

NO SHORTCUT TO AI

AI can accelerate what an insurer knows. It cannot compensate for data that the organization does not understand, trust, govern, or connect.

“Before AI can deliver reliable business results, the fundamentals of data management need to be in place.”

Every insurance company is talking about artificial intelligence.

The questions are familiar:

How can AI improve underwriting?

Can it help claim adjusters work more efficiently?

Can generative AI make better use of information already sitting inside the organization?

These are legitimate questions. But there is another question that often receives far less attention:

Is the organization’s data foundation ready for AI?

AI can process enormous volumes of information. It can identify patterns, summarize documents, generate responses, and support decisions. But AI does not eliminate the need to understand the data it is using.

In many insurance organizations, the underlying problem is not a shortage of data. It is that the organization does not have a consistent, governed understanding of its data.

Different systems may use different definitions.

Business units may maintain their own terminology.

Data may move through multiple applications without clear lineage.

Critical fields may have no accountable owner.

Quality problems may be discovered only after data reaches a report or operational process.

Adding AI to that environment does not make the foundation stronger. It makes the foundation more important.

The Data Management Building Blocks Matter

AI readiness starts with capabilities that have existed long before the current AI conversation. They may not be the most visible parts of an AI strategy, but they establish what the data means, where it comes from, who owns it, how it changes, and whether it can be trusted.

01 Business Glossary

Establishes a common language for the organization. Everyone needs to understand what terms such as customer, policy, claim, exposure and written premium actually mean.

02 Metadata Repository

Provides the context behind the data—what it means, where it comes from, who owns it, how it is used, and how it relates to other data.

03 Data Lineage Shows where data originates, how it moves and changes through systems, and where it ultimately gets used. Lineage helps identify downstream impacts when data changes.	04 Data Ownership & Stewardship Defines accountability for critical data and establishes who maintains its definition, quality, appropriate use, and resolution of business disagreements.
05 Data Quality Management Determines whether data is accurate, complete, consistent, timely, and fit for the business purpose for which it is being used.	06 Modern Data Architecture Provides the structure needed to connect information across policy, claims, billing, customer, rating, and other operational environments.
07 Data Governance Creates the policies, roles, decision rights, standards, and oversight needed to manage data as an enterprise asset rather than a collection of departmental resources.	08 Business–IT Alignment Connects data initiatives to actual business objectives so technology investments support decisions, processes, and outcomes rather than becoming isolated technical projects.

Why a Business Glossary Matters to AI

Consider something as basic as the word customer.

Does it mean the named insured? The policyholder? A household? An individual? A commercial account? An organization that may have multiple policies?

If different parts of the organization answer the question differently, an AI application cannot simply determine which definition the business intends.

The same problem exists with policy, claim, exposure, premium, producer, account, loss, and expense. A Business Glossary establishes the agreed business meaning behind those terms. It gives people, applications, analytics, and AI systems a common language to work from.

Metadata: The Context Behind the Data

If the Business Glossary explains *what data means*, metadata helps explain *what the data is and how it behaves*.

Where did the data originate?

Which system owns it?

What table and field contain it?

Who is responsible for it?

How frequently is it updated?

What other data does it relate to?

Where is it used?

What rules transform it before it reaches a report, model, or AI application?

A metadata repository turns this information into institutional knowledge. Without it, organizations frequently depend on tribal knowledge—information held by individuals who know how a particular system works because they have worked with it for years.

That is a fragile foundation for an AI-enabled enterprise.

Data Lineage: Knowing Where the Answer Came From

Insurance data rarely travels directly from a source system to a decision. A policy transaction may move through applications, databases, integration processes, warehouses, transformations, reports, analytical models, and AI applications.

When an executive asks, “Where did this number come from?” the organization should be able to answer.

When a source field changes, it should also be possible to determine what downstream reports, processes, models, and AI applications could be affected.

That is the value of data lineage.

