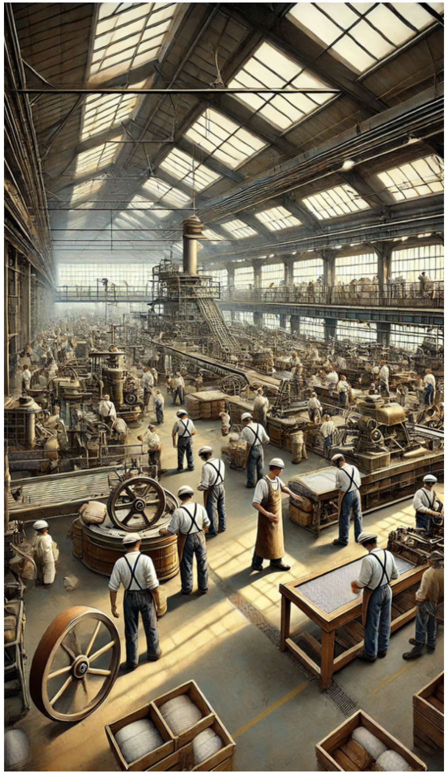
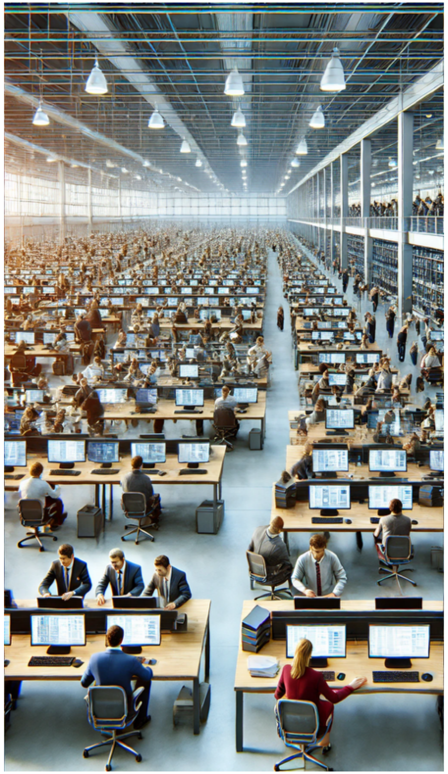
The Dawn of a New Epoch

And the Life Insurance industry is about to be disrupted.





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Prologue

I always envisioned this tale as a three-part arc.

The first part, **the-story**—published elsewhere—began on May 23, 2024, with my headfirst fall into the machine learning rabbit hole and the intense, exploratory journey that followed. This piece, **the-opportunity** (subsequently renamed *The Dawn of a New Epoch—And the Life Insurance Industry Is About to Be Disrupted*), was mentally written over the two weeks surrounding the Fourth of July in 2024 and is recounted in **the-story** itself. It captures the moment when things truly clicked—making it fitting that the final edits, at least for now, are being completed on July 4, 2025.

The final piece—**the-plan**—is, in truth, not an ending, but the end of the beginning. It's the business plan. It began taking shape in the summer of 2024 and has matured since—but the core concepts remain largely unchanged.

I struggled to finish this document—not because I didn't know what to say, but because I've realized how few people truly understand this technology. Most won't get it. The question kept coming up: who is this for? What's the point beyond helping me clarify my own thinking?

As a result, it wasn't written to offer a glib snapshot of a technology that requires at least a basic understanding of machine learning. It was written with depth, and while I always try to synthesize, I didn't constrain myself by word count—as you'll see.

So, enjoy—or don't—what I consider the-opportunity: the turning point that led me out of the industry and onto the path of becoming a **life insurance disruptor**.

Rod Rishel, July 4, 2025

TABLE OF CONTENTS

I know, I know. You have heard the story before. Maybe as many times as I have.

> *The traditionally slow-moving conservative life insurance industry is going to be disrupted. Some smart people realized how the industry was built on a business model that hadn't fundamentally changed in almost 50 years. They saw the operational inefficiency and said, this is low-hanging fruit. We will show these neophytes how it should be done.*

I joined GE just as they were starting to realize that they weren't going to just impose the GE way on the life insurance industry. And collectively, these were the smartest, hardest-working people I have ever known.

In fact, throughout my tenure at AIG, I can't count how many leaders I worked with that were going to remake the life business. All well-intentioned, but none of them with the understanding of the **complexity and sophistication** of the US Life Insurance market. Some stayed and learned.

