THE AI TRUST GAP REPORT

For Financial Services and Insurance

GLOBAL EXECUTIVE INSIGHTS

What financial services leaders reveal

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Executive Summary

The Outcome Problem, Not the AI Problem

AI in financial services and insurance is no longer experimental. Banks and insurers are investing heavily in real-time fraud prevention, intelligent underwriting and risk scoring, hyper-personalized customer engagement, and automated claims workflows.

However, not all organizations have been able to turn agentic AI projects into successful mission outcomes. Successful agentic AI initiatives require access to live data, comprehensive business context, and compliance with governance and regulatory guardrails, all of which can be challenging for many organizations to provide.

This paper summarizes findings conducted for us by Arlington Research to shed light on these and other requirements, that warrant a fundamental rethink in enterprise data management strategies and architecture in order to ensure agentic AI success.

Live Data Gap **72%**

72% of organizations in this sector say AI data must be real-time or within-the-minute to be trustworthy — yet traditional data architectures, designed for historical analytics, cannot support this sub-minute latency, creating a critical bottleneck.

This is notably higher than the global average of 66%, underscoring that financial services organizations face a more acute real-time data imperative than most other sectors — driven by the zero-latency demands of fraud detection, transaction monitoring, and real-time risk decisioning.

Relevance Gap **65%**

64% of BFSI organizations struggle to identify trustworthy data or prepare and integrate it for AI initiatives.

Even when data exists, determining which data is authoritative across fragmented agency systems remains a major challenge.

Complexity at Scale **489** DATA SOURCES

Enterprise AI initiatives in BFSI draw on an average of 489 data sources, with nearly one in five organizations accessing over 1,000.

This distributed data landscape increases the difficulty of ensuring consistency, governance, and performance.

Guardrail Gap **61%**

61% of respondents in this sector struggle with AI data security and access controls.

As AI systems interact with operational systems and sensitive data, consistent policy enforcement becomes critical.

Performance Gap **55%**

Even among organizations using data catalogs and lakehouses, 55% of BFSI leaders report difficulty optimizing performance for AI workloads.

As AI workloads grow more data-intensive, performance and cost efficiency become critical to scaling AI initiatives sustainably.

KEY FINDINGS

Survey responses from **233 enterprise leaders in the financial services and insurance sectors** reveal several gaps between what trustworthy AI requires and what most organizations can currently deliver.

Where AI Is Expected to Deliver Value in BFSI

AI is increasingly embedded into **core operational workflows**, not just analytics. Priority outcomes include preventing fraud in real time (payments, transactions, claims), improving credit and underwriting decisions, delivering hyper-personalized experiences, and automating regulatory reporting. **These are decisioning and action-oriented use cases in which AI must operate in the moment, within business processes.**

Introduction

Agentic AI is moving enterprise AI from answering to doing. Agents perceive conditions, decide what to do next, and then execute actions, often by calling tools and autonomously interacting with systems of record. This shift raises the bar for data management, as the quality and relevance of data used by agents directly impacts the trustworthiness and effectiveness of those agents. More specifically, agents break trust when they (a) lack **live situational awareness**, (b) act on incomplete or wrong data due to missing business context and inconsistent semantics, or (c) operate outside **compliance and business-SLA guardrails.** [1]

Independent research reinforces the same pattern: many organizations are struggling to translate "AI enthusiasm" into durable production outcomes. Gartner forecasts that **over 40% of agentic AI projects will be canceled by the end of 2027**, citing escalating costs, unclear business value, or inadequate risk — three constraints that are frequently downstream of data readiness, governance, and integration complexity. [2]

McKinsey, likewise reports broad AI adoption but limited scaling; in its 2025 survey results, only 7% of respondents said AI had been fully scaled across their organizations. [3]

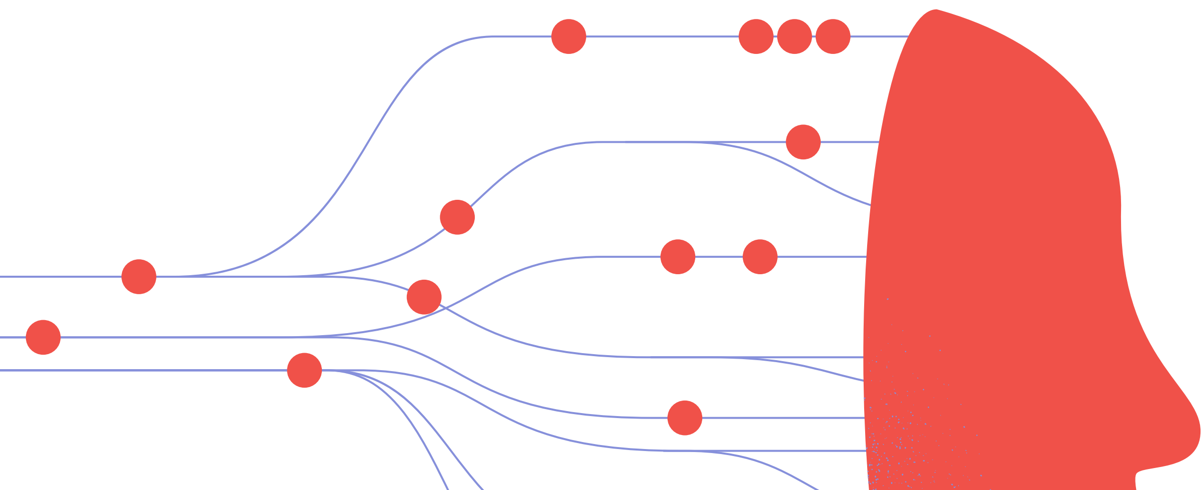
In Financial Services, this translates to an **AI Reality Check**: fraud detection models are not operationalized, personalization initiatives are disconnected from real-time data, and compliance automation is constrained by governance complexity.