Data Ownership and Stewardship

Technology cannot determine who is accountable for a business definition. People have to do that. Someone needs to own the definition of a critical data element. Someone needs to determine what constitutes acceptable quality. Someone needs to resolve disagreements between business units. Someone needs to decide whether a particular use of the data is appropriate.

Effective governance is not about creating another committee that meets once a month. It is about establishing clear accountability for the data that matters to the business.

Data Quality Is a Business Issue

AI does not make poor data good.

If customer records are incomplete, inconsistent, or duplicated, AI has more information to process—but not necessarily better information.

Organizations need to know which data elements are critical, what good quality means, how quality is measured, where defects originate, who is responsible for correcting them, and whether problems are recurring.

A Practical Test

Can You Trust the Data Behind the Question?

Suppose an executive asks an AI application: “How many customers do we have, how many have multiple policies, and how profitable are they?”

The technical ability to generate an answer is not the same as having a trustworthy answer. The organization first needs consistent definitions, connected customer information, appropriate data quality, clear ownership, and an understanding of the calculations behind profitability.

The AI answer is only as reliable as the foundation beneath the question.

What This Looks Like in Practice: CEO-Level Outcomes

When the data foundation is weak, the impact shows up in the metrics CEOs own. When it is strong, AI and analytics begin to deliver results that move the P&L and the board conversation.

Public research and published case results illustrate the scale of opportunity—and why trusted data is the prerequisite.

Example 1 — Claims Performance and Leakage

A mid-sized P&C carrier invested in AI-assisted claims triage and severity prediction. Early results looked promising in pilot. When the models moved into production, adjusters and managers quickly lost confidence: three different systems used inconsistent definitions of “closed claim,” “reopened claim,” and “indemnity paid.” Lineage was incomplete, so no one could explain why the AI recommendation differed from the claims system of record.

Industry research shows why the foundation matters. Bain & Company has estimated that generative AI applied effectively to P&C claims handling could reduce leakage by 30–50% and loss-adjusting expenses by 20–25%, with potential global benefits exceeding \$100 billion for insurers and customers.

Early published results include coverage-related leakage reductions and meaningful time savings per claim. PwC has long noted that while a rough industry benchmark for leakage is around 3%, many carriers operate well above that level, with process improvements often yielding savings in the 5–10% range of claims costs.

After establishing clear business definitions, ownership for key claims data elements, and basic lineage, the same AI tools produced recommendations that claims leaders could trust. The CEO’s question shifted from “Why don’t the AI numbers match our claims reports?” to “How do we scale this across the book?”

Example 2 — Underwriting and Portfolio Visibility

An executive team asked for a clear view of customer and account profitability to support pricing and appetite decisions. Multiple reports produced different answers because “customer,” “account,” and “written premium” were defined differently across policy, billing, and actuarial environments. AI-powered portfolio analysis simply amplified the inconsistency—one view showed a segment as several points underpriced; another showed it near target.

Published analyses underline the stakes. Research associated with Willis Towers Watson has linked strong portfolio management to combined ratios roughly 8 points better than weaker approaches—the difference between a profitable and an unprofitable book for many carriers.

Shift Technology and others have reported that complementary AI solutions across fraud, claims, and related processes can contribute on the order of 3–6 points of combined-ratio improvement when effectively deployed; fraud detection alone has been associated with roughly 1 point, and improved subrogation/recovery with additional points.

A focused effort on the business glossary, customer data quality, and ownership produced a single, governed view of profitability. Underwriting and product leaders could then use both traditional analytics and newer AI tools with confidence. Outcomes visible to the CEO included clearer identification of combined-ratio opportunity in underperforming segments, more consistent pricing discipline, and board-level portfolio discussions grounded in one set of numbers rather than competing reports.

Example 3 — AI Investment ROI and Board Confidence

A carrier committed a material share of its technology budget to generative AI for underwriting support and customer-facing applications. Industry surveys indicate that AI already accounts for a meaningful portion of tech spend—commonly in the mid-teens percent range on average, with some analyses showing allocation rising from roughly 8% toward 20% or more over a multi-year horizon—and that many insurance CEOs plan to direct 10–20% of relevant budgets toward AI initiatives.