Of course, I had some naivete when I began pricing individual life insurance products over 30 years ago. I mean, isn't it obvious we should just go directly to the consumer? However, over time, I went broad and deep. From lead generation to claim payments, underwriting, distribution, actuarial work, finance, technology, operations, and regulatory matters. I gained a true appreciation for just how **complex and sophisticated** the U.S. life insurance industry is.

While I came to understand:

- Life insurance is sold, not purchased.
- The anti-selection considerations arising from the underwriting expertise of the distributors who sell our products.
- The impact of the length of the life insurance liability.
- The equity considerations inherent in every product, underwriting, operational, and supply chain decision.

It was still easy to see what these "disruptors" saw. As far as industries ripe for disruption go, I wonder if there is one more so.

It also became easy to believe that despite the inevitable march of technology, the **complexity and sophistication** of the life insurance industry that befuddle those disruptors would gradually be chipped away. Yet, any wholesale transformation seemed like a distant future—something theoretical rather than immediately actionable.

That was until I realized we are at the **Dawn of a New Epoch**—where the impact of technology's once-inevitable march will no longer be incremental but **exponential**. This shift will be as profound as the transition from the agricultural era to the industrial and information ages.

The disruption—or more accurately, **the wholesale transformation**—of the life insurance industry is no longer a distant future but **an imminent reality**.

I. THE DAWN

The **Dawn**, as I have come to think of it, for me started one evening in late summer 2023. I had it on my list to finally figure out what all the hoopla was about with 'AI'. It wasn't high on my priority list. I understood programming and already believed that, with enough "if-then" statements, you could build anything. Equally important, I knew how difficult it is to create good "if-then" statements, so I assumed I had a general understanding of the constraints of the world in which we live.

I was mistaken

At 10:00 p.m., I started having a discussion with ChatGPT. Three hours later, when I fell asleep exhausted, I had two explicit thoughts:

- The world had just changed.
- I had become smarter and more productive, in perpetuity.

I also knew I was going to have to understand the math that facilitated this predictive power. The relationships I saw the Large Language Model (LLM) make **made me feel embarrassed by how flawed my worldview had been.**

We no longer Live in an 'if/then' World

I think the best analogy I have come up with for how that predictive power will change the world is this: **we no longer live in an 'if/then' world.** Computer programming, *greatly simplified*, is nothing other than a series of 'if/then' statements, and with enough of them, we've done some incredible things.

A simple API call into a large language model delivers a response that mimics the effect of **running billions of "if/then" statements**—not by explicitly coding them, but through a system that predicts outcomes based on patterns learned from data.

If, suddenly, you could instantly insert a billion 'if/then' statements—whenever you wanted, as many times as you needed—how much more could we achieve?

The Obvious

This obviously has some big implications. For me personally, it meant **abandoning a risk advisory service** focused on the intersection of underwriting, pricing, and risk management—the culmination of over 30 years of domain expertise that I had spent the previous 12 months preparing to launch.

But once I went down the proverbial machine learning rabbit hole on May 23, 2024, within days I began lobbying my son to skip college and focus only on this. Within weeks, I had abandoned the advisory service entirely to start the life-nervous-system—a development company dedicated to not only automating the knowledge work I had spent decades mastering but also redefining it.

That's the level of conviction this technology creates when you can truly understand what it does.

For the life insurance industry, **the implications are even more staggering**. The same **complexity and sophistication** that has kept disruptors at bay for the past 50 years now goes **into the teeth of this technology**. What follows is how this disruption and transformation will unfold.

II. LET'S NOT CALL IT AN 'AI' DISRUPTION

While Large Language Models (LLMs) **will be the accelerant** of this transformation, reducing it to merely an "AI disruption" misses the broader technological convergence reshaping the world.

This **shift extends far beyond** any single technology, emerging from the intersection of multiple machine learning advances, infrastructure maturation, and the industry's accumulated brittleness.

I avoid the term "Artificial Intelligence" (AI) not to be contrarian, but because it's both imprecise and unhelpful. The term ranges from mystical "black box" to apocalyptic threat, creating more confusion than clarity. More critically, "AI" fails to illuminate how this transformation will unfold—which requires understanding the specific machine learning technologies driving it, each creating its own distinct disruption pathway.