In a survey commissioned by Denodo, Arlington Research conducted primary research into AI adoption patterns, which points to why agentic AI programs often stall. The operational bar is high (freshness expectations skew towards real-time), the "right data" problem is not solved by traditional data management solutions (relevance and trust are contextual), and implementing guardrails across distributed sources remains difficult, especially for organizations still planning or piloting AI initiatives.

This report structures the evidence around the three requirements most predictive of agentic AI success:

- **Live data:** agents can only act safely when they have live situation awareness, informed by data that mirrors real-time reality as closely as possible. [1]
- **The right data:** agents need source-of-truth clarity based on consistent semantics that identifies the data most relevant to the situation at hand. [1]
- **Guardrails:** agents must operate under security, privacy, and other regulatory compliance constraints, as well as internal business SLA constraints, consistently across all tools and sources. [1]

To overcome these barriers, this report also explores how to optimize AI cost and performance across distributed, hybrid data environments, and examines how distributed AI ownership impacts enterprise data strategy. Finally, it outlines exactly what this means for financial services leaders, providing a clear 90-day blueprint to close the AI trust gap and turn stalled pilots into measurable business outcomes.



Live Data for Operational Awareness

SURVEY INSIGHT

72% of BFSI organizations say AI data must be real-time or within-the-minute to be trustworthy.

As AI systems move into operational workflows, access to live data becomes a prerequisite for safe decision-making. Organizations already running AI in production are significantly more likely to require real-time or near-real-time data access than those still planning initiatives

This demand is notably higher in BFSI than globally — 72% vs. 66% — reflecting the zero-latency requirements of fraud detection, transaction monitoring, and real-time risk decisioning.

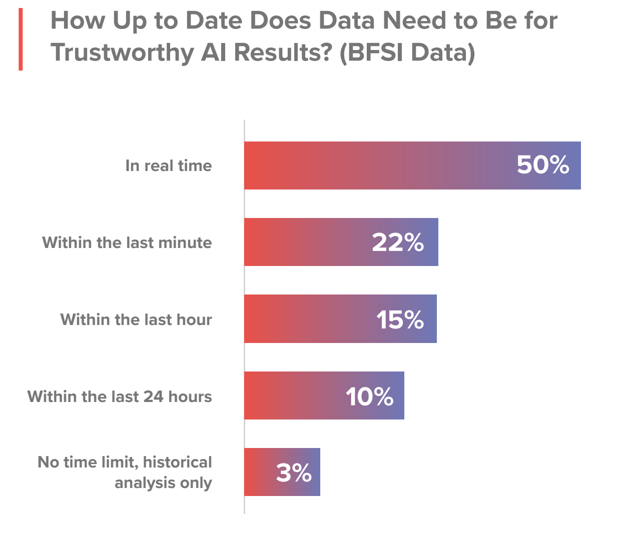


Figure #1

AI systems cannot act reliably without real-time visibility into transactions, risk signals, and customer behavior. Yet, most architectures are still designed for historical analytics, and data pipelines introduce latency. As a result, fraud is detected too late, risk decisions are based on stale information, and customer interactions are reactive.

Most enterprise data architectures were designed for analytics and reporting, where data is aggregated and prepared in advance. This introduces latency between operational systems and the data environments AI systems rely on.

As AI moves into production, this limitation becomes more visible. The survey results suggest that organizations already running AI are more likely to encounter the challenges created by delayed or aggregated data, while those still in earlier stages may not yet fully recognize the impact.

For AI systems embedded in operational workflows, real-time awareness is not optional — it is essential for reliable and trustworthy decision-making. Architectures built primarily for historical analytics can struggle to support AI that needs to sense and act on live conditions.

Data Freshness Requirements Differ by AI Maturity

Organizations already running AI in production are significantly more likely to require real-time or near-real-time data than those still planning initiatives. This suggests that the need for live operational data becomes clearer once AI systems move from experimentation into real-world workflows.

This pattern is particularly pronounced in financial services and insurance, where 73% of organizations already have AI in production — above the global average of 67% — reinforcing that the urgency of live data requirements is felt most acutely in this sector.

Many enterprises have historically separated operational systems from analytics platforms for good reason. Traditional data warehouses are widely considered to be designed for reporting and analysis rather than operational control loops, emphasizing curated historical insight rather than real-time decision-making. [4]

Agentic AI blurs this boundary. When AI systems must sense and act on changing business conditions, the most current and authoritative data often remains in operational applications and SaaS platforms rather than in analytics stores. Once data is copied from its original source, it immediately begins to lose its "liveness."

Even modern analytics architectures can reintroduce staleness through pipeline structures. Coordinating lakehouse and warehouse environments often involves multiple processing stages, and additional extract, transform, and load (ETL) layers can introduce latency and data quality risks.

As a result, organizations deploying AI in operational environments often find that providing **live access to distributed operational data** becomes a core architectural requirement.

