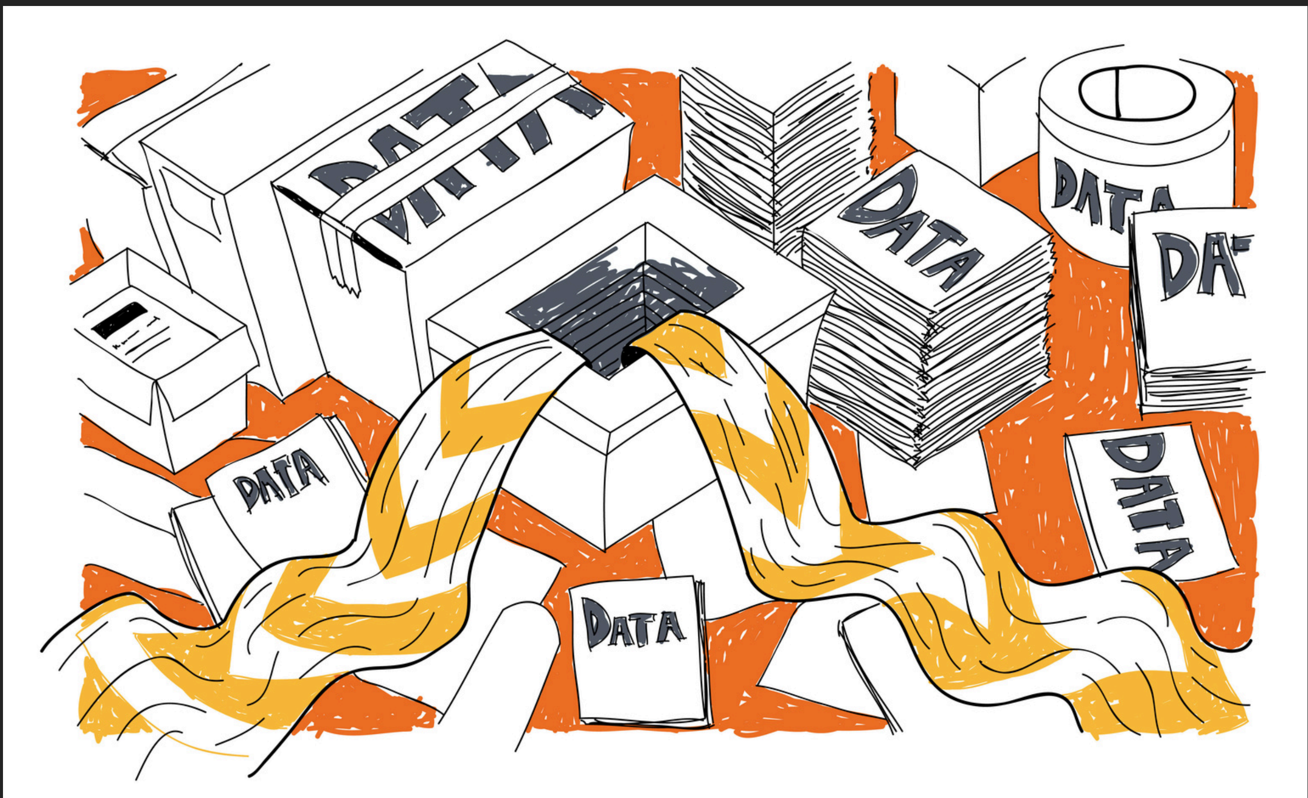
Modern Data 101
Q1 2026 EDITION

THE CATALYST

WHERE DATA & AI IGNITE BUSINESS



STATE OF DATA PRODUCTS

A Tech-Reporting Initiative
Muskan Purohit x Modern Data 101

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Founding Author's Note

THE CATALYST

WHERE DATA & AI IGNITE BUSINESS

This issue is packed with the innovations and newly emerged concepts that disrupted the data & AI landscape in 2026.

I write to you at the close of a quarter that feels less like the beginning of a year and more like the continuation of an inflexion point. If 2025 was about crossing a threshold, Q1 of 2026 has been about discovering what lies on the other side of it.

What has become increasingly clear over these past few months is that the centre of gravity has shifted again. The conversation is no longer just about behaviour in the real world, but about adaptation in real time. Data products are not being evaluated solely on their correctness or reliability, but on their ability to respond, recalibrate, and remain aligned in systems where AI is no longer a consumer of data, but an active participant in shaping it.