What's happening is the convergence of three distinct technological forces:

- LLMs – the cognitive accelerants
- Adaptive ML systems – that evolve and learn
- Mature infrastructure – making cognition deployable at scale

Understanding these technologies is essential because they are about to collide with a uniquely vulnerable target: a brittle life insurance industry that has accumulated decades of technological debt and structural vulnerabilities.

II.A. LLMs – 🔥 The Cognitive Accelerant

The industry calls them '**Foundation Models**,' but I prefer the simplicity of '**LLMs**.' These models are foundational not just because of their scale—often trained on trillions of tokens (essentially words) and massive corpora spanning diverse domains, with parameter counts reaching 400 to 600 billion or more—but also because they serve as the backbone for a wide range of Natural Language Processing applications.

They will also be the driver behind machine learning's disproportionate impact on knowledge work. LLMs excel at the complex reasoning, synthesis, and domain bridging that defines knowledge work. It is that ability to handle **complexity and sophistication**—the very characteristics that have historically protected knowledge workers from automation—that makes this transformation fundamentally different.

This transformation is particularly significant for the life insurance industry, which operates primarily in the four work categories where 'AI' can deliver its highest return: knowledge work, creative work, service work, and research & development.

How LLMs Will Systematically Transform Knowledge Work

Individual Capabilities	Workflow Transformation	Organizational Impact
bidirectional domain bridging *LLMs democratize specialized knowledge—enabling, for example, actuaries to rapidly gain medical domain understanding & reason across fields that once required years of training.*	***interactive analysis acceleration*** *Lengthy reviews & synthesis are compressed into real-time conversations, accelerating decisions. What once took research cycles, committees, & iterative analysis now unfolds through structured dialogue with the model.*	***knowledge codification at scale*** *LLMs capture & preserve institutional expertise by transforming tacit reasoning into scriptable, repeatable workflows—ensuring continuity through turnover, eliminating reliance on tribal knowledge, & standardizing quality at scale.*
scalable expertise with hierarchy *Expertise & tools are now accessible, empowering individuals to execute complex, multi-role tasks—reducing dependence on hierarchy & enabling scale through autonomy rather than delegation.*	***process systematization*** *LLMs convert expert reasoning into structured, repeatable workflows—standardizing quality, minimizing variability, and enabling auditability. Tacit knowledge becomes explicit, transferable, and scalable across the organization.*	***organizational redesign*** *The shift moves from designing around human workflows to building systems with humans in the loop—minimizing involvement where possible & architecting processes optimized for automation & machine intelligence.*
communication barriers eliminated *Enables knowledge transfer across technical vocabularies, experience levels, & even languages. The LLM becomes a universal translator—not just of words, but of concepts, methodologies, & domain-specific reasoning patterns.*	***error reduction & decision consistency*** *By removing human variability—fatigue, mood, bias—LLMs ensure repeatable, high-accuracy outputs across processes, improving trust & reliability at scale.*	***business model transformation*** *LLMs shift the economics of knowledge work—delivering expert-level output instantly & continuously at near-zero marginal cost. This enables fundamentally new business models, unbound by the time, availability, or expense of human specialists.*

To be technically precise, the transformation described above **extends beyond LLMs alone to include the cognitive architectures that will wrap**, orchestrate, and train in tandem with these models—as we'll explore shortly.

Beyond facilitating the capabilities above, this cognitive architecture creates what I call the **snowball effect**: as more work becomes fundamentally automated, the more tools exist that allow us to automate additional work. The cycle accelerates because we're not just solving problems—**we're expanding our capacity to solve harder problems faster**.

LLMs are just one part of the broader machine learning ecosystem, and some of the other technologies are equally compelling in how they may transform the industry.

II.B. Machine Learning – 🏗️ The Infrastructure of Intelligence

Large Language Models represent one specialized discipline within the broader field of machine learning—loosely defined as the field of study that uses methods that enable computers to learn without being explicitly programmed. This foundational field has undergone a technological revolution over the past decade, with breakthrough innovations emerging across multiple domains simultaneously.

Key technological developments that enabled this ML transformation:

- **Generative Adversarial Networks (2014):** Enabling synthetic data generation that mirrors real-world patterns
- **GPU Technology (2016):** Powered rapid model training at unprecedented scale
- **Transformer Architecture (2017):** A breakthrough in attention-based sequence modeling that enabled LLMs.
- **Cloud Computing (2017):** Scaled machine learning globally and made it broadly accessible
- **Transfer Learning (2018):** Making 'AI' more adaptable and efficient across domains
- **Reinforcement Learning (2020):** Enhancing 'AI' decision-making with human feedback

What makes this moment unique is the convergence of these breakthroughs, rapidly moving **from theoretical potential to practical, scalable infrastructure.** This convergence enables us to tackle the complexity and sophistication that once stumped disruptors.

