

Closing the Intelligence Gap: The Race to Intelligent Underwriting

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Abstract: *The underwriting function is at an inflection point. Third-party data maturity, AI-powered decision agents, and modernized workflow architecture are giving carriers a genuine opportunity to accelerate time-to-quote, free underwriters from administrative work and bring more rigor to underwriting. But the gap between carriers who are experimenting and those who are executing is widening and the operational design choices being made today will determine competitive positioning for the next decade.*

Keywords: Underwriting, Third-Party Data, Artificial Intelligence, Data Maturity, Property and Casualty Insurance

1. Introduction

Ask ten underwriting leaders about their external data strategy and you'll get ten different answers. This is not because the question is complicated, but because carriers are genuinely at very different points in their journeys [1]. A consistent pattern across the industry reveals a five-stage spectrum, ranging from carriers that still acknowledge the need for third-party

data but haven't yet acted, to those quietly building proprietary data repositories that combine external signals with internal loss history to generate entirely new underwriting inferences [5], [6].

2. Literature Survey

Almost all P&C carriers recognize the importance of leveraging external data for underwriting, but they are at various levels of maturity.



Figure 1: The P&C carrier data maturity spectrum, from Aspirers to Experts

At one end are Aspirers, carriers that recognize data is a competitive necessity but are still in assessment mode, evaluating vendor options without committed investment. This is not due to lack of ambition but because of integration complexity, data governance requirements, and internal prioritization battles. This makes moving from awareness to action harder than it looks from the outside.

Moving up the curve, Initiators have made the leap. They are using external data, they have seen positive results on prefill rates and accuracy, and they are now exploring how to expand coverage across more lines of business, more submission types, more risk profiles. The lesson from these carriers is consistent: the first win is rarely the hard part. The hard part is to scale with acceptable accuracy. Several carriers report that prefill accuracy degrades materially when scaled, particularly when relying on single-source enrichment strategies [7], [9].

Rather than relying on a single data partner and accepting whatever quality gaps come with it, Advancers have established relationships with multiple vendors for the same data point and built scoring models to evaluate which source

is most reliable for a given context. This is more expensive and more operationally complex. It is also meaningfully better. Data quality variability across vendors is one of the most underappreciated risks in external data programs, and carriers that have built the infrastructure to manage it operate with a materially higher level of model confidence [8].

Achievers represent a qualitative shift in how external data is deployed. Rather than using data to fill fields later in the workflow, Achievers surface third-party intelligence at the submission stage enabling faster triage decisions, more intelligent routing, and earlier identification of risks that fall outside appetite. When the underwriting decision is informed by better data earlier, outcomes at every subsequent stage improve [2].

Experts sit at the top of the maturity curve. They have built a proprietary data asset. By maintaining a repository that integrates external data with internal performance data, they can derive inferences that no vendor sells with insights about how specific risk characteristics correlate with their own loss experience, in their own geographies, through their own distribution channels. This is durable competitive advantage.

It takes time, governance, and sustained investment to build. It is also extraordinarily difficult to replicate [1].

3. Problem Definition

Most carriers sit in the early-to-middle part of this spectrum. The question for every carrier is not whether to invest in external data, but how quickly to close the distance to the capabilities that change outcomes [1], [10].

“When the underwriting decision is informed by better data earlier, outcomes at every subsequent stage improve.”

4. Approach

The five-stage progression described above has, historically, played out over years. The barriers were real: vendor API

integration timelines that stretched for years, scarcity of data science talent needed to build and maintain scoring models, the cost of multi-source data infrastructure, and the organizational effort required to embed data into underwriting workflows at scale. Each transition demanded sustained investment and patience.

AI is changing the economics and the timeline of that journey [1], [2]. AI removes or meaningfully reduces specific barriers that have historically made each stage transition slow and expensive. For the first time, a carrier that commits to the right program can compress a multi-year maturity journey into a fraction of the time [10].