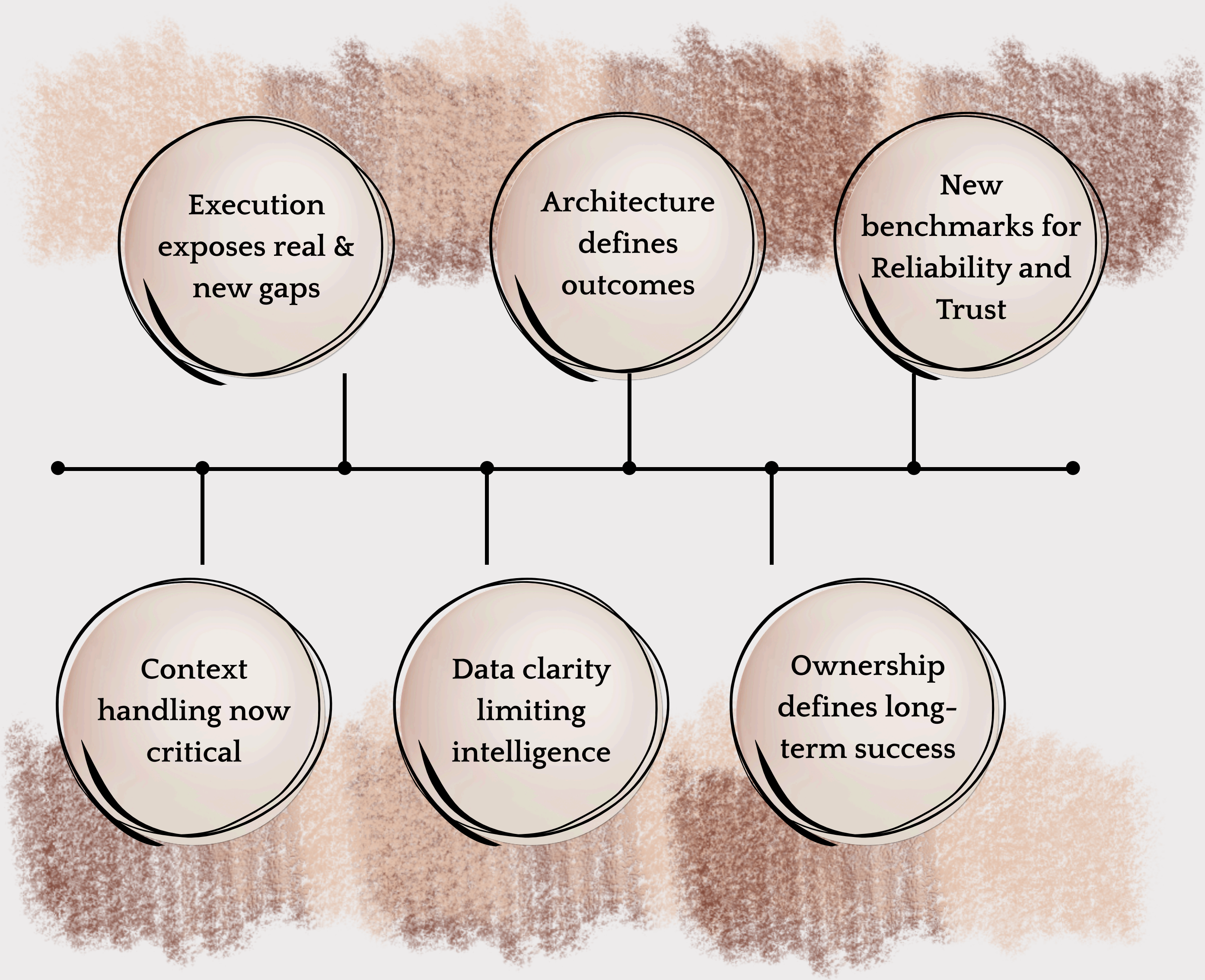
One of the most striking developments we've observed, echoed across practitioner conversations: the growing discomfort with static definitions of data quality. There is a rising acknowledgement that quality, in an AI-driven context, is not absolute. It is situational, model-dependent, and continuously negotiated. Teams are beginning to realise that what was once considered "clean data" can quickly become misaligned when interpreted through the probabilistic lens of large language models.

Governance is evolving from control to real-time guidance, while evaluation and continuous feedback are becoming essential to AI systems. Metadata is shifting from description to instruction, guiding how models reason. At the same time, user expectations demand context and continuity. AI-readiness is no longer about data preparation, but about building systems that can sustain ongoing dialogue.

Animesh Kumar

2026 Q1

KEY PIVOTS



The Integration Innovation

Q1 2026 saw the rapid rise of Model Context Protocol (MCP) as the standard way to connect AI systems with enterprise tools and data.

It positioned itself as a universal integration layer, allowing models to:

- Access APIs
- Interact with business systems
- Retrieve real-time data

For the first time, enterprises could skip custom integrations for each tool-model pair, cutting complexity and reinforcing the belief that AI was ready to scale in real-world use.

But beyond industry narratives, developers and builders questioned this quickly. On platforms like Reddit, the tone shifted from excitement to skepticism almost immediately:

> **"Are skills going to kill MCPs?"**
> **"Skills can already teach LLMs anything, why do we even need MCP servers anymore?"**

A growing section of practitioners argued that MCPs, while powerful, often felt over-engineered for many real-world workflows. With the rise of skills-lightweight, instruction-based approaches, many started questioning whether the same outcomes could be achieved with simpler, more flexible abstractions.

