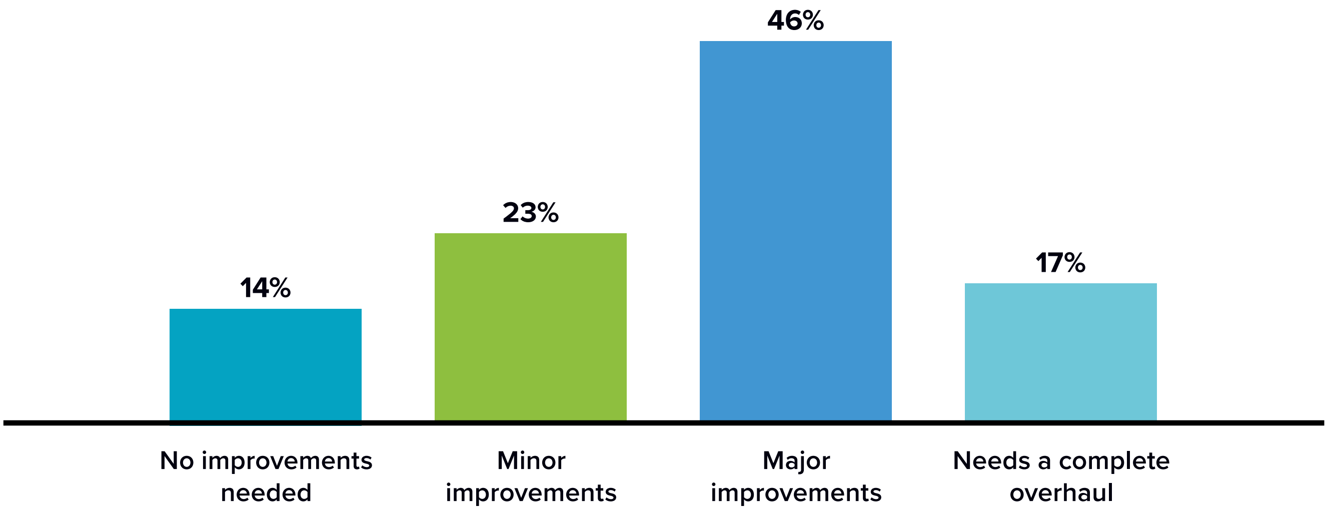
One of the most important areas of overall resource efficiency needs confirmed by our survey relates to storage optimization: 63% reported that their storage needs major improvement or a complete overhaul to be optimized for AI use (see **Figure 15**, next page).

FIGURE 15

Improvement Needed to Rightsize Storage for AI

How much improvement is needed to ensure that storage is optimized and rightsized across the enterprise for use in AI?

(Percentage of respondents)



n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

With the high cost of capital and current economic uncertainty, it can be dangerous for organizations to overprovision resources to ensure they're getting the capacity and performance necessary to make AI work in their enterprise.

It can also take focus and resources away from other critical IT projects, increasing risk and building technical debt in the organization. However, trying to deploy AI or GenAI on a shoestring can impact time to value, resource utilization, and worker productivity lowering total return.

Finding the right balance between these two extremes is an organizational imperative. Removing bottlenecks, making data available quickly and seamlessly to the most cost-effective infrastructure in a hybrid multicloud environment, and ensuring that the right data — and only the right data — is part of AI workflows are all keys to optimizing the AI infrastructure environment and AI benefits. This approach also ensures that model training is as targeted and efficient as possible for each use case.

In my role, the main areas of improvement to enhance efficiency and productivity in supporting AI initiatives include streamlined data access and integration processes and enhanced inter departmental collaboration. Improving these areas would facilitate quicker and more effective development of AI solutions."

VP of Operations,
Manufacturing, USA

ITOps need to ensure pipelines are built with as much shift-left testing as possible for both data trustworthiness and security. Data scientists need to be better at explaining what data they need, and developers need to communicate their end state and what they need to use data products for."

CIO, Data Science,
Healthcare, U.K.

Avoiding Data Issues While Scaling AI

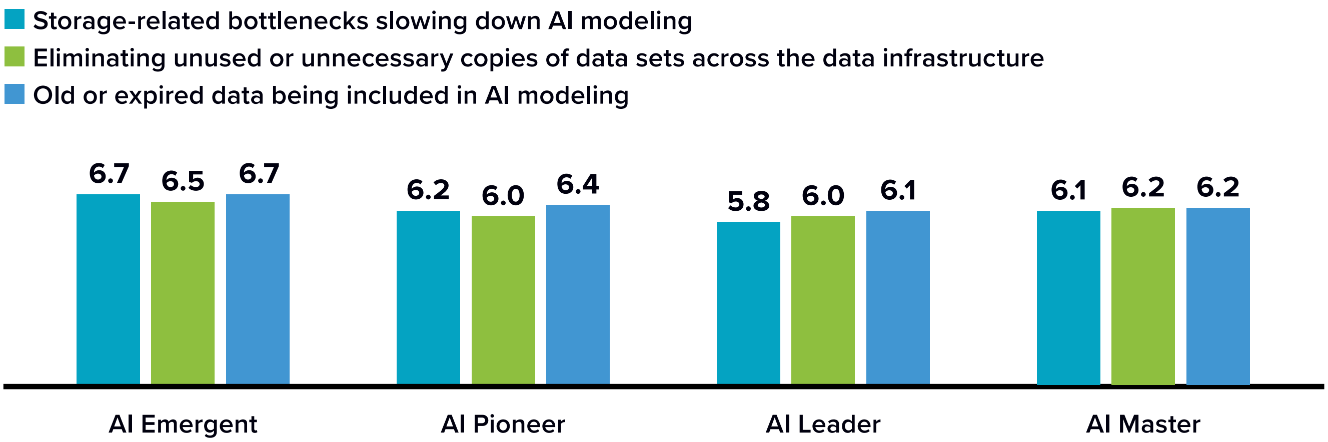
AI initiatives improve efficiency at scale when storage infrastructure enables organizations to avoid storage performance bottlenecks, and to break down isolated dataset silos. This approach avoids unnecessary copies of data while managing the lifecycle of all data within the organization.