Consider the following possibility:

> *Imagine combining two now-mature technologies: knowledge graphs—which make it possible to model and navigate complex, interconnected information—and Generative Adversarial Networks (GANs), which generate high-quality synthetic data that reflects real-world patterns. This pairing could enable a new model for underwriting, mortality prediction, or both—linking conditions (ICD-11 or others), severity classifications, and scale-based assessments into a unified reasoning system.*
>
> *Such a system could instantly traverse these relationships with far greater precision and speed than traditional approaches ever allowed. And beyond underwriting accuracy, this foundation enables entirely new business models and analytical methods—expanding not only what we can solve, but how fast and flexibly we can solve it.*

You could certainly optimize the reflexive questions: Does this sound too futuristic? Think the medical community isn't already building this?

That said, at least for natural language processing, the blistering pace of model-over-model breakthroughs has clearly shifted. The most visible leaps—especially in natural language processing—peaked around 2020. I wasn't around during the GPT-1 or GPT-2 days, but even from 3.5 to 4 to 4o, the deceleration is obvious.

There will be more breakthroughs, and yes, the Transformer architecture will be eclipsed someday—but the era of easy scaling is behind us.

But it doesn't matter. The technology we already have is enough to **change everything—because here comes cognitive architecture.**

II.C. Cognitive Architecture – 🧠 Intelligence to Orchestration

Cognitive architecture **sounds impressive**, right? Your friendly neighborhood consultant is probably tossing around words like agents, wrapped in flashy terms like graph-based orchestration or declarative programming instead of plain old imperative code.

But strip away the buzzwords—**it's just software**.

Whether you call it a cognitive architecture or an agent, it's a program: code that wraps logic around one or many LLM calls, each injecting those billions of "if/then" decisions I mentioned earlier. Technologically, it's straightforward. It's just a new way to build automation flows.

Practically, the field—and the tools to build these solutions—is still young but maturing rapidly.

Consider this simple example:

```
python

def agent(user_input):
    prompt = "Summarize this: " + user_input
    response = LLM_Call(model="gpt-4o", temperature=0, tools=[web_search], prompt=prompt)
    return response
```

This mirrors what a user might do in a ChatGPT interface, but now the interaction is embedded in a software program—and from there you can:

- Extract structured data from unstructured input
- Make branching decisions based on extracted facts

- Fill in gaps using retrieval (e.g., search or Retrieval-Augmented Generation (RAG))
- Invoke custom tools or APIs to gather more input
- Cross-check decisions with another LLM call
- Chain multiple steps into a reusable reasoning workflow

Take our knowledge-graph-driven underwriting system, for example. It will be a while before we extract medical information and traverse our knowledge graph, but it's not that many conceptual steps—and it's getting **easier every day as this cognitive layer matures.**

More importantly, the **economics of automation have changed**—tasks that were once too complex, too sophisticated, or even too small are now fair game. Given that, how much more can be automated? Or which fifty-year-old processes might you reimagine?

A lot, I think.

II.D. Technology Infrastructure – 🧱 The Scaffolding

The scaffolding for cognitive architecture is already built. Over the past decade, we've seen explosive progress not only in machine learning—but across every layer of technology that enables cognition at scale. This includes:

- **Computational Foundation:** GPU acceleration, cloud computing, quantum hardware
- **Cloud-Native Architecture:** Containerization, microservices, real-time streaming
- **Connected Intelligence:** 5G, edge computing, Internet of Things
- **Emerging Platforms:** Blockchain, augmented and virtual reality

These advances didn't just create a foundation for machine intelligence—they made it deployable. What was once theoretical is now production ready.

Despite a broader technological transformation—where infrastructure has made cognition deployable at scale—the life insurance industry has remained slow to adopt modern technology. **Nowhere is that gap more visible** than in two of the most powerful leverage points of the last decade: open-source software and APIs.

II.D.1. The Open-Source Intelligence Explosion

The **machine learning revolution wasn't led by internal enterprise R&D**. It was driven by the open-source community—millions of developers, researchers, and engineers globally, contributing tools and infrastructure freely and continuously. This changed the economics of innovation.