At the same time, others pushed back on this narrative: "MCPs provide structured, deterministic access to real systems. Skills manage context, they're not the same thing."

This led to a more nuanced understanding emerging from the community:

- MCP handles connection to systems (APIs, databases, tools)
- Skills handle how tasks are executed using that access

In practice, many developers found themselves using a combination of both, rather than choosing one over the other.

Kurtis Van Gent • 3rd+
AI + Databases @ Google Cloud
2mo •

A lot of the discussion around Skills right now is "MCP vs Skills". I think this is asking the wrong question.

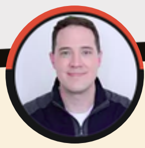
MCP addresses connectivity - how do you wire N agents to M data sources without N×M integrations?

Skills tackles a context saturation - how do you give agents hundreds of capabilities without stuffing 30k tokens of schemas into the context window?

Different problems. Different solutions. Better together?

This debate signaled something deeper than just a tooling preference. It marked a shift in how practitioners were evaluating AI systems, not by what they could connect to, but by how effectively they could execute.

Connectivity was no longer the bottleneck. Execution was.

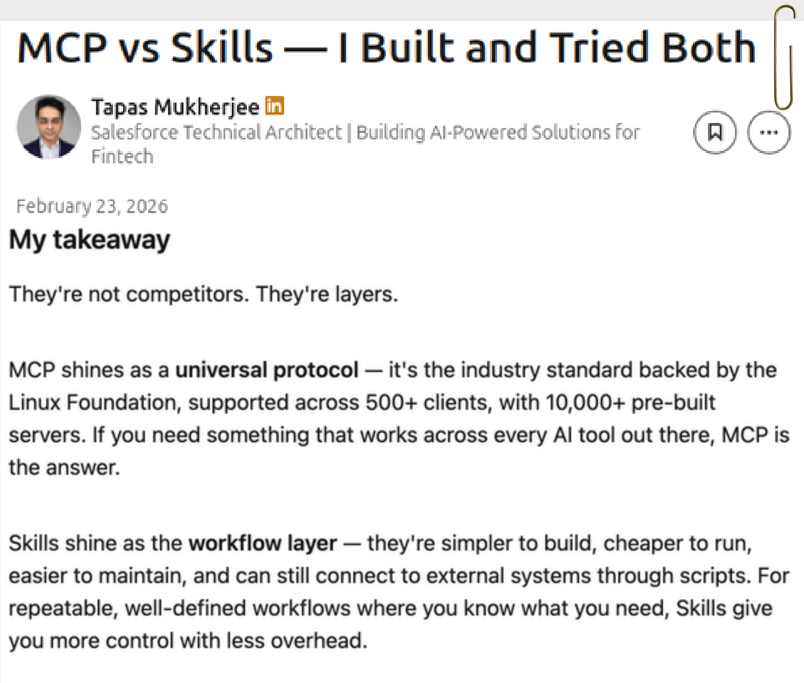


Travis Thompson
@travisthompsonsays
Chief Architect, DataOS

"Models need structure. Agents need context. Enterprises need systems that don't break when the interface shifts from dashboards to dialogue."

Source: Thriving in the Agentic Era, A Case for the Data Developer Platform

Access vs Execution Confusion



MCP vs Skills — I Built and Tried Both

Tapas Mukherjee
Salesforce Technical Architect | Building AI-Powered Solutions for Fintech

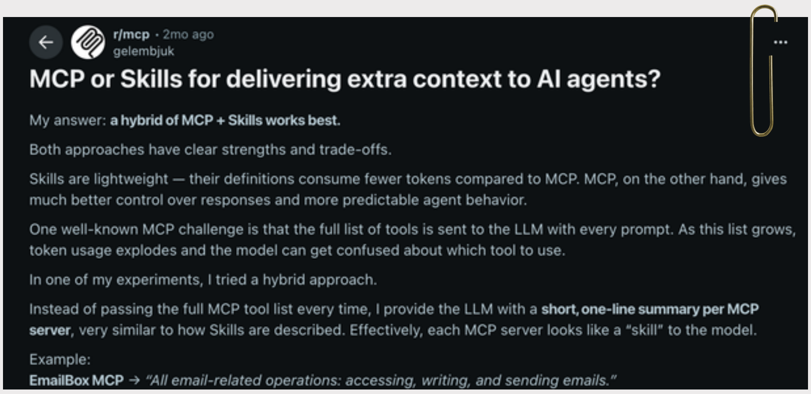
February 23, 2026

My takeaway

They're not competitors. They're layers.

MCP shines as a **universal protocol** — it's the industry standard backed by the Linux Foundation, supported across 500+ clients, with 10,000+ pre-built servers. If you need something that works across every AI tool out there, MCP is the answer.