AI Masters have standardized metrics and processes for efficiency, yet avoiding storage bottlenecks, eliminating unnecessary data set copies and excluding old data from AI models remain persistent problems for most organizations regardless of maturity level. (see **Figure 16**, next page).

FIGURE 16

Frequency of Data Issues in AI Modeling

How often has your organization experienced these issues in managing the data used in AI modeling?
(On a scale from 0 to 10, with 10 = Regularly and 0 = Never)



n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

For an accessible version of the data in this figure, see Figure 16 Supplemental Data in Appendix 2.

Productivity

The most basic measure of productivity in AI initiatives is the fundamental availability of in-house skills. This limitation is a far greater challenge to AI Emergents than it is to AI Masters that have acquired the necessary skills to drive success (**Figure 4**, page 11).

Once key staff are upskilled through training or acquisition, AI transformation achieves its stated business outcomes quickly and consistently only when every stakeholder involved in the AI workflow is functioning and collaborating at their highest potential. The technologies and processes of AI transformation are methods that ensure end-user productivity. They provide the foundation for the workstreams of their users and operators and create the innovative and competitive environment required to succeed in AI and GenAI transformation. And when skills are in short supply, technology and processes can help make those rare talents as productive as possible (e.g., flexible data architecture and data governance and security).

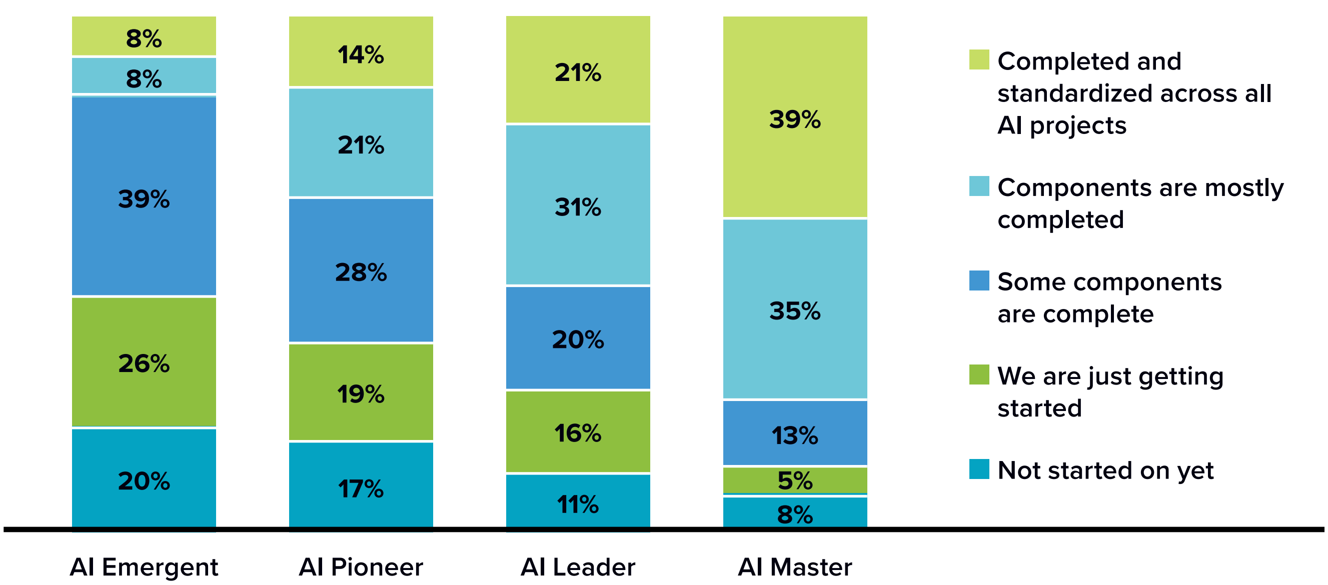
For instance, AI Masters seek productivity optimization not just operationally but throughout AI transformation, and they have processes for identifying and using data in AI models (see **Figure 17**, next page).

> RAG-driven enhancements can help with efficiency gains on employee productivity, freeing up more time on resources to engage in more AI initiatives."
>
> Director of Data Science,
> Software and IT Services, Canada

FIGURE 17

Data Preparedness

How developed are processes for identifying and using data in AI models?
(Percentage of respondents)



Note: Totals may not add up to 100% due to rounding. n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

For an accessible version of the data in this figure, see Figure 17 Supplemental Data in Appendix 2.

AI Masters have achieved a higher level of harmony between ITOps, data science and engineering, and developer teams than their less mature peers. They report perfect or excellent collaboration levels between the three roles (**Figures 18A–C**), thus leading to consistent and measurable efficiencies directly tied to the business outcomes expected from AI initiatives.

A hallmark of mature organizations is an IT Center of Excellence (COE), with an AI COE that operates as a subgroup within the IT COE. An AI COE approach has many benefits, including centralizing resourcing and infrastructure, ensuring governance of processes, access to data, and eliminating data siloes.

Organizations with an AI COE also leverage enterprise-managed MLOps control planes rather than proprietary public cloud platforms. The latter are easily started but tend toward unwanted long term lock-in.