Frameworks like TensorFlow, PyTorch, and Hugging Face made advanced model development accessible to anyone. Platforms like GitHub, which surpassed 94 million developers[1], enabled compounding knowledge-sharing at unprecedented scale. Libraries like Beautiful Soup made web automation and data extraction trivial—no procurement cycle, no vendor onboarding, no license fees. Just install and go.

Life insurance, by contrast, remained largely closed and proprietary—**missing the collaborative leverage** that fueled the global leap in capability. While the world built faster together, the industry stayed siloed.

II.D2. APIs – The Connective Tissue of Intelligence

While open-source democratized capability creation, APIs made intelligence composable. Today, nearly **every layer** of modern software architecture is API-native. Systems are modular by default. Intelligence and functionality now move freely, embedded into any process, product, or channel on demand.

Yet APIs—the connective tissue of modern systems—have been slow to take hold in life insurance. They remain underutilized across most tech stacks, resulting in brittle monoliths, trapped logic, and persistent integration friction.

[1] GitHub, "The State of the Octoverse: 10 Years of Tracking Open Source", GitHub Blog, 2022. https://github.blog/news-insights/research/octoverse-2022-10-years-of-tracking-open-source

III. A BRITTLE INDUSTRY - WHAT THE DISRUPTORS SAW, WHY THEY FAILED, AND WHY THAT MATTERS NOW

You can't be too critical of the disruptors. When they looked at life insurance, they saw a textbook case of **an industry ripe for disruption**. But understanding why they failed also reveals just **how significant the coming change will be.**

III.A. What Those Disruptors Saw

III.A.1. Customer Dissatisfaction Beyond Frustration

It's important to distinguish between the relief a beneficiary feels when a claim is paid and the experience of acquiring and managing a policy. In that context, calling life insurance customers—or anyone across the supply chain—"frustrated" is an understatement. The industry lags significantly—and, to the *uninitiated*, even embarrassingly, behind the broader financial services sector in meeting modern expectations.

I remember being happy five or so years ago when I could finally pay my life insurance premium online—though not without some difficulty. At the time, it was common to hear the complaint: "The only reason I still need a checkbook is to pay my life insurance premium."

III.A.2. Market Underpenetration and Massive Opportunity

The "protection gap"—the difference between the life insurance coverage individuals should have and what they hold—is often cited as evidence of low market penetration. Swiss Re estimates this gap at $25 trillion.[2]

[2] Swiss Re Institute. "Life underinsurance in the US: bridging the USD 25 trillion mortality protection gap." Swiss Re Institute, 2017. https://www.swissre.com/institute/research/topics-and-risk-dialogues/economy-and-insurance-outlook/life-underinsurance-US.html

While this figure is interesting in its magnitude, the tangible opportunity is better illustrated by commentary from the NAIC spring meeting in Louisville, where Andrew Melnyk, chief economist and vice president of research for ACLI, noted:[3]

> *Anyone connected to the life insurance industry knows that the number of Americans covered by life insurance has steadily declined for decades… The number of families reporting any life insurance coverage peaked at 85.4% in 1971. That number has declined nearly every year since and was expected to decrease further in 2022 from the 59.4% reported in 2021…*

While a return to 85% coverage is unlikely, even a 5–10% increase would represent a major opportunity. Interestingly, demographic trends are as favorable as they've been in some time, with millennials in their peak life insurance purchasing years and Gen Z just beginning to enter the market.

III.A.3. Accumulated Technological Debt

I would be interested to see a comparison of the technological debt in the life insurance industry compared to other sectors. It must be staggering. During my career, I have directly observed not only how slow the industry is to adopt any technologies but also its consistent underinvestment in infrastructure.

I came across a blog on Hyperexponential, "Tackling Technical Debt in the Insurance Industry"[4], that, while it may have a P&C bent, summarizes the challenges of technical debt in the life insurance industry quite well.