Skills shine as the **workflow layer** — they're simpler to build, cheaper to run, easier to maintain, and can still connect to external systems through scripts. For repeatable, well-defined workflows where you know what you need, Skills give you more control with less overhead.



r/mcp · 2mo ago
gelembjuk

MCP or Skills for delivering extra context to AI agents?

My answer: **a hybrid of MCP + Skills works best.**

Both approaches have clear strengths and trade-offs.

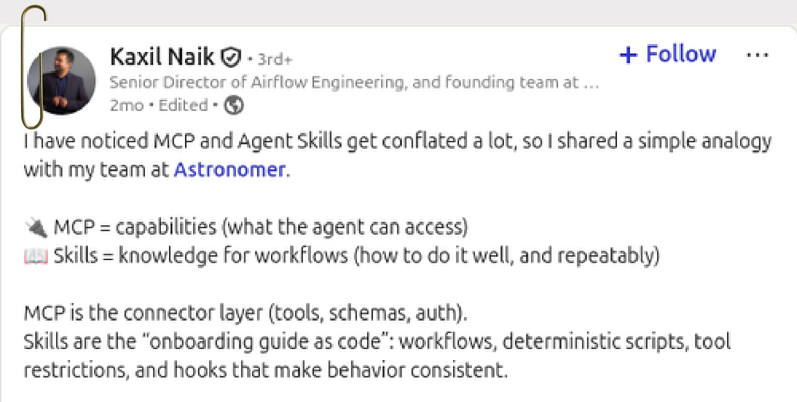
Skills are lightweight — their definitions consume fewer tokens compared to MCP. MCP, on the other hand, gives much better control over responses and more predictable agent behavior.

One well-known MCP challenge is that the full list of tools is sent to the LLM with every prompt. As this list grows, token usage explodes and the model can get confused about which tool to use.

In one of my experiments, I tried a hybrid approach.

Instead of passing the full MCP tool list every time, I provide the LLM with a **short, one-line summary per MCP server**, very similar to how Skills are described. Effectively, each MCP server looks like a "skill" to the model.

Example:
EmailBox MCP → *"All email-related operations: accessing, writing, and sending emails."*



Kaxil Naik · 3rd+
Senior Director of Airflow Engineering, and founding team at ...
2mo · Edited

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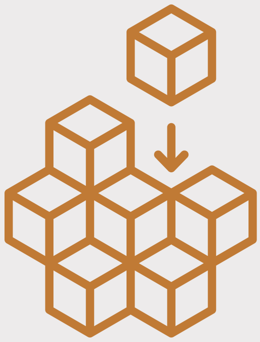
I have noticed MCP and Agent Skills get conflated a lot, so I shared a simple analogy with my team at Astronomer.

🔌 MCP = capabilities (what the agent can access)
📖 Skills = knowledge for workflows (how to do it well, and repeatably)

MCP is the connector layer (tools, schemas, auth).
Skills are the "onboarding guide as code": workflows, deterministic scripts, tool restrictions, and hooks that make behavior consistent.

"MCP solves connectivity. Skills solve context saturation. Different problems, different solutions. The surface-level overlap in primitives doesn't make them competitors any more than a hammer and a screwdriver are competitors because they're both on your tool belt,"

points out Kurtis Van Gen, Senior Staff Software Engineer at Google.



A story that remains uncovered is that MCPs connect your agent to external systems, such as GitHub, databases, browsers, files.

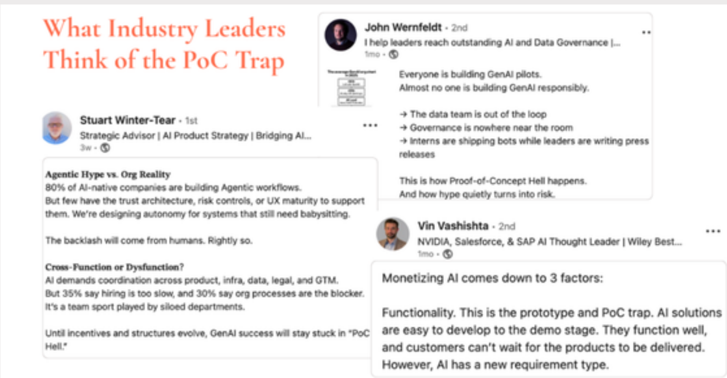
Skills tell the agent what to do with that access. So MCPs are like a new connection layer, while skills are the instruction layer with agents being central to execution.

Pilot to Production Challenge
The Pattern Returns

MCP made it significantly easier for AI systems to connect to tools, APIs, and data sources. On the surface, this looked like a breakthrough, removing one of the biggest friction points in the brief history of enterprise AI adoption.