Providing live data for AI systems therefore involves more than reducing ingestion latency. In practice it often requires:

- On-demand access to operational data sources without always copying the data into a central store
- Performance optimization mechanisms such as caching or pushdown to support high-volume queries
- Governance controls to ensure real-time access does not bypass security or policy enforcement

At the same time, the broader AI ecosystem is evolving toward architectures where models retrieve data and invoke tools dynamically at runtime. For example, Anthropic's Model Context Protocol (MCP) standardizes how AI systems connect to external tools and data sources, acting as a common interface between models and enterprise systems. [6]

This shift further increases the importance of governed, real-time access to enterprise data across distributed environments.

The Right Data: Relevance, Context, and Semantic Consistency

Survey responses indicate that identifying and preparing the "right data" is one of the most significant barriers to trustworthy AI in production. In particular, respondents frequently cite the challenge of identifying relevant and trustworthy data and preparing or integrating it for AI systems.

What Do Your AI Teams Consider as the Top Data-Related Challenges for Trustworthy AI in Production? (Respondents were able to choose their top two challenges.)

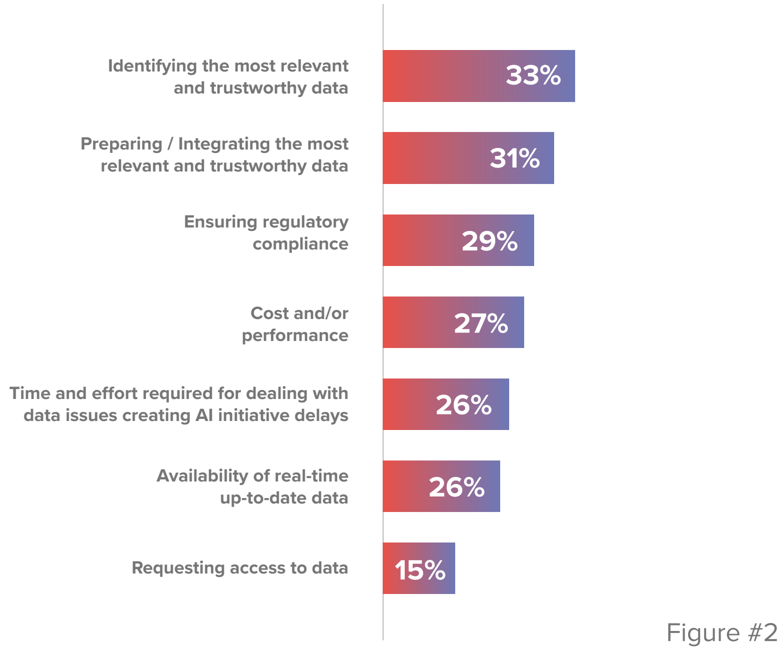


Figure #2

While access to live data is essential, it does not guarantee that AI systems are acting on the correct data. Even accurate data can become misleading when business definitions differ across systems or when the data lacks the appropriate business context for a given decision.

In BFSI, this manifests as different definitions of customer, risk, or exposure across core banking, claims, and compliance systems. When definitions vary across systems, automated decisions can quickly become unreliable.

Traditional data catalogs and governance tools typically capture static metadata — business terms, ownership, and policy definitions defined in advance by data stewards. However, operational AI systems often encounter dynamic situations where context must be interpreted at runtime, making static definitions alone insufficient. As a result, organizations must increasingly address not only data availability, but also data relevance and semantic consistency across systems.

The survey results reinforce that identifying and preparing the "right data" remains a major challenge for organizations deploying AI systems. In particular, respondents frequently cite difficulties identifying relevant and trustworthy data sources and preparing or integrating that data for AI use cases.

THE "RIGHT DATA" CHALLENGE

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The "right data" challenge is also reflected in how organizations say they currently ensure relevance and trustworthiness. Many rely on a combination of BI and analytics tools, governance platforms, and lakehouse environments. However, most respondents selected multiple approaches.

This suggests that ensuring trustworthy data for AI remains a **multi-layered problem** for many organizations, often requiring multiple tools and processes to identify, validate, and prepare the most relevant data for AI systems.