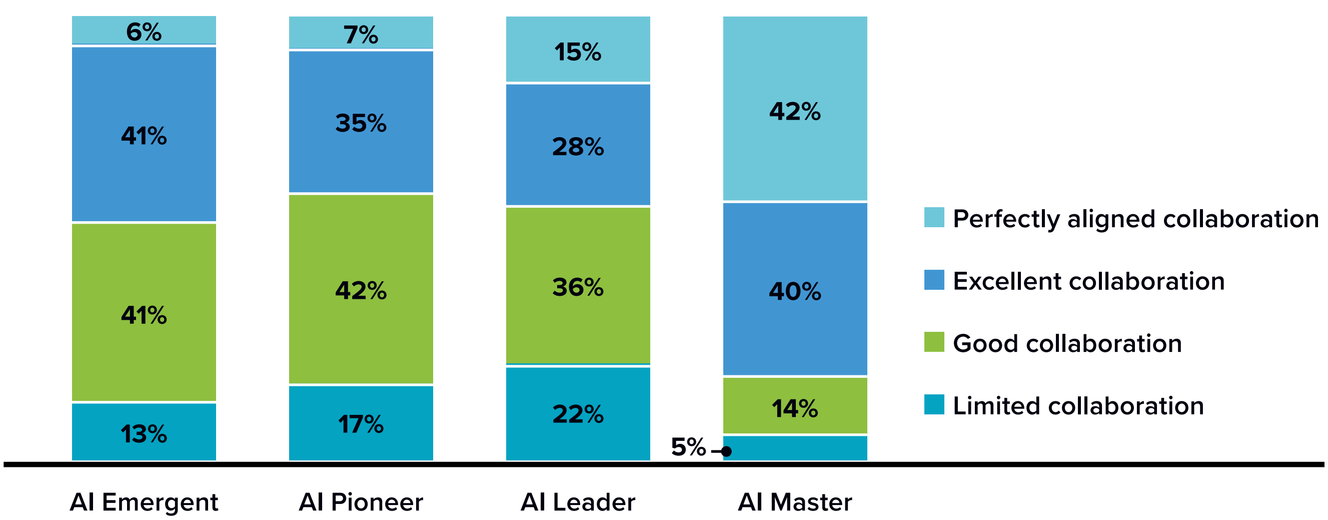
Further, because of this alignment, AI Masters have reached a level of optimal productivity and, therefore, their IT Ops teams don't have to make many ongoing improvements when managing unstructured, structured, and streaming data types (see **Figure 19**, page 31).

FIGURE 18A

Collaboration — ITOps and Developers

What is the current level of collaboration in your organization among these three functions in managing, executing, and operationalizing AI initiatives?

(Percentage of respondents)



Note: Totals may not add up to 100% due to rounding. n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

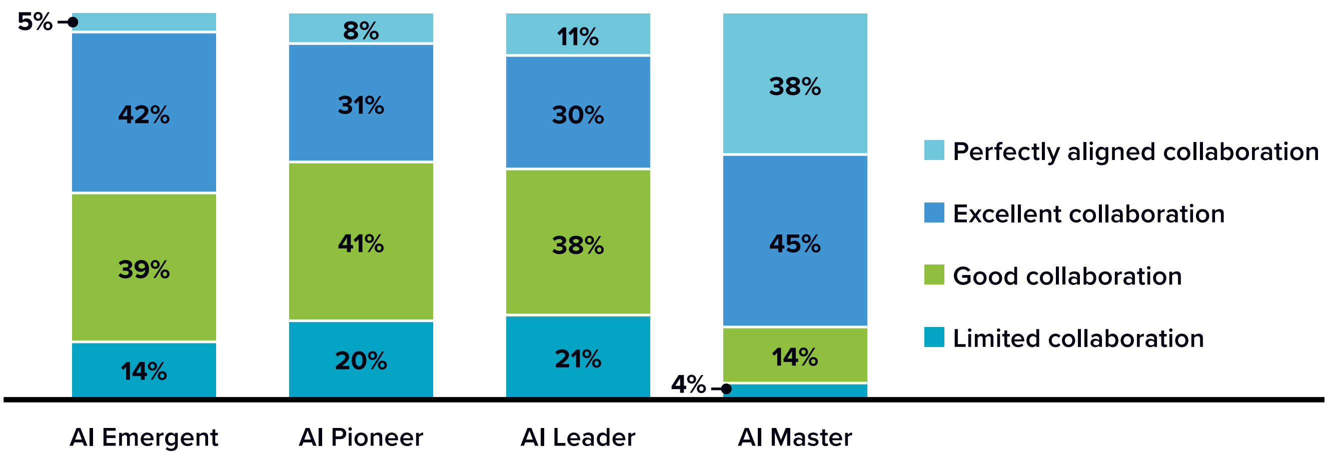
For an accessible version of the data in this figure, see Figure 18A Supplemental Data in Appendix 2.

FIGURE 18B

Collaboration — ITOps and Data Scientists

What is the current level of collaboration in your organization among these three functions in managing, executing and operationalizing AI initiatives?

(Percentage of respondents)



Note: Totals may not add up to 100% due to rounding. n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

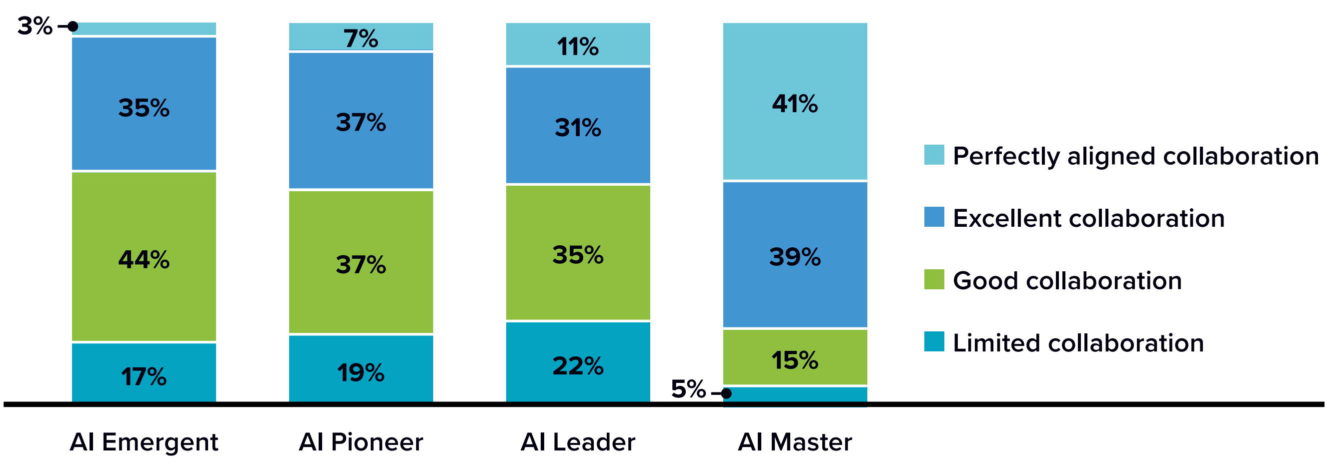
For an accessible version of the data in this figure, see Figure 18B Supplemental Data in Appendix 2.