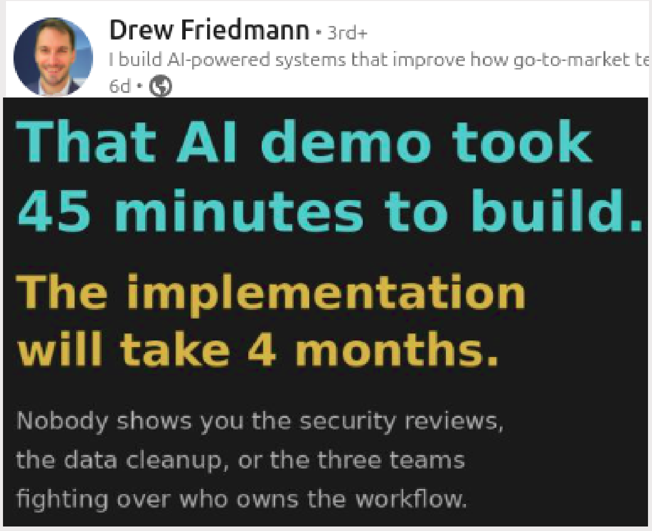
But very quickly, a familiar pattern resurfaced.
AI systems could access everything, yet still struggled to produce consistent, reliable outcomes in real workflows.

This wasn't entirely new. As highlighted by industry discussions, many organisations were already grappling with the "PoC trap," which is a cycle where AI performs well in controlled demos but fails to translate into production value. Reports from the World Economic Forum echo this divide, with only a small set of organisations successfully moving from experimentation to scaled impact.



The issue was not about whether AI connects well or not. Rather, it was about what happens after it connects. A number of structural gaps became increasingly visible:

Challenge 1: While agents could now retrieve data from multiple systems, they still lacked clarity on what that data represented, whether it could be trusted, or how it should be used. Access without semantics led to fragile outputs.



Challenge 2: Even with richer context windows and better retrieval mechanisms, AI systems often misinterpret data. More information did not translate into better reasoning, especially when the underlying data lacked structure or consistency.

Challenge 3: As "plug-and-play" agents were deployed, longstanding issues quickly reappeared. Inconsistent definitions across systems, missing or incomplete lineage.

In other words, MCP removed the integration bottleneck, but exposed the data layer as the real constraint.

This is why many early "plug-and-play agent" experiences plateaued. The agents were failing because the data ecosystem they depended on was not designed for reliable consumption.

> The question on stacks revives again at this juncture, as AI-readiness, whether with MCPs or skills, require a stack that is fit for the purpose.

MCP vs Skills: Rethinking the AI Stack

The rapid adoption of Model Context Protocol (MCP) in early 2026 positioned it as a standardised interface layer for connecting AI systems with enterprise tools, APIs, and data sources. By abstracting integration complexity, MCP enabled agents to access external systems in a consistent, tool-agnostic manner.

However, while this solved the problem of connectivity, it did not address execution fidelity. Access to tools does not inherently provide the model with an understanding of when, why, or how to use them within a business workflow. As a result, many implementations remained brittle, producing inconsistent outcomes when exposed to real-world variability.

“Where Data Products unify around business purpose, MCP unifies around AI interaction.

One defines why value exists. The other defines how intelligence engages with it.”

Traditional stacks were built for storage and querying. They are not built for reasoning, memory, or agent interaction. A Data Developer Platform (DDP) is the architectural response to this.

This gap led to the emergence of “skills” as a complementary execution layer within the AI stack. Unlike MCPs, which focus on exposing capabilities, skills encapsulate structured logic, contextual boundaries, and task-specific instructions that guide model behaviour.

By enabling selective context loading, deterministic sub-steps (often via APIs or CLI wrappers), and reusable workflow definitions, skills significantly improve reliability, token efficiency, and outcome consistency. This marks a fundamental architectural shift from integration-centric design to capability-driven systems, where the focus moves from what the model can access to how effectively it can execute within defined operational constraints.

A standardised layer like an MCP allows models to request information, execute actions, and interface with tools safely and predictably. For many teams, MCP is becoming the connective tissue that turns AI from “nice experiments” into reliable production workflows.

Animesh Kumar · 1st
CTO, DataOS: Data Infrastructure for AI

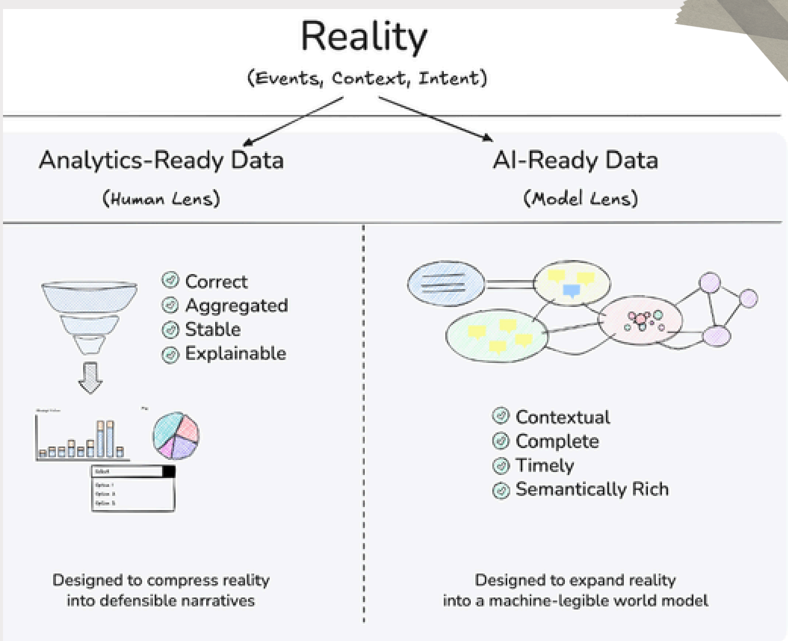
The Data Reality Check

AI systems are not failing at inference; they are failing at data readiness.