The quotes alone tell the story:

- *Many insurers continue to struggle with serious technical debt.*
- *Sprawling legacy systems.*

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[3] Hilton, John. "Life insurance industry sales focus change cited in falling policy counts." InsuranceNewsNet, March 29, 2023.https://insurancenewsnet.com/innarticle/life-insurance-industry-sales-focus-change-cited-in-falling-policy-counts
[4] Hyperexponential. "Tackling technical debt in the insurance industry." Hyperexponential Blog, 2024. https://www.hyperexponential.com/us/blog/technical-debt-in-insurance/

- *Updates and patches can only do so much to address the issue.*
- *…outdated pricing models, fragile spreadsheets, inefficient and highly manual workflows, …, and a lack of quality accessible data.*
- *Data goes wasted, and so does effort.*
- *Insurers are often risk-averse by nature, and addressing technical debt can appear to offer an uncertain return on investment.*
- *Cultural resistance to change.*
- *Lack of advanced in-house technical knowledge.*
- *Difficult recruiting and retaining talent.*
- *Compliance issues.*
- *Suboptimal decision-making.*
- *The problem gets worse over time; insurers are less effective, less efficient, and ultimately less competitive.*

This accumulated technological debt exacerbates every problem in every part of the supply chain. In fact, even the roles that have the title of distribution or sales are often more focused on problem resolution and service than on lead generation, recruiting, or other revenue-generating activities.

III.A.4. Stagnant Innovation Over Decades

While those disruptors would have seen an industry lacking innovation, that view overlooks the ingenuity required to navigate its deep complexity and sophistication.

One example amongst many: In response to conservative reserving requirements like Regulation XXX, insurers developed capital strategies that were innovative even by capital markets standards and produced entirely new mechanisms, such as "shadow accounts," to guarantee premiums on permanent life products.

Yet despite this kind of internal creativity, the industry's core business models, markets, and acquisition methods have remained virtually **unchanged for almost 50 years**.

They also so an **industry resistant to change**.

To a certain degree, the industry's resistance to change is justified. Life insurance is—and should be—a conservative business, given the stakes involved. Prudence isn't a flaw; it's a necessary design principle.

In addition, this resistance has been reinforced over time. The industry has seen no shortage of disruptors fail. After enough failed attempts, skepticism becomes instinctive. You build up a long list of "I told you so" moments, and over time, dismissal becomes a reflex.

But there's a deeper pattern worth naming. The industry has grown insular in its thinking, often reacting to new ideas with a posture that sounds like: "They don't know what I know about why that won't work." And here's the irony: if you're a disruptor—if you believe something can be done differently—this kind of confident resistance is exactly what you want. It's not a threat. **It's a signal.**

III.A. 5. Societal Winds

I acknowledge there are various societal headwinds for the industry, but from a disruption standpoint, the conditions are favorable.

The generation that built and ran the current model—across every dimension of the supply chain including product, marketing, distribution, underwriting, actuarial, etc.—**is aging out,** and as that occurs, they are being replaced by younger generations with significantly different preferences in every facet: purchasing, employment, communication, and values.

Further, while much of the work is decomposable and documentable, it often hasn't been—resulting in **a steady loss of institutional knowledge**. That additional strain on an already brittle system acts as a tax on the historical model—one you don't have to pay if you're building from scratch.

III.B. Why They Failed: The Complexity They Couldn't Grasp

If I had to reduce every prior disruptor's failure to its root, it's this:

They misunderstood the nature of the life insurance industry—its deep **complexity**, its hard-earned **sophistication**, and, most importantly, the **interconnected web of human knowledge work** that makes operating at that level possible.

Where they saw inefficiency—bloated processes, manual steps, high costs—**they missed a mature intelligence system**: a purpose-built network of human knowledge work designed to manage one of the most multidimensional industries on earth.

Eventually, once you're *initiated*, the **complexity and sophistication** fade into background noise. But even as I wrote the examples below, I was reminded how intricate—and deliberately constructed—this system truly is.

III.B.1. Regulatory Framework & Policyholder Equitability

Regulatory Framework

Let me start with the relatively easier topic—and a perfect example of complexity.

Maybe there's a consumer product more harshly regulated than life insurance—prescription drugs come to mind—but find me one that's more broadly and redundantly regulated.

The sheer redundancy is staggering. Thanks to the McCarran-Ferguson Act, regulation was pushed down to the states—creating 50 regulatory bodies out of the gate. But that's just the beginning.
There's the SEC and FINRA. Then the DOL, the IRS (especially from a product design perspective), and the FIO. There's also a swarm of quasi-regulators, like the NAIC and the Actuarial Standards Board.

And it doesn't stop there. There's deep consumer protection oversight—FTC, CFPB—and a parallel medical regime, with HIPAA and related frameworks governing data and privacy.

I haven't even mentioned the complexity of financial accounting—especially across capital, reserves, and the rating agencies. Or the plaintiffs' bar, a de facto regulator varying across state and federal levels. International laws even come into play depending on the market.