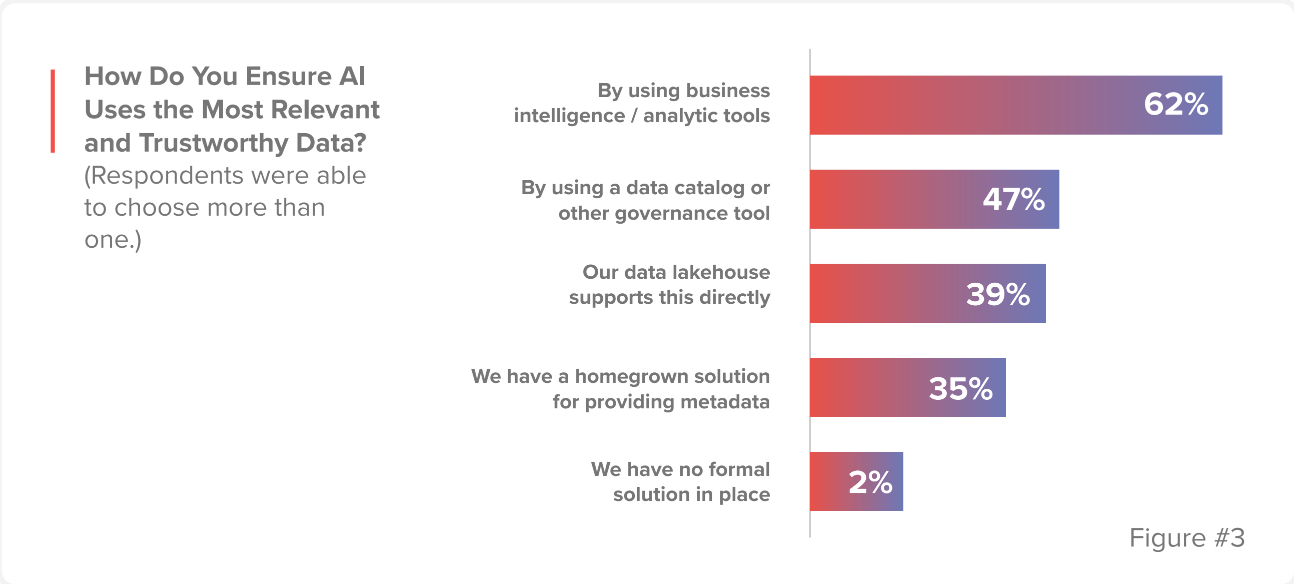


Figure #3

Why Semantic Consistency Becomes a Gating Factor for Agents

Agentic AI systems rely on consistent business meaning across data sources. When definitions vary across systems, automated decisions can quickly become unreliable.

Semantic ambiguity becomes particularly problematic when agents execute actions rather than simply generate responses:

- If terms such as “customer,” “account,” “active,” “revenue,” or “risk” are defined differently across systems, an agent may select incorrect records, invoke the wrong tools, or trigger unintended workflow actions.
- If an agent cannot determine which source is authoritative for a given task, it cannot reliably justify or automate decisions.

These challenges explain why many organizations are investing in semantic-layer approaches that centralize business definitions and ensure consistent interpretation of data across distributed systems.

Platforms such as Denodo position a **universal semantic layer** as a way to harmonize business meaning across complex data environments while preserving access to live operational sources. [7] This aligns with a broader industry shift: many data platforms now emphasize semantic layers as a foundation for governed self-service analytics and AI systems that rely on consistent context at runtime. [8]

“Right Data” as a Retrieval and Provenance Problem

Modern AI architectures increasingly address the “right data” challenge through retrieval-based approaches. In foundational research on retrieval-augmented generation (RAG), the authors note that parametric models alone struggle to maintain up-to-date knowledge and reliable provenance. Instead, they propose retrieving information from external sources at runtime to ground AI outputs in authoritative data. [9]

This principle becomes even more important in enterprise environments. AI agents must not only retrieve live data from original sources, but also determine which sources are the most authoritative for the given task. The most relevant or trusted source, out of potentially hundreds or thousands in a typical enterprise, often may only be determined at runtime.

These challenges reinforce why many organizations are exploring metadata-driven approaches that help AI systems identify the most relevant and authoritative data sources dynamically.

Denodo describes its approach to this problem as **Query RAG**, a metadata-driven framework that uses semantic context to determine which live data sources should be accessed at runtime. [10]

Guardrails: Policy, Security, Compliance, and SLA-Bound Autonomy

SURVEY INSIGHT

61% of respondents in this sector struggle with AI data security and access controls.

This reinforces a consistent pattern in early-stage AI programs: before production processes and governance stabilize, organizations experience guardrail friction most acutely — particularly around consistent access controls, metadata standardization, and governance across distributed systems

AI in financial services must operate within strict regulatory frameworks: AML/KYC, transaction monitoring, data privacy, and auditability.

Guardrails are the defining difference between a “helpful assistant” and a “trusted agent.” Agents break trust when they operate outside compliance and business-SLA guardrails, and fragmented governance and security controls across sources are a common cause of failure. [1]

Survey results indicate that governance and guardrail challenges remain among the most difficult obstacles when deploying AI systems into production environments. This risk is increasingly codified in security and risk frameworks for AI systems:

- The Open Security Foundation's OWASP Top 10 for LLM Applications explicitly lists "Excessive Agency" and "Insecure Plugin Design," reflecting the reality that tool-connected agents can take unintended actions or expand the attack surface if permissions and control paths are weak. [11]
- Industry leaders such as Amazon Web Services (AWS) similarly identify excessive agency as a key threat typically introduced through agentic architectures, and AWS recommends least-privilege and permission boundaries for agentic workflows. [12]
- The National Institute of Standards and Technology (NIST) AI Risk Management Framework (AI RMF 1.0) is designed to help organizations manage AI risks and promote trustworthy AI through lifecycle practices, and NIST has also published a generative AI profile aligned to AI RMF practices. [13]

The survey data indicates that organizations consider guardrail-adjacent problems among the **most difficult** to address — especially security/access control consistency and metadata standardization across systems:

How Difficult or Easy Is It to Address the Following Data-Related Issues? (BFSI Data)