Core issues:

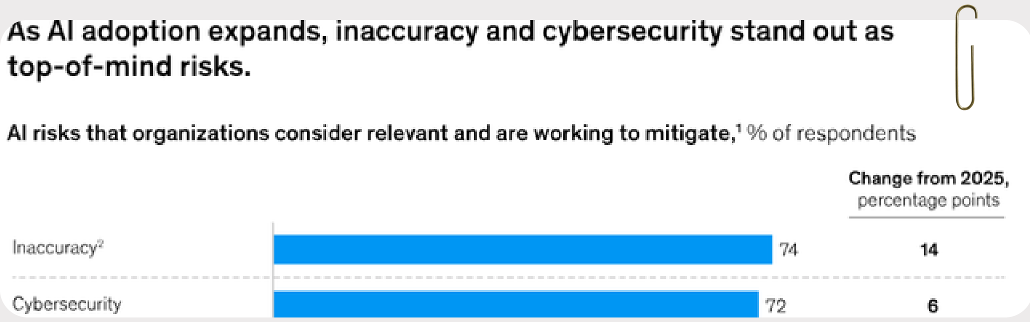
- Non-deterministic outputs due to inconsistent data inputs
- Lack of lineage → no traceability or auditability
- Fragmented ownership → no single source of truth

Reality check:
Demos operate on curated datasets. Production systems depend on live, fragmented data ecosystems.



Source: AI-Ready vs. Analytics-Ready Data

As AI adoption grows, 74 percent of respondents identify inaccuracy and 72 percent cite cybersecurity as highly relevant risks (Exhibit 7). These risks remain foundational concerns even as newer agentic risks emerge, highlighting that organizations must manage both traditional model risks and the expanded threat surface introduced by autonomy.



McKinsey & Company

Trust is not a model-layer problem, it is a data-layer failure.
And connectivity alone won't fix it, execution needs structure.

Focus Back on Architectures

As AI systems moved beyond isolated use cases, architectural weaknesses became systemic constraints. Disconnected pipelines, inconsistent semantics, and unclear ownership models limited reliability.

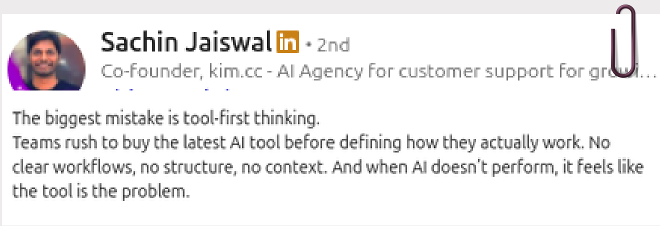
The absence of standardised interfaces and governed data flows exposed a deeper issue: enterprises were scaling access to AI, but not the underlying systems required to sustain it.

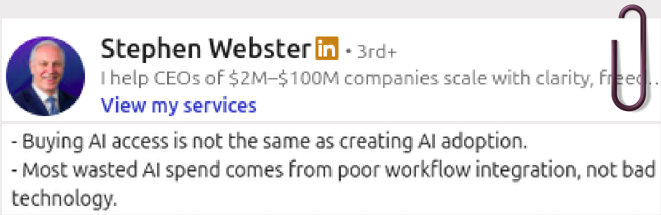
This triggered a shift toward architecture as a first-class concern. Organisations began prioritising unified data models, explicit contracts, and embedded governance across the stack. The focus moved from enabling experimentation to ensuring determinism, traceability, and repeatability, prerequisites for production-grade AI systems operating at scale.

What made this shift more pronounced was how consistently these challenges surfaced in practitioner communities.

“The more fragmented your data stack is, the higher the chance of breakage.”

Fast Build → Fragmentation → Structured architecture


Sachin Jaiswal • 2nd
Co-founder, kim.cc - AI Agency for customer support for gr...
The biggest mistake is tool-first thinking.
Teams rush to buy the latest AI tool before defining how they actually work. No clear workflows, no structure, no context. And when AI doesn't perform, it feels like the tool is the problem.


Stephen Webster • 3rd+
I help CEOs of $2M–$100M companies scale with clarity, freed...
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- Buying AI access is not the same as creating AI adoption.
- Most wasted AI spend comes from poor workflow integration, not bad technology.