<u>Policyholder Equitability</u>

The industry should be applauded. Not because it is legally required to treat all policyholders equally (or non-discriminatorily), but because I genuinely believe it wants to uphold this commitment and understands the gravity of its product. While buyers should always "beware," this is not the *caveat emptor* model typical of much of the commercial world.

This requirement can be easily summarized as: two insureds who are otherwise identical must receive equivalent pricing for equivalent benefits. Of course, there are clear and codified examples where you must fairly discriminate between two individuals. For example, we would not expect a 30-year-old woman to pay the same amount for life insurance as a 60-year-old unhealthy male.

Beyond that, there's a lot of grey. For example, even if you can demonstrate a strong correlation between good mortality and a high credit score, can you fairly use that to differentiate between individuals? The prevailing view seems to be 'no,' as it's considered a proxy for discrimination (for example, race)—even though one could argue it's a proxy for behavior. And to illustrate just how nuanced this topic is, consider that you could legally differentiate between two otherwise identical individuals simply because one lives in North Carolina and the other in South Carolina. Remember that 50-state framework? You can use state as a life insurance class construction parameter.

This is one that—even regardless of how 'initiated' you are—is tricky and impacts everything from small to large. Every exception you make risks running afoul of this principle. Want to backdate a premium because it was mishandled? You're probably okay, provided you make that exception for everyone—which effectively means it's now your process.

How about an exception an underwriter makes on a rating class offered to an insured because they had dinner with the distributor the week before? That's a problem.

From a larger perspective this has a direct and material implications for pricing strategies—ones that aren't clear to those *who haven't been initiated*.

III.B.2. UNDERWRITING

While all the examples in this section point to **sophistication**, none more so than underwriting. Underwriting in the U.S. individual life insurance market is arguably one of the most **complex and sophisticated** forms of underwriting in the world. On a per-case basis, I doubt there is a close second.

Insurance company underwriters have historically studied from the same Anatomy & Physiology texts used in medical schools. A single application can involve over 1,000 data points. Medically, applicants may present with any combination of 74,000+ ICD-10-CM codes. Blood and urine analyses are evaluated. EKGs? Check. Financially, underwriters assess tax returns, financial statements, debt ratios, liquidity, and coverage levels. Personal avocation? How about the number of hours flown and the type of aircraft. I could go on.

Underwriting is so **sophisticated**—and such a significant source of competitive advantage—that distributors must at least understand the basics. In fact, it's not uncommon for a core part of their value proposition to involve in-house expertise comparable to that of the insurer, particularly with the goal of arbitraging underwriting outcomes across carriers to secure the best possible offer for their client.

But let's go ahead and add a little more **complexity** to this dynamic. It also exposes a particularly nuanced risk that must be underwritten: the information asymmetry between the applicant and the liability underwriter. The applicant inherently knows more about their own risk status. And while the sales agent is technically an agent of the insurer, they are economically aligned with the applicant—which introduces a material anti-selective risk, even when not nefariously driven.

III.B.3. Odd, Multi-layered, Hyper Competitive Market

Layer	Competitive Arena	Description
1. 🙋‍♀️ Consumer Wallet Share	Life insurance competes with all other consumer spending—automobiles, vacations, savings, etc.	A few thousand dollars a year, paid over 20 years, becomes a $40,000+ commitment—yet it's one the consumer is reluctant to confront and re-evaluates with every premium.
2. 👔 Retail Producer Competition	Retail producers compete with one another to win the client.	For all practical purposes, the consumer has access to numerous distribution sources—making producer-level competition intense and frequently realigning.
3. 🤝 Wholesale Competition	Intermediaries compete to win the producer.	Value-added services—training, education, underwriting support, operational infrastructure, compensation—shape producer allegiance and shelf access. These vary widely, and distributor–producer dynamics shift often.
4. 🗃️ Distributor Shelf	Distributors compete for carrier partnerships; carriers compete for shelf space.	Inherently multi-dimensional and bi-directional, shelf inclusion reflects product fit, pricing, underwriting philosophy, business quality, and infrastructure—and shifts frequently as priorities and relationships evolve.
5. 🎯 Product Inclusion	Carriers compete to have their product selected for the client case.	Even once on the shelf, only a few products are quoted—typically 3 to 5. Competition focuses on pricing, features, compensation, and underwriting flexibility.
6. 🩺 Underwriting Offer	Carriers compete on final underwriting outcome or "final price."	The product must still "win" in underwriting with numerous factors contributing—such as class offer, exclusions, table shave programs, speed, and consumer preferences, to name a few.