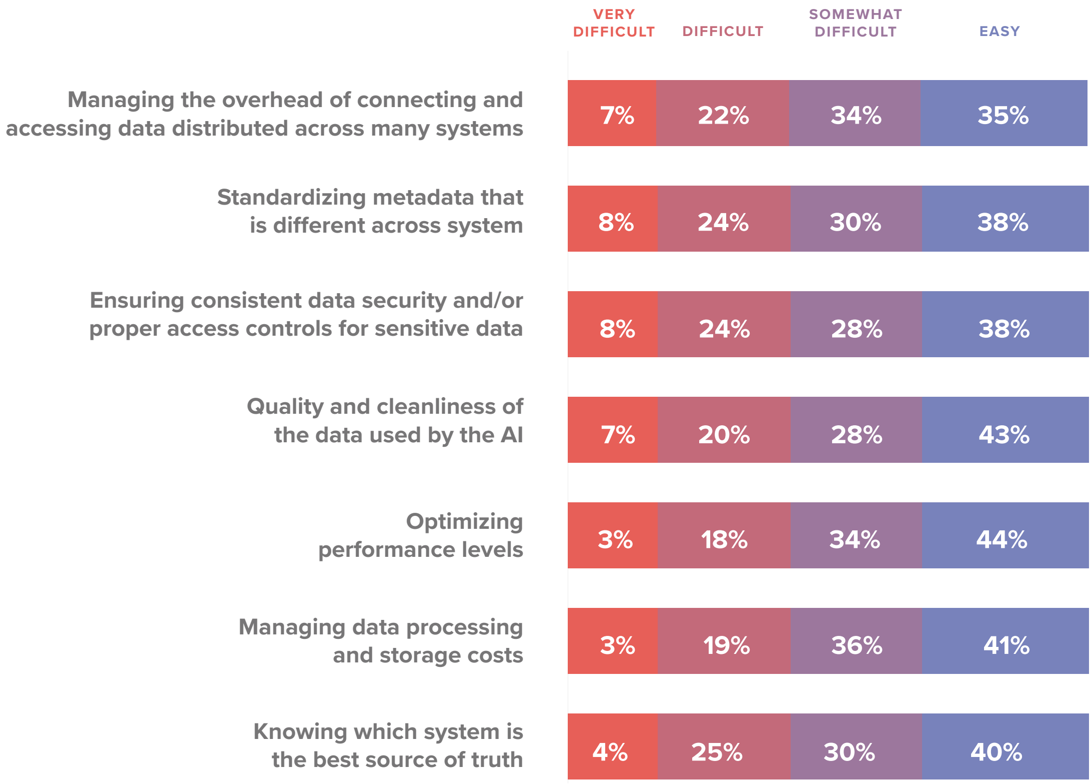


Figure #4

The “guardrail gap” is particularly visible early, before production systems and governance processes stabilize. When comparing organizations planning AI with those already in production, respondents at the planning stage report greater difficulty across several guardrail-related capabilities, particularly around access control consistency, metadata standardization, and data governance.

What Guardrails Require in Practice

For agentic AI, guardrails extend beyond model alignment or safety prompts. In enterprise environments, they typically require several operational capabilities:

- **Consistent access controls and policy enforcement across sources**, so governance cannot be bypassed in downstream systems.
- **Auditability and traceability** of what data agents accessed and what actions they executed.
- Least-privilege tool access, ensuring agents can only invoke permitted actions under defined conditions. [12]
- **Semantic clarity,** so policies map consistently to business meaning (for example what constitutes "sensitive," "regulated," "PII," or "financial" data). [11]

These requirements explain why many organizations are exploring architectures that centralize governance and policy enforcement across distributed data environments. Platforms such as Denodo position logical data management as one approach to enabling these guardrails consistently across heterogeneous systems. [1]

The Role of Lakehouses, and the Criticality of Logical Data Management

SURVEY INSIGHT

Even among organizations using data catalogs and lakehouse environments, 55% of BFSI leaders report difficulty optimizing performance for AI workloads.

This signals that modernized central platforms are necessary infrastructure, but not sufficient on their own for operational, agentic AI — where cost, performance, and real-time access patterns increasingly determine whether pilots can scale sustainably.

Modern lakehouses and cloud platforms provide scalable compute and storage foundations for analytics and AI workloads. Vendors such as Databricks and Snowflake define lakehouse architectures as unifying aspects of data lakes and data warehouses to reduce silos and support analytics/AI workloads.

However, emerging evidence suggests that traditional data modernization alone does not fully address the operational requirements of agentic AI.

Gartner notes that many organizations still lack AI-ready data management practices and predicts that a substantial share of AI projects will be abandoned when those foundations are missing, despite significant investments in data modernization. [14]

Similarly, even leading data platform vendors acknowledge that pipeline complexity can introduce new operational constraints. For example, IBM notes that long processing times and additional ETL layers can contribute to data staleness and data quality risks — an architectural tension when systems must support both accurate analytics and real-time operational decisions. [5]

These signals suggest that while lakehouses remain essential infrastructure for analytics and AI development, additional architectural capabilities are often required when AI systems must operate across distributed enterprise environments.

Agentic AI systems typically require:

- Access to live operational data
- Consistent business semantics across distributed systems
- Centralized governance and policy enforcement
- Performance optimization and cost controls for AI workloads
- Access across hybrid, multi-cloud, SaaS, on-premises, and third-party data environments

Hybrid, Multi-Source Reality Is the Norm for AI Initiatives

In the global survey of enterprise AI leaders commissioned by Denodo, financial services and insurance organizations report that AI initiatives often draw from large numbers of original data sources, not a small number of consolidated systems.

The same survey suggests that organizations use multiple data access patterns simultaneously, including embedded data product teams, data marketplaces, central request processes, and direct-to-source access.

How Many Original Data Sources Feed AI Initiatives?