FIGURE 18C

Collaboration – Data Scientists and Developers

What is the current level of collaboration in your organization among these three functions in managing, executing, and operationalizing AI initiatives?

(Percentage of respondents)



Note: Totals may not add up to 100% due to rounding. n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

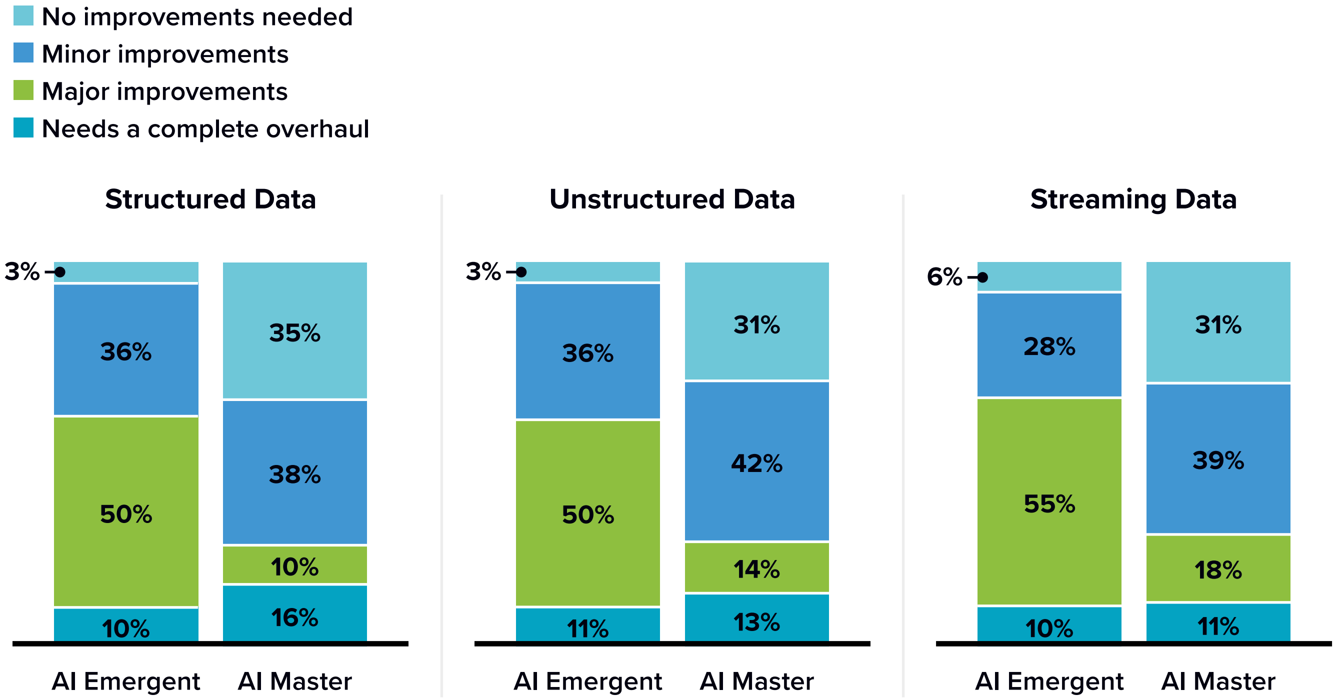
For an accessible version of the data in this figure, see Figure 18C Supplemental Data in Appendix 2.

FIGURE 19

Productivity Improvements Needed in Managing Data

Overall, how much improvement is needed so that ITOps teams can better manage and optimize these types of data for use in AI?

(Percentage of respondents)



Note: Totals may not add up to 100% due to rounding. n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

For an accessible version of the data in this figure, see Figure 19 Supplemental Data in Appendix 2.

AI Masters have reached a level of optimal productivity and, therefore, their ITOps teams don't have to make many ongoing improvements when managing unstructured, structured, and streaming data types.

Essential Guidance for IT Decision Makers

IDC found that, on average, 13%–20% of AI initiatives will fail despite the best intentions and efforts of transformative organizations. Organizations that approach AI transformation from a cohesive people, process, and technology approach and emphasize efficiency, flexibility, governance, and security will have a head start in achieving desired business outcomes. The behavior of AI Masters uncovered in this study can inform best practices and minimize the unintentional pitfalls of less experienced AI practitioners to extract maximum value from these efforts.

Minimize Failure

Inability to access data — infrastructure failure

Despite being near the middle of the pack for immature AI organizations, this is the TOP reason that AI Masters fail in their AI initiatives. Getting the right data into the right environment at the right time is key to extracting quality insights in a timely manner for organizations at every stage of AI transformation. Selecting the wrong deployment model, infrastructure provider, or data architecture can drastically decrease the value of any AI project. Flexibility and efficiency are the imperatives that support positive outcomes in this space.

Inability to access data — business restrictions

The flip side of the data coin is the collaboration and productivity story for data access. Without ubiquitous access to data that is clean and appropriate and complies with privacy, security, governance, and regulatory rules for a particular use case, there is no chance of gleaning meaningful insight from an AI initiative. Collaborative efforts can be undermined by infrastructure silos, and productivity depends on the ability of AI transformation teams to share data in a secure, compliant manner between teams and personas. AI is not "special", needing its own storage infrastructure; rather, the best case is that the existing enterprise storage infrastructure can handle the demands of AI. This way, all corporate data is potentially available (within governance guidelines) and not locked up in an isolated storage silo or other part of the organization.

Maximize Success

Increase data availability with flexible infrastructure.

AI Masters deploy flexible infrastructure for transformational AI initiatives to enable ease of access to corporate data with zero or minimal preparation or preprocessing. These organizations understand that a unified, hybrid, multicloud operating environment must support multimodal data as well as multiple data access methods.

Governance and security aren't cost centers, they are innovation enablers.