According to IBM, How to maximize AI ROI in 2026 and Forbes’ 22 Top AI Statistics And Trends, AI adoption is accelerating—but impact remains uneven. While 72% of businesses have implemented AI in at least one function, only 25% of initiatives actually deliver expected ROI, and fewer than 20% scale across the enterprise.

The gap is clear: AI adoption is high, but real scaling still lags. Core data and architectural constraints continue to hold it back.

•AI ADOPTION — DIAGNOSTIC OVERVIEW•

Before	What Surfaced	Where It Shifted
1 Rapid experimentation	Fragmented data ecosystems	Architecture-first thinking
2 Tool-first adoption (LLMs, MCPs)	No consistent system of record	Embedded governance models
3 Focus on speed and demos	Governance and ownership gaps	Focus on reliability and repeatability
4 Assumption of plug-and-play scalability	Conflicting architectural approaches	Designing for production, not demos

Image Source: Modern Data 101

Adoption is scaling. Impact is not.

The Enterprise-AI Gap

Dissolution of Trust

- AI outputs may look correct but fail in real-world scenarios.
- One incorrect response can quickly erode confidence.
- Users stop relying on the system instead of improving it.
- Over time, AI shifts from a decision-support tool to something teams avoid.

Abhishek Ojha • 3rd+
SVP & Head of Enterprise Architecture | Digital Transformatio...
1mo •

But when it moves from POC to a live environment, actual issues begin.

Data is inconsistent.
Data is in silos
Ownership is unclear.
Systems don't integrate smoothly.
Governance questions slow everything down.

And slowly, momentum fades.

Not because AI failed.
Because the enterprise was not architected for it.

In complex environments like banking, AI is not just a technical layer you plug in. It sits on data architecture, integration architecture, security architecture, process architecture, and ultimately, organizational clarity.

> AI doesn't break at the model layer, it breaks across data, trust, and ownership. Weak foundations create unreliable outputs, eroding confidence and preventing systems from scaling beyond controlled environments into production.

Meenakshi E • 3rd+
Data Analytics Lead | Data Governance | IIIT-B | LJMU (UK)
2mo •

AI models don't fail silently — they fail because of data.

When data quality is weak, even the most advanced models produce unreliable and risky outcomes.

3. Wrong Insights
a. Incorrect labels or inconsistent definitions
b. Duplicate or inaccurate records
c. Poor feature quality
📌 Result: Confident-looking predictions that are simply wrong.

4. Loss of Trust
a. Business users stop trusting AI outputs
b. Manual overrides increase
c. AI adoption slows down

Breakdown of Ownership & Governance

- When ownership is unclear, no one is accountable for outcomes.
- Errors persist because no team is responsible for fixing them.
- Governance gaps lead to inconsistent data, logic, and outputs.
- Without accountability, systems stagnate and fail to scale.

Where AI Breaks in the Enterprise

> **Solving the Engineering Problem that Makes AI Actually Useful: Building the Axle**
>
> Precision-engineering for the four tolerance challenges of enterprise AI
>
> SAGAR PAUL
> FEB 02, 2026
>
> AI models are the wheel. They spin impressively. Everyone can see them work. Executives watch demos and understand, at least superficially, what is happening.
>
> But connecting these models to enterprise data and workflows is the axle problem

Most failures stem from tool-first thinking instead of system design.

AI adoption in Q1 2026 is clearly shifting beyond tools to systems.

- Models ("the wheel") demonstrate capability
- But value depends on integration ("the axle")
- Without data, workflows, and infrastructure, AI remains surface-level

The focus is moving from what AI can do to how it actually works in reality. Source: The Wheel and the Algorithm

Lessons from AI Deployments That Didn't Meet Expectations

Paty Diaz

Other industry sources suggest that only 10–20% of AI pilots ever transition successfully from pilot stage to organization-wide implementation.

AI often succeeds in controlled demos but fails in production.

- Clean data vs messy reality
- Single-use case vs real-world scale
- Model focus vs missing system design

Balaji(Bala) Veeravalli • 3rd+
Founder & CEO at Datastreet Solutions | QE & AI Leader |
Visit my website

The model got all the attention. The system got none.

In demo mode, everything is neat: Handpicked data, controlled queries, zero edge cases One user, one use case, no scale pressure - No compliance team asking questions yet then it goes live. Real users. Real data. Real chaos. And the cracks don't appear slowly - they appear all at once.

The model got all the attention. The system got none.

The gap isn't capability, it's readiness for real-world complexity

AI failures rarely stem from the model itself, they emerge from unresolved foundations. Poor data, unclear ownership, fragile trust, and tool-first thinking compound as systems move into real-world conditions. The gap isn't capability, but operational readiness: without strong data, defined accountability, and integrated systems, even promising AI initiatives fail to translate into sustained, scalable value.

From AI Potential to Operational Reality

What Q1 2026 ultimately revealed:
AI didn't fail to perform;
it failed to operate reliably in real environments.