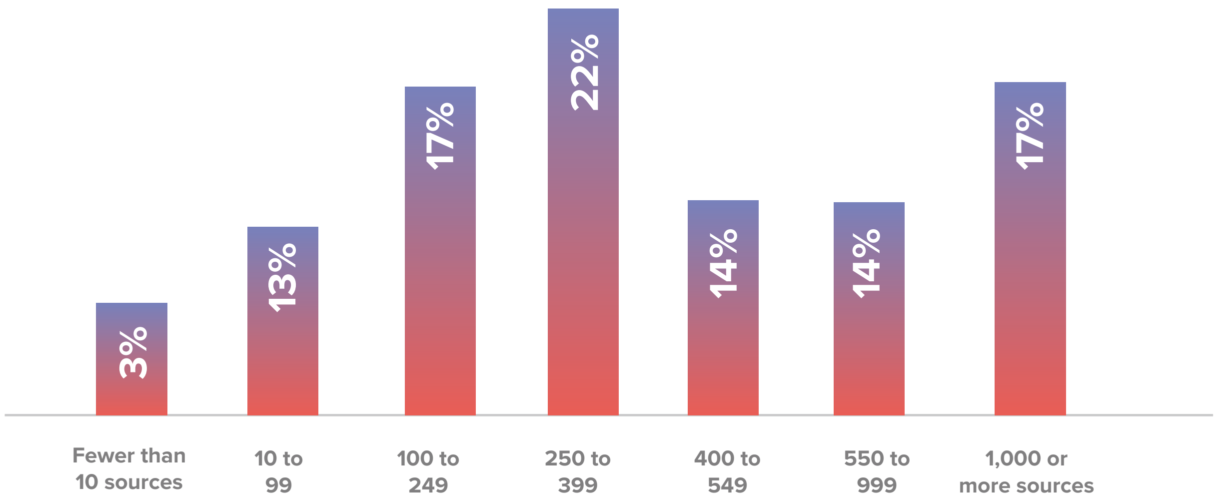


Figure #5

This diversity of access paths, combined with the sheer volume of original data sources, significantly increases the difficulty of applying consistent guardrails and semantics across enterprise data environments.

How Do Your AI Builders Access the Data They Need?
(Respondents were able to choose more than one.)

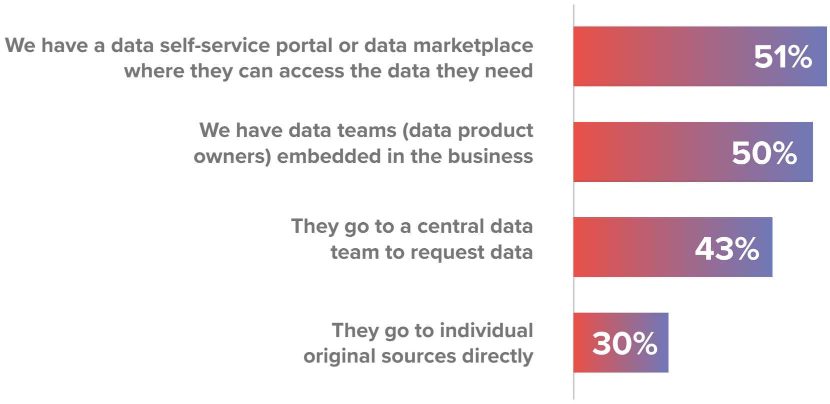


Figure #6

Logical Data Management as "Supplementation," Not Replacement

Lakehouses continue to serve a critical role in most enterprises for analytics, reporting, and many AI development workloads, while logical data management complements these environments when AI systems require live access to distributed operational data.

A useful way to interpret this architectural implication is as follows:

- **Lakehouses and warehouses** provide essential storage/compute and are well suited for many analytics and AI tasks, but they are often not designed to provide governed, real-time, business-ready data to every operational consumer across every system including most AI agents embedded in business workflows. [15]

- **Logical data management** is widely defined as providing a virtual layer that enables access to and integration of data across disparate sources "without requiring replication or movement," creating unified representations and accelerating integration for analytics and AI. [16]

- Platforms such as Denodo position logical data management as a way to centralize data practices — including discovery, access management, security, integration, monitoring, and sharing — through logical representations rather than duplicating governance and integration logic across individual systems. [16]

This "supplement, don't replace" positioning is also consistent with external analyst framing that modernization often involves layering capabilities rather than replacing existing platforms. [18]

Cost and Performance Optimization Is a Critical Requirement for AI ROI

Agentic AI can be cost-sensitive because agents may call multiple tools, perform repeated retrieval, iterate, and require logging/auditability for each task. This raises the bar for data performance and cost controls, as AI-intensive workloads can exceed the data consumption patterns that preceded it. [1] Gartner similarly cites escalating costs as a key driver for agentic AI project cancellations. [2]

Industry analysis increasingly highlights cost and performance optimization as critical factors in determining whether AI initiatives can scale economically. In financial services, this pressure is also significant: regulatory complexity and the cost of operating at scale mean AI initiatives must demonstrate clear business and compliance value. The data reflects this — ensuring regulatory compliance ranks as the third-highest challenge for BFSI AI teams (29% vs. 27% globally), reflecting the heightened compliance burden in the sector.

For example, an independent study commissioned by Denodo and conducted by analyst firm Veqtor8 compared lakehouse-only architectures with environments supplemented by a logical data management layer, reporting improvements in ROI, cost avoidance, and time-to-insight when organizations introduced a unified logical access layer. [17]

Such findings illustrate how organizations evaluate architectural approaches not only in terms of technical capability, but also in terms of economic sustainability for AI workloads.

Ownership, Funding, and Why It Changes the Data Conversation

SURVEY INSIGHT

Survey results indicate that responsibility for developing and maintaining AI initiatives is often distributed across multiple functions, rather than owned by a single central team.