Six months in, the board asked a straightforward question:

What business results have we achieved, and how do we know the answers are reliable?

The organization struggled to answer because critical data elements lacked clear owners, quality metrics, and lineage. Published case work illustrates both the upside and the dependency on foundations: McKinsey’s work with Aviva on claims AI reported a 23-day reduction in time to assess liability for complex cases, 30% improvement in routing accuracy, and a 65% reduction in customer complaints, alongside large gains in employee engagement.

Deloitte has documented multi-day cycle-time reductions and tens of millions in expense improvement in claims transformation programs. These results rest on data and processes the organization can trust and explain.

Addressing the foundational gaps—definitions, ownership, quality, and architecture—turned the conversation. The same AI capabilities could then be tied to specific underwriting efficiency and decision-quality measures, with model recommendations traceable to governed source data. The CEO gained a narrative the board could accept: the investment rested on data the organization understood and governed, not on black-box outputs.

In each case the pattern is the same. AI did not create the data problem, and it could not solve it. Public benchmarks show material opportunity in leakage, cycle time, combined ratio, and expense. Realizing that opportunity at scale depends on a data foundation the organization understands, governs, and trusts.

Modern Data Architecture

Most insurers have accumulated systems over decades: policy administration, claims, billing, customer management, rating, document management, data warehouses, data lakes, reporting platforms, and third-party data.

The challenge is not simply connecting everything. The challenge is creating an architecture in which the organization can understand, govern, and use information consistently across those environments.

Modern architecture should support the business's ability to move from:

Data → Information → Insight → Decision → Action

AI becomes another consumer—and potentially another producer—within that environment. It does not replace the architecture.

This Is Not Just an AI Issue

The underlying problem predates AI. Insurance organizations have been dealing with fragmented information, inconsistent definitions, disconnected systems, and departmental data silos for decades.

The current AI conversation simply exposes the issue more clearly.

A company cannot become truly data-driven by purchasing another technology platform. It has to establish the disciplines that allow technology to work across the enterprise.

That is why data governance, architecture, quality, metadata, business definitions, and ownership remain important even as technology changes.

The tools will continue to evolve. The fundamentals will not.

From Data Management to Business Performance

The objective is not to manage data better for its own sake. The objective is to use trusted data to improve the business.

- Better underwriting decisions
- More effective claims operations
- Improved customer understanding
- Faster product development
- More reliable reporting
- Reduced operational complexity
- Better analytics
- More effective use of AI

This connects directly to a broader AIA principle: data management should be tied to business performance rather than treated as an isolated technology discipline.

The Real AI Readiness Question

The question for an insurance executive should therefore not simply be:
“What can we do with AI?”

A better starting point is:

“Do we have the data foundation necessary to use AI effectively?”

That question leads to a different conversation.

Do we have common definitions?

Do we know where critical data comes from?

Can we trace it through the organization?

Do we know who owns it?

Can we measure its quality?

Can our architecture connect it?

Do our people and processes support its effective use?

Can we trust the information on which our AI initiatives will depend?

There Is No Shortcut

AI is changing how insurers work with information. But it does not change the fundamentals of information management.

Business Glossary. Metadata. Lineage. Ownership. Stewardship. Data Quality. Architecture.

Governance. Business–IT alignment.

These are not yesterday’s data-management concepts.

They are part of the foundation for tomorrow’s AI-enabled insurance organization.

There is no shortcut to AI.

The path starts with understanding the data, governing it, connecting it, and making it trustworthy.

How AIA Can Help

Agile Insurance Analytics helps property and casualty insurers assess their current data and analytics capabilities, identify the gaps that matter, and develop practical roadmaps that connect data management to business performance.

The starting point does not have to be a massive transformation program. It can begin with a focused assessment:

Where are you today? What is missing? What matters most? And what should you do next?