Proper security, data sovereignty, and regulatory compliance approaches can reduce or eliminate risk in AI and GenAI initiatives. Companies that put governance and security at the forefront of attention and investment when embarking on an AI initiative can ensure that data engineers and scientists aren't wasting cycles ensuring they're working with the right, "safe" data but rather always working at maximal efficiency and productivity. Well-defined processes and KPIs for addressing bias, privacy and security, data sovereignty, and responsible AI use are essential for organizations seeking to increase the success rate of business outcomes.

AI Architectures Require Intelligent Storage Infrastructure.

Infrastructure decisions can help achieve positive business outcomes while managing the resource intensity and cost of AI. Ensuring cost optimization and efficient compute, storage, and resource utilization is critical. AI solutions must be effective but also economically and operationally sustainable, or the value derived from these activities will be undermined by execution costs. Companies need clear processes and metrics to embed appropriate and efficient resource use into the criteria for AI project success.

To increase AI transformation efficiency, storage infrastructure decisions should be made with the following in mind:

- Maximize the utilization of your compute infrastructure (e.g. GPU-accelerated servers)
- Increase energy efficiency by reducing footprint, power, and cooling costs
- Avoid the proliferation of data silos that hinder data access
- Manage data lifecycles, as well as copy data management, deduplication, and compression to avoid older, duplicate, or useless data from being integrated into modelling processes

- Deploy a fit for purpose data architecture supported by unified storage
- Limit the unnecessary movement of data (e.g., adopt "in-place ingest"-generating vector embeddings for RAG)

Technology and processes make highly skilled teams as productive as possible.

Collaborative efforts between ITOps, data scientists, and developers are key to AI and GenAI transformation. Optimized technology and processes are the underpinning enablers of this effective collaboration. Streamlined data access, data pipelines that ensure data trustworthiness, governance and security, and collaborative access to structured, unstructured, and streaming data can ensure that everyone from the AI Center of Excellence to individual practitioners is contributing the maximum value to these new and evolving AI and GenAI use cases.

Organizations can truly unlock the value of their data and drive meaningful and substantial business outcome improvement for years to come.

Conclusion

AI is not a fleeting trend but one of the most disruptive forces to impact businesses worldwide. The business value of AI is real, and as per IDC research, early adopters capitalize on AI and are reporting an average ROI of 3.5X for every dollar spent. While the excitement around AI/ML and GenAI is understandable, it is vital to maintain a balanced perspective. Only 15% of the respondents in this study are AI Masters.

AI Masters are developing best practices that are pointing the way forward across data architecture, governance and security, resource efficiency and team productivity.

Building an intelligent data infrastructure should be the first step aspiring organizations take to leverage the power of AI effectively. An intelligent data infrastructure embodies a flexible architecture allowing data access anywhere, active data management to meet critical security and governance requirements, adaptive operations to meet performance and efficiency goals, and it enables important resource efficiency and cost management capabilities that are critical business imperatives. With this comprehensive approach, exemplified by the practices taken of AI Masters, organizations can truly unlock the value of their data and drive meaningful and substantial business outcome improvement for years to come.

Appendix 1: AI Maturity Framework — Self-Assessment

TABLE 1

AI Maturity Framework – How Does Your Organization Compare?

Maturity Factors	AI Emergent	AI Pioneer	AI Leader	AI Master
Overall AI strategy progress Overall preparedness for AI execution and determining how and where to invest across the enterprise	Starting line	Beginning	Midway	Nearing finish
GenAI strategy	Starting line	Beginning	Midway	Nearing finish
AI issues addressed Organization-wide deployment and benefits achieved, people/process/technology/ cost efficiencies achieved, AI sustainability goals achieved, data privacy/security achieved	Starting line	Beginning	Midway	Nearing finish
Data architecture Importance recognized for managing data in different locations of differing formats/ structures/data access mechanisms and successfully leveraging data across multiple public clouds	Low recognition of required architecture. Disparate structures in place, dependent on format and access mechanisms. Data stored in different locations, often isolated/ disconnected.	Beginning to plan to unify data structures and access mechanisms or effectively managing multiple locations or using multiple clouds, but significant gaps exist.	Unified architecture vision in place, significant progress made on enterprise-side data format/access mechanisms, effectively managing mulitple locations.	Nearly cohesive architecture supporting variety of formats, structures, and access mechanisms. Data effectively stored and managed in any location (public cloud, private, on-premises).

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Maturity Factors	AI Emergent	AI Pioneer	AI Leader	AI Master
Storage infrastructure progress Progress made in a variety of storage infrastructure attributes to better support AI, including reduced latency, improved scalability, endpoint management, streaming data support, data access, single control plane, data movement, auditability for traceability-error detection, ransomware protection, add sensitive data functionality	Greatest focus on storage-efficient auditable copies of data for traceability-error detection, single control plane, improved data access, store-once-used-anywhere functionality to prevent sensitive data from being used in AI training, and securing endpoints easily	Greatest focus on single control plane, storage-efficient auditable copies of data for traceability-error detection, fast data movement and migration between on-premises and multiple cloud locations, advanced ransomware detection and recovery, and securing endpoints easily	Greatest focus on storage-efficient auditable copies of data for traceability-error detection, functionality to prevent sensitive data being used in AI training, and single control plane	Greatest focus on fast data movement or migration between on-premises and multiple clouds and improved access
Governance Creation of auditable copies of AI models, data bias detection tools and auditing, algorithm bias detection, data sovereignty compliance monitoring, traceability and error detection tools, data quality/life cycle tools	Starting line	Beginning	Midway	Nearing finish
Data security and privacy Progress in removing sensitive information from model ingestion, enabling real-time monitoring prevent tampering, real-time cybersecurity monitoring, instant cybersecurity threat response, end-to-end data encryption, global privacy compliance, dynamic internal AI initiative access controls	Starting line	Beginning	Midway	Nearing finish