This distributed ownership changes the data conversation: the data foundation must support not only traditional analytics and governance workflows, but also fast-moving AI delivery teams and business sponsors who need timely, governed access to operational data within real workflows.

A defining operational reality of enterprise AI is that ownership is shared beyond traditional data teams. While this sometimes occurs, AI is more frequently driven by central AI teams within technology leadership or by distributed business initiatives aligned to specific operational outcomes (customer operations automation, risk controls, cost reduction, productivity, etc.). These AI teams often operate under different mandates than traditional data programs, specifically to bring innovation to market and drive business impacts faster than competition.

This creates a practical requirement: the data foundation must work for fast-moving AI teams and business sponsors, not only for traditional analytics and data governance programs often prioritized by data teams. The survey evidence below shows how organizations describe responsibility for developing and maintaining AI initiatives.

The survey indicates that responsibility for AI initiatives is often distributed across multiple functions rather than centralized in a single team.

With 73% of BFSI organizations already running AI in production — above the global average of 67% — the sector leads on AI maturity, yet governance frameworks are still struggling to keep pace with deployment.

Who Is Responsible for Developing and Maintaining AI Initiatives? (Respondents were able to choose more than one.)

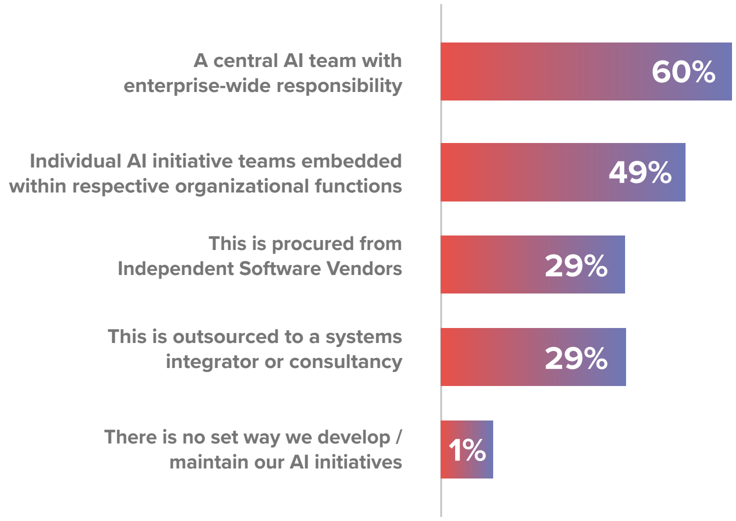


Figure #7

These ownership patterns help explain why agentic AI can expose limitations in existing data access and governance models. When AI investment is owned closer to mission outcomes, there is less tolerance for slow access cycles, prolonged data onboarding, or unclear governance pathways.

This aligns with Gartner's warning that many projects will be canceled due to cost, unclear value, and inadequate risk controls, each of which can be amplified when organizations struggle to deliver timely, governed access to the data required for AI systems. [2]

Who Is the Executive Sponsor for AI Initiatives?
(Respondents were able to choose more than one.)

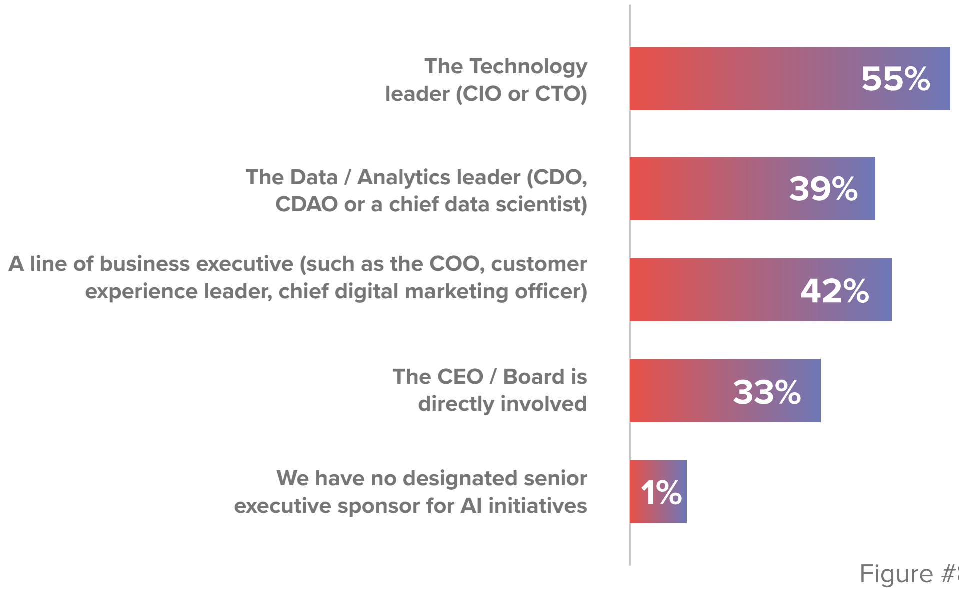


Figure #8

What This Means for Financial Services Leaders

Agentic AI success criteria tend to converge on a small set of architectural outcomes:

- **Business & Operations Leaders:** Struggle to deliver measurable outcomes (fraud reduction, CX improvement) and cannot rely on AI for critical decisions.
- **AI & Innovation Teams:** Spend more time preparing data than delivering models, struggling to operationalize agentic AI workflows.
- **Data & Technology Leaders:** Face the challenge of managing hundreds of distributed data sources (489 on average in BFSI) and struggle to enforce consistent governance.