How AI is now being evaluated:

- **Response reliability**
- **Context continuity**
- **Decision consistency**

Demos → Workflows

AI must execute repeatable, real-world tasks, not just perform in controlled scenarios.

Access → Execution

Connecting to systems is solved. Using them correctly, consistently, and contextually is not.

Models → Systems

Model capability is no longer the constraint. System design sets whether AI actually works.

Hype → Readiness

Success depends on data quality, architecture, and operational clarity, not experimentation.

AI success is no longer defined by what models can do, but by how reliably organisations can make them work.

Data and AI for Business
with State of Data Products

MODERN DATA 101 QUARTERLY

STATE OF DATA PRODUCTS

QUARTERLY PULSE OF THE INDUSTRY

So far, 2024 has indisputably been a monumental year in the ever-evolving data products and artificial intelligence landscape. With the massive rate of adoption of AI and LLM solutions, the second quarter of the year arguably remained a blend of failures and successes of such projects.

While Data Products attracted the limelight, remaining the centrepiece of several podcasts, blogs, forums, and other conversations across the internet, the volume of possibilities for integrating AI and LLM solutions into existing architectures also raised eyebrows.

The past months have been more like rollercoaster rides, with conversations about crafting a niche definition and putting a data product into function.

In this piece, we attempted to explore the state of data products and AI. In shaping this effort, the insights shared by various industry experts, highlighting some of the best practices for leveraging these trend-setting uproars in the technologies, came in handy.

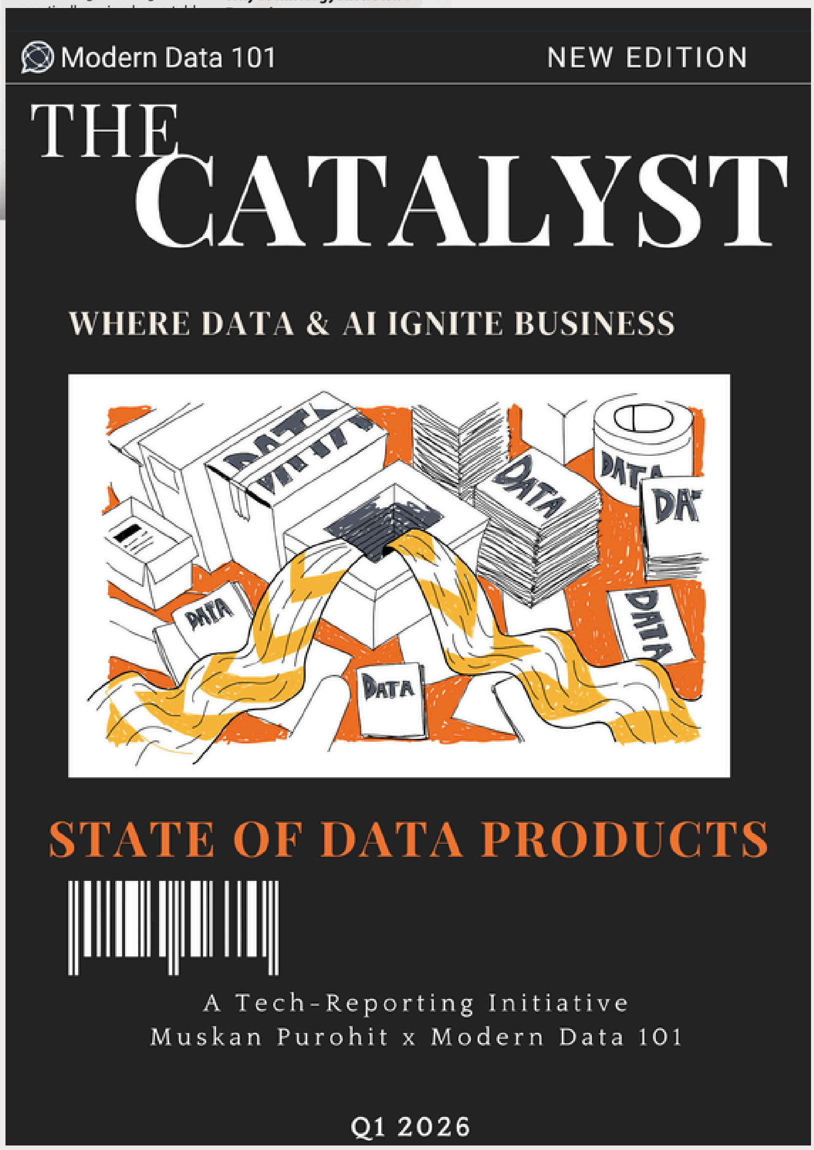
Talk of the Town

Data Products — Where Theory Meets Practice

Data Products definition, assumably so, was the most looked-for concept that grabbed eyeballs. From being a theoretical construct to maturing into a logical and

Scoping Data Projects: Why Technology Alone Isn't

WE ARE IN OUR NEW COVER!



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