5. Results and Discussion

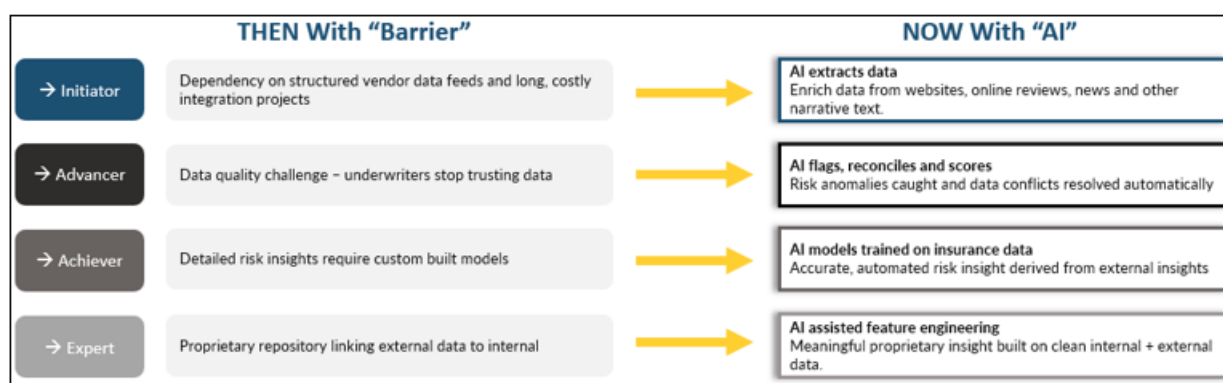


Figure 2: How AI compresses each stage transition- from barrier to AI-enabled capability

5.1 Unstructured Data Becomes Structured Intelligence

One of the biggest limitations for carriers at the Aspirer stage has always been dependence on pre-structured vendor data feeds and the lengthy integration projects that come with them. Large language models change this [3]. They can extract meaningful underwriting signals from unstructured sources that have always existed but were never economically accessible: company websites, public business filings, news and adverse event coverage, online reviews, inspection narrative text [4]. A carrier that previously faced a complex and expensive roadmap can now build a useful submission enrichment capability in months. The entry into Initiator-level capability is no longer gated by IT capacity alone.

5.2 Data Quality Validation at Machine Speed

The transition from Initiator to Advancer has historically stalled on one consistent problem: data quality that underwriters eventually stop trusting. Building the multi-vendor scoring models needed to cross-validate sources required data science resources that most carriers couldn't prioritize at scale. AI-assisted data quality tools can now flag anomalies, detect conflicts between sources, and generate confidence scores automatically without the same level of manual overhead [8]. The Advancer stage becomes more reachable when the data quality problem is solvable with AI tooling rather than headcount.

5.3 Accurate Insights Without Years of Model Development

The Achiever stage depends critically on accurate, automated understanding of what a risk is based on external signals, not just what an application says. Historically, building that capability from scratch requires custom model development. Foundation models, fine-tuned on insurance-relevant data, can now produce results at a level of accuracy that previously took far longer to achieve [3]. What was once a multi-year build is becoming an accelerated reality. The time to Achiever-level capability has compressed in ways that would not have been credible three years ago.

5.4 Accelerating the Expert Stage Data Repository

Even the Expert stage is no longer as distant as it once was. Building a proprietary data repository that links external signals to internal loss outcomes traditionally required 5 or more years of data engineering and actuarial iteration. Modern data platforms with AI-assisted feature engineering can identify correlations between external attributes and loss behavior faster than traditional analytical approaches [1]. Carriers that combine clean internal data with structured external enrichment are finding that meaningful proprietary insights are achievable within 18 to 24 months of serious, committed investment. That compression represents a genuine strategic opportunity.

6. Conclusion

AI compresses the timeline but does not eliminate the discipline. Carriers that deploy AI-assisted enrichment without proper governance frameworks, model validation processes, and regulatory awareness are creating problems they will have to solve under pressure [4]. The leapfrog is real, but it must be earned through operational commitment, not just by technology selection.

7. Future Scope

“A carrier that commits to the right program can compress a multi-year maturity journey into a fraction of the time. The gap between stages is closing for carriers that are willing to make the investment.”

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Author Profile

Toby Chembakassery Mathew has more than 15 years of experience in Property & Casualty insurance spanning Commercial, Specialty, Personal, and Excess & Surplus lines- across distribution, product, underwriting, and operations. A Chartered Property and Casualty Underwriter (CPCU) through The Institutes and a certified SAFe Agilist, he holds a B.Tech. in Mechanical Engineering and a Post Graduate Diploma in Risk Management and Insurance. He currently works for Selective Insurance, responsible for Product & Strategy in Specialty, following earlier roles in management consulting. His work focuses on modernizing underwriting capabilities, building data-driven journeys for agents and underwriters, and enabling generative AI.