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Maturity Factors	AI Emergent	AI Pioneer	AI Leader	AI Master
AI efficiency Progress addressing identification/filtering of unnecessary/unused data, effective power management, integrating data access with AI analytic tools, handling complex datasets, having scalable AI analytic tools that adjust to changing data requirements, having accessible data in cost-effective environments	Starting line	Beginning	Midway	Nearing finish
Rightsizing storage Improvement needed to ensure storage is optimized and rightsized, enterprise-wide, for use in AI	Starting line	Beginning	Midway	Nearing finish
Data science productivity Improvement needed to ensure data scientist productivity in automating AI training workflows, simplifying and accelerating data provisioning, and having better data pipeline tooling	Starting line	Beginning	Midway	Nearing finish
Developer productivity Improvement needed to ensure developers can leverage streaming data, unstructured data, synthetic data, structured/database data, and third-party data for applications with embedded AI	Starting line	Beginning	Midway	Nearing finish

Source: IDC, 2024

TABLE 2

12-Month Improvement in Business Outcomes Due to AI, x AI Maturity Levels

Business Outcomes	AI Emergent	AI Pioneer	AI Leader	AI Master
Revenue growth	23%	21%	18%	19%
Cost savings	26%	23%	20%	17%
Increased profits	25%	22%	20%	19%
Improved customer experience	25%	22%	20%	18%
Increased operational efficiency	25%	22%	19%	18%
Improved employee productivity	25%	24%	19%	20%
Faster innovation	24%	22%	21%	17%
Reduced business risk	23%	23%	19%	17%
Faster time to market	24%	22%	19%	18%
Improved business agility	23%	23%	19%	19%
Increased sustainability	24%	23%	20%	17%
Improved business resilience	24%	22%	20%	17%