What “Good” Looks Like and the 90-Day Blueprint

Closing the AI trust gap requires a shift from data aggregation to data activation. A modern AI-ready data foundation must provide live data access, business context with semantic consistency, and governed access.

Leading BFSI organizations are adopting a 90-day blueprint:

- **Days 1 – 30 (Define Outcomes):** Align on KPIs (fraud reduction, approval speed) and map required data sources and gaps.
- **Days 31 – 60 (Build Data Products):** Create governed, reusable data products aligned to use cases to enable real-time access and semantic consistency.
- **Days 61 – 90 (Operationalize):** Integrate AI into business workflows, enable real-time decisioning, and monitor compliance.

Closing the AI Trust Gap in Financial Services

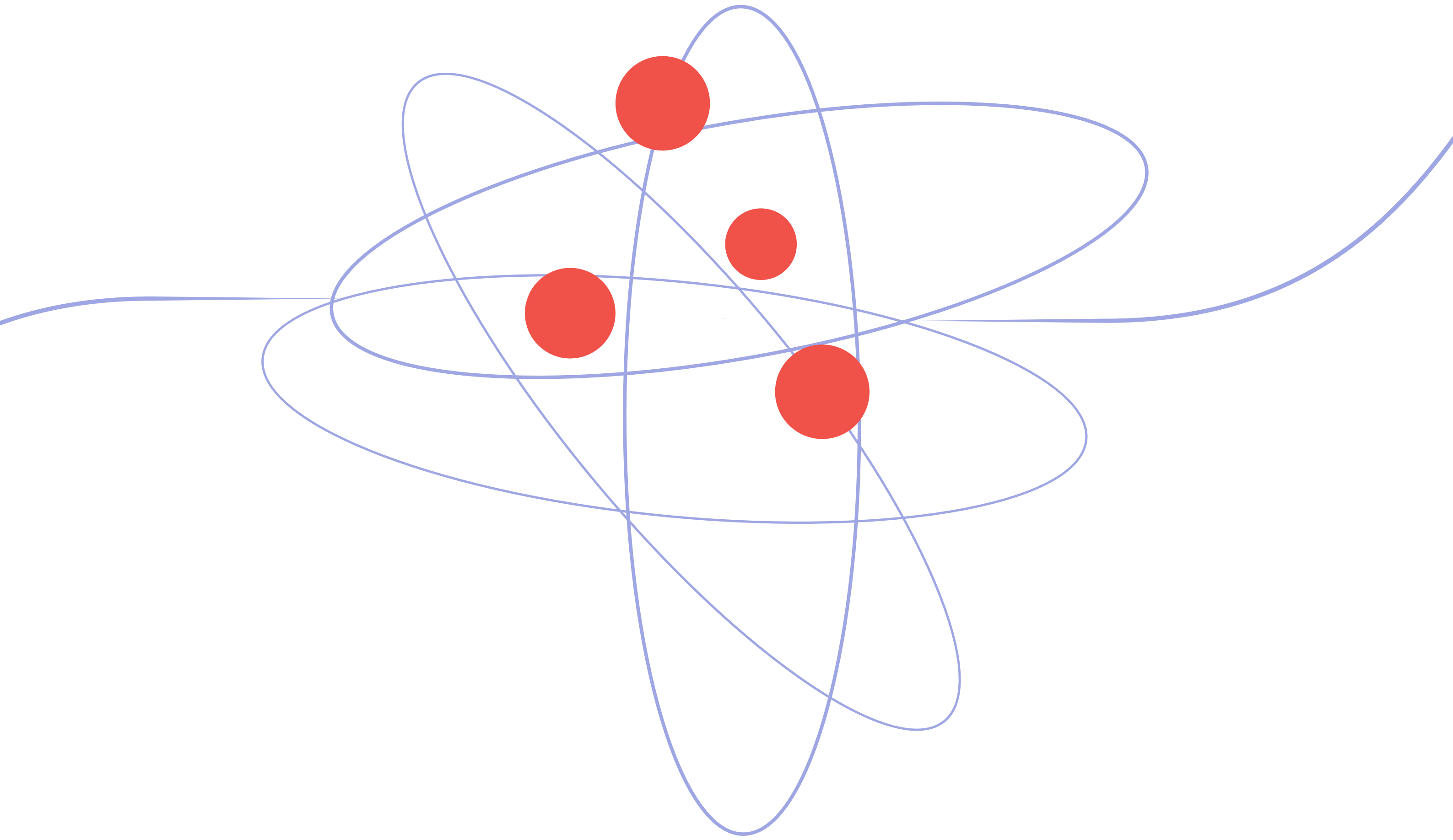
The future of AI in financial services is not about more models. It is about trusted data, real-time access, and governed decision-making. Organizations that close this gap will deliver measurable outcomes and build trust with regulators; those that don’t will remain stuck in pilots with diminishing returns.

Methodology

Arlington Research conducted this online survey in June 2025. Respondents consisted of 850 executives and business decision-makers in organizations with **1000+ employees**. The data presented in this specific report is drawn exclusively from a targeted subset of **233 enterprise leaders within the Financial Services and Insurance sectors.**

The survey was conducted across the Americas, Europe / Middle East, LATAM and Asia-Pacific regions, in the following countries:

- 75 each in the US, the UK, France, Germany, Japan, and Australia
- 50 each in Canada, Brazil, Italy, Spain, China, Singapore, South Korea, and the UAE



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