Source: IDC, 2024

FIGURE 18

Demographic — Quantitative Survey Respondents

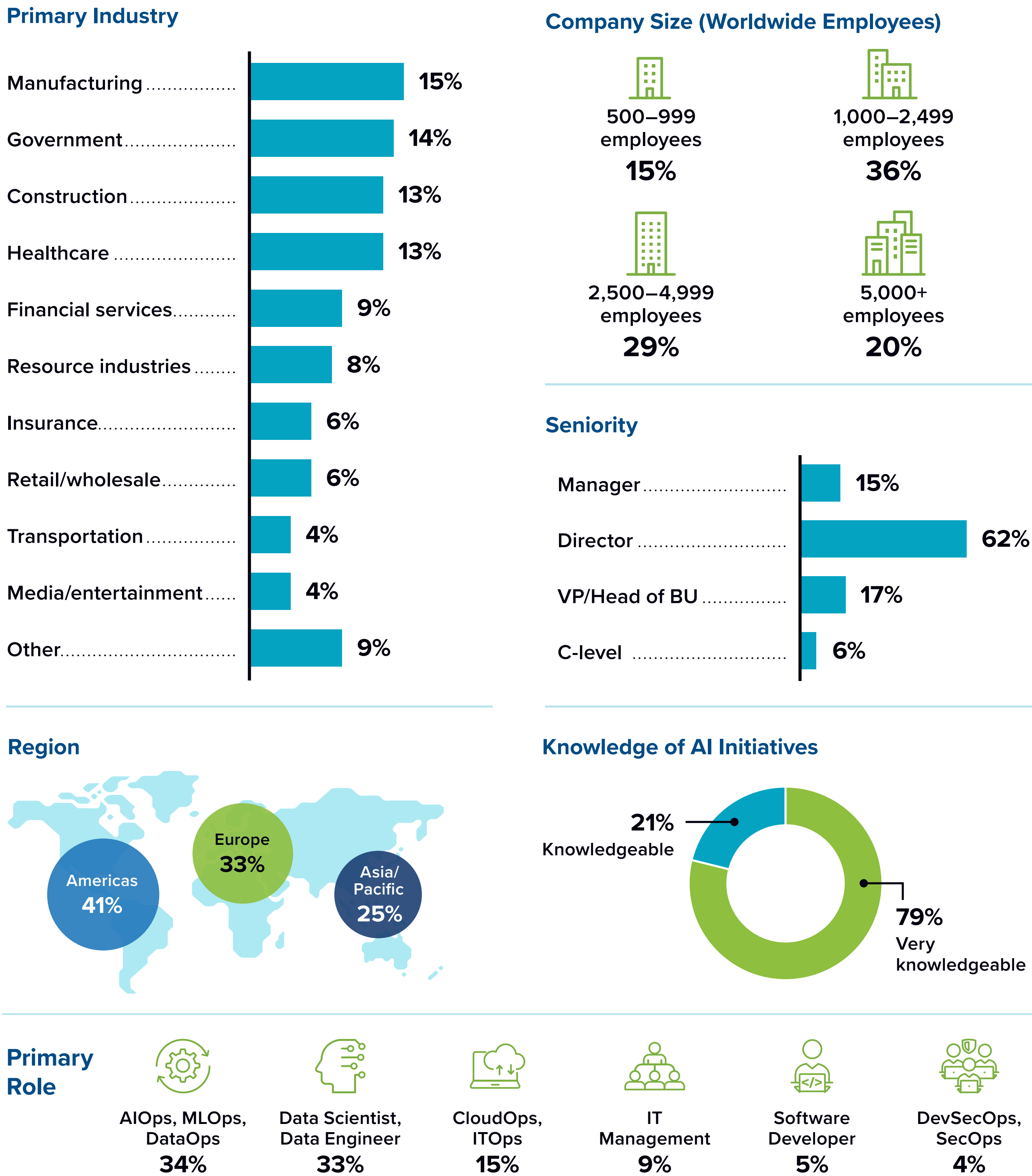

TABLE 3

Demographic — Qualitative In-Depth Interviews

	Name	Role	Company Size (number of employees)	Industry	Seniority	Generative AI	Interpretive AI	Predictive AI
1	**Emile R.**	IT Operations	1,000–2,499	Financial services — Securities and investment services	C-level	X	X	X
2	**Eric K.**	Data Science	5,000–9,999	Financial services — Securities and investment services	VP/Senior VP/Head of BU	X	X	X
3	**Sanjay S.**	Developer, Data Science, IT Operations	2,500–4,999	Manufacturing — Discrete	Director	X	X	X
4	**Brian D.**	Developer, Data Science	5,000–9,999	Media and entertainment	VP/Senior VP/Head of BU	X	X	X
5	**Shiva R.**	Data Science, IT Operations	10,000 or more	Life sciences	VP/Senior VP/Head of BU	X	X	X
6	**William W.**	Developer, Data Science	10,000 or more	Healthcare services providers	Director	X		X
7	**Laurence K.**	Data Science, IT Operations	10,000 or more	Healthcare services providers	Director	X	X	X
8	**Chip S.**	Data Science	10,000 or more	Telecommunications	Director	X		X
9	**Saurabh G.**	Developer, Data Science	5,000–9,999	Retail trade	Director	X	X	X
10	**Johnathan A.**	IT Operations	10,000 or more	Manufacturing — Discrete	VP/Senior VP/Head of BU	X	X	X
11	**Henry L.**	Developer, Data Science, IT Operations	10,000 or more	Manufacturing: Discrete	VP/Senior VP/Head of BU	X	X	X
12	**Pavel K.**	Data Science, IT Operations	2,500–4,999	Telecommunications	Director	X	X	X

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	Name	Role	Company Size (number of employees)	Industry	Seniority	Generative AI	Interpretive AI	Predictive AI
13	**Andrew C.**	Data Science	10,000 or more	Telecommunications	VP/Senior VP/Head of BU	X	X	X
14	**Himanshu J.**	Developer, Data Science, IT Operations	10,000 or more	Financial services — Banking and credit institutions	C-level	X	X	X
15	**Nick C.**	Data Science	2,500–4,999	Education	VP/Senior VP/Head of BU	X	X	X
16	**Justin H.**	Developer, IT Operations	1,000–2,499	Government	Director	X	X	X
17	**Nagesh C.**	Developer, Data Science, IT Operations	1,000–2,499	Insurance — Other types of insurance	VP/Senior VP/Head of BU		X	X
18	**Shaun G.**	Developer, Data Science, IT Operations	1,000–2,499	Retail trade	VP/Senior VP/Head of BU	X		X
19	**Steve R.**	Developer, Data Science, IT Operations	1,000–2,499	Retail trade	C-level	X	X	X
20	**James K.**	Developer, IT Operations	1,000–2,499	Education	VP/Senior VP/Head of BU	X	X	X
21	**Andreea I.**	Data Science, IT Operations	1,000–2,499	Financial services — Banking and credit institutions	VP/Senior VP/Head of BU	X		X
22	**Eddie P.**	Developer, Data Science, IT Operations	1,000–2,499	Software and IT services	C-level	X	X	
23	**Stuart C.**	Developer, Data Science, IT Operations	1,000–2,499	Healthcare services providers	C-level	X		X
24	**Karandeep S.**	Data Science	10,000 or more	Software and IT services	Director	X	X	X

Source: IDC, 2024

Appendix 2: Supplemental Data

This appendix provides an accessible version of the data for the complex figures in this document. Click "Return to original figure" below each table to get back to the original data figure.

FIGURE 6 SUPPLEMENTAL DATA

Data Availability for AI

	AI Emergent	AI Pioneer	AI Leader	AI Master
Structured Data				
Instantly available for all AI projects	26%	27%	27%	48%
Available with minor processing to prepare	40%	37%	36%	28%
Available with significant processing to prepare	30%	23%	18%	14%
Not available to AI projects	4%	13%	19%	11%
Unstructured Data				
Instantly available for all AI projects	20%	21%	22%	43%
Available with minor processing to prepare	35%	35%	34%	35%
Available with significant processing to prepare	33%	25%	23%	13%
Not available to AI projects	12%	20%	19%	10%

Note: Totals may not add up to 100% due to rounding. n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

Return to original figure

Appendix 2: Supplemental Data (continued)

FIGURE 8 SUPPLEMENTAL DATA

AI Governance Policies and Procedures

	AI Emergent	AI Pioneer	AI Leader	AI Master
Completed and standardized across all AI projects	8%	13%	20%	38%
Components are mostly completed	9%	18%	28%	34%
Some components arecomplete	31%	27%	29%	15%
Some components are complete	33%	22%	14%	7%
Not started on yet	19%	20%	9%	6%

Note: Totals may not add up to 100% due to rounding. n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

Return to original figure

FIGURE 9 SUPPLEMENTAL DATA

Policies to Ensure AI is Used Responsibly and Safely

	AI Emergent	AI Pioneer	AI Leader	AI Master
Standardized policies are in place and are rigorously enforced by an independent group within the organization	3%	9%	24%	51%
Polices are in place and are enforced by employees themselves	11%	33%	48%	33%
Some policies have been implemented but are mainly viewed as guidelines	53%	46%	25%	11%
Policies and procedures are currently being developed	33%	12%	3%	5%

n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

Return to original figure

Appendix 2: Supplemental Data (continued)

FIGURE 10 SUPPLEMENTAL DATA

Policies in Place to Address Bias or Data Sovereignty

	AI Emergent	AI Pioneer	AI Leader	AI Master
There are a specific set of standardized protocols and procedures for this followed by a centralized independent team	24%	26%	31%	42%
Issues are escalated to a special team on a case-by-case basis	28%	30%	27%	15%
Issues are handled on a case-by-case basis by data scientists	48%	44%	42%	43%

n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

Return to original figure

FIGURE 11 SUPPLEMENTAL DATA

Policies in Place to Address Data Security and Privacy

	AI Emergent	AI Pioneer	AI Leader	AI Master
There are a specific set of standardized protocols and procedures for this followed by a central independent team	17%	51%	78%	74%
Issues are escalated to a special team who address on a case-by-case basis	53%	39%	20%	23%
Issues are handled ona case-by-case basisby those doing the work	30%	10%	2%	3%

n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

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Appendix 2: Supplemental Data (continued)

FIGURE 12 SUPPLEMENTAL DATA

Assessing the Efficiency of Resource Use

	AI Emergent	AI Pioneer	AI Leader	AI Master
Completed and standardized across all AI projects	9%	14%	22%	43%
Components are mostly completed	10%	23%	29%	31%
Some components are complete	31%	25%	24%	13%
We are just getting started	24%	21%	15%	8%
Not started on yet	26%	17%	10%	5%

n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

Return to original figure

FIGURE 13 SUPPLEMENTAL DATA

AI Datacenter Energy Consumption

	2022	2023	2024	2025	2026	2027
AI Energy Consumption	23 TWh (7.14% of total datacenter energy consumption)	36 TWh	55 TWh	78 TWh	106 TWh	146 TWh (16.47% of total datacenter energy consumption

Source: IDC *Datacenter Trends - Sustainable Datacenter Builds and CO2 Emissions* (Lead Analyst: Sean Graham)

Return to original figure

Appendix 2: Supplemental Data (continued)

FIGURE 16 SUPPLEMENTAL DATA

Frequency of Data Issues in AI Modeling

	AI Emergent	AI Pioneer	AI Leader	AI Master
Storage-related bottlenecks slowing down AI modeling	6.7	6.2	5.8	6.1
Eliminate unused or unneeded copies of datasets across the data infrastructure	6.5	6.0	6.0	6.2
Old or expired data being included in AI modeling	6.7	6.4	6.1	6.2

n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

Return to original figure

FIGURE 17 SUPPLEMENTAL DATA

Data Preparedness

	AI Emergent	AI Pioneer	AI Leader	AI Master
Completed and standardized across all AI projects	8%	14%	21%	39%
Components are mostly completed	8%	21%	31%	35%
Some components are complete	39%	28%	20%	13%
We are just getting started	26%	19%	16%	5%
Not started on yet	20%	17%	11%	8%

Note: Totals may not add up to 100% due to rounding. n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

Return to original figure

Appendix 2: Supplemental Data (continued)

FIGURE 18A SUPPLEMENTAL DATA

Collaboration – ITOps and Developers

	AI Emergent	AI Pioneer	AI Leader	AI Master
Perfectly aligned collaboration	6%	7%	15%	42%
Excellent collaboration	41%	35%	28%	40%
Good collaboration	41%	42%	36%	14%
Limited collaboration	13%	17%	22%	5%

Note: Totals may not add up to 100% due to rounding. n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

Return to original figure

FIGURE 18B SUPPLEMENTAL DATA

Collaboration – ITOps and Data Scientists

	AI Emergent	AI Pioneer	AI Leader	AI Master
Perfectly aligned collaboration	5%	8%	11%	38%
Excellent collaboration	42%	31%	30%	45%
Good collaboration	39%	41%	38%	14%
Limited collaboration	14%	20%	21%	4%

Note: Totals may not add up to 100% due to rounding. n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

Return to original figure

FIGURE 18C SUPPLEMENTAL DATA

Collaboration – Data Scientists and Developers

	AI Emergent	AI Pioneer	AI Leader	AI Master
Perfectly aligned collaboration	3%	7%	11%	41%
Excellent collaboration	35%	37%	31%	39%
Good collaboration	44%	37%	35%	15%
Limited collaboration	17%	19%	22%	5%

Note: Totals may not add up to 100% due to rounding. n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

Return to original figure

Appendix 2: Supplemental Data (continued)

FIGURE 19 SUPPLEMENTAL DATA

Productivity Improvements Needed in Managing Data

	AI Emergent	AI Master
Structured Data		
No improvements needed	3%	35%
Minor improvements	36%	38%
Major improvements	50%	10%
Needs a complete overhaul	10%	16%
Unstructured Data		
No improvements needed	3%	31%
Minor improvements	36%	42%
Major improvements	50%	14%
Needs a complete overhaul	11%	13%
Streaming Data		
No improvements needed	6%	31%
Minor improvements	28%	39%
Major improvements	55%	18%
Needs a complete overhaul	10%	11%

Note: Totals may not add up to 100% due to rounding. n = 1,220; Source: IDC's *AI Transformation Study,* January 2024

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About the IDC Analysts

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Ritu is group vice president, covering worldwide artificial intelligence and automation research with IDC's Software Market Research and Advisory Practice. Ritu is responsible for leading the development of IDC's thought leadership for AI research and managing the research team. Her research focuses on the state of enterprise AI efforts and global market trends for rapidly evolving AI and machine learning innovations and ecosystems. She also leads insightful research that addresses the needs of AI technology vendors and provides actionable guidance on how to crisply articulate their value proposition, differentiate, and thrive in the digital era.

More about Ritu Jyoti

Ashish Nadkarni
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Ashish is group vice president within IDC's Worldwide Infrastructure Practice. He leads a team of analysts who engage in delivering qualitative and quantitative research on computing, storage, and data management infrastructure platforms and technologies via syndicated research programs (subscription services), data products (IDC Trackers), and custom engagements. Ashish's vision for his team is to take a holistic, forward-looking, and long-term view on emerging and established infrastructure-related areas in the datacenter, in the cloud, and at the edge. His core research starts with an objective assessment of heterogeneous, accelerated, fog, edge, and quantum computing architectures; silicon, memory, and data persistence technologies; composable and disaggregated systems; rackscale design; software-defined infrastructure; modern operating system environments; and physical, virtual, and cloud computing software. It is complemented by research on current and next-gen applications and workloads, vertical and industry-specific use cases, emerging storage and server form factors and deployment models, and upcoming IT vendors. Ashish also takes a keen interest in tracking the ongoing influence of open and open-source communities such as OpenStack and Open Compute Project on infrastructure.

More about Ashish Nadkarni

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Dave is research vice president for the Storage and Converged Systems practice within IDC's worldwide infrastructure research organization. He also oversees IDC Canada's Infrastructure Solutions research practice. Dave manages a team of analysts that cover both research domains. On the worldwide infrastructure research side, he and his team are responsible for IDC's storage, integrated, hyperconverged, and composable systems and platforms. This includes storage for performance-intensive use cases such as high-performance computing, artificial intelligence, and analytics. It also includes cloud-enabled infrastructure and infrastructure used for cloud deployments. On the Canadian side, he and his team are responsible for research on computing, storage, networking, and security, as well as contributing to edge, cloud, cognitive, and infrastructure software research.

More about Dave Pearson

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