III.B.4. Product Complexity and Proliferation in Insurance

Life insurers are prolific product designers. While some of that proliferation is necessary—driven by interest rate shifts, capital markets, and evolving profitability constraints—much of it reflects the pressures of a hyper-competitive, commoditized market.

But that proliferation sits atop already deep product **complexity**—and it manifests everywhere. Each new product, rider, or pricing variation doesn't just impact the front end; it ripples through illustrations, compensation structures, regulatory compliance, administrative systems, and technical infrastructure.

<u>Simple Products, Complex Differentiation</u>

Even the most basic product—term life—is competitively complex. Pricing runs to the penny. Differentiation emerges through nuances like conversion privileges that span decades.

<u>Permanent Products: Actuarial by Design</u>

Products like indexed universal life with secondary guarantees offer immense flexibility—but that flexibility introduces actuarial-level complexity. These products are governed by long-duration, dynamically resetting illustrations, tracking multiple account values and reacting to shifting inputs like premiums, interest rates, caps, and asset allocations over decades.

Regulatory Architecture: §7702, SNFL, Reserves, Capital, and More

Beyond the broader regulatory complexity discussed above, several foundational frameworks introduce a distinct layer of structural sophistication that directly shapes—and often necessitates—product complexity. For example, IRC §7702, which governs tax qualification and treatment, imposes strict and nuanced actuarial and legal constraints on product design. Similarly, reserving frameworks such as Regulation XXX and AXXX have materially driven complexity, prompting insurers to adapt product structures to manage capital strain.

Illustrations

Rather than sales tools or compliance artifacts, illustrations serve as the primary abstraction of the complex product calculations referenced above. Highly regulated and generated throughout the policy lifecycle, illustrations translate those mechanics into consumer-facing outputs. The systems that produce them often sit **alongside** the administrative book of record—sometimes tightly integrated, sometimes fully manual.

Compensation Structures

When I joined AIG, a core value proposition to independent distributors was the ability to manage and pay complex, hierarchical compensation structures. It wasn't uncommon to see commission scales with 20 or more levels on a single product, often layered with various override programs. These structures were in constant flux—driven by distributor movement, pricing changes, and ongoing realignments. While some rationalization has occurred, today's compensation engines still support deeply entangled hierarchies—with legacy dependencies and edge cases embedded throughout.

III.B.5. Distribution

If you wanted a clear window into the **complexity and sophistication** of the life insurance supply chain, underwriting and distribution would be the two most revealing domains. As with underwriting, distribution is defined by a breadth of complexity and nuance—combined with an unusually mature and hyper-competitive market structure.

That **complexity and sophistication** show up in the competitive dynamics, compensation structures, and anti-selection risks we've already covered—each shaped by the underwriting expertise of those who sell our products. And there are countless other examples I could include.

But if I had to pick just one example of how hard distribution was for those disruptors to understand, it would be the role it plays in the supply chain. A life insurer may underwrite a multi-million-dollar policy it will carry on its books for the next 100 years. It may even be the legal owner of the consumer relationship. Yet despite holding the long-tail liability, the insurer doesn't own that consumer—or more aptly stated, that point of influence. The distributor does. They make the sale, own the relationship, are compensated almost entirely up front, and can practically walk away the moment the policy is placed.

Let that sink in. And remember—I'm not being critical. I'm initiated but, you can certainly see how this would be hard to understand.

This is where the impact of the adage '**life insurance is sold not purchased**' can so clearly be seen.

III.B.6. Time Impacts Everything

In my first actuarial role, I repriced a dividend scale for a participating life insurance company, which included policies based on the 1941 CSO table. That took me into the company's historical library, where I pulled agent manuals from behind glass shelves—the only place the original rate scales existed. Some of those policies are likely still in force.

Just consider the examples I've provided—the proliferation of products, the complexity of those products, the dynamic nature of compensation scales, and the shifting relationships across competitive layers—each an interrelated cohort that imposes persistent demands on the supporting infrastructure.

Now consider that each of these cohorts persists for decades—sometimes a century. It is easy to see how the technological debt can accumulate.

But even the cognitive load is a heavy tax to bear, as each of these cohorts must be actively managed, with key parameters often buried in legacy systems or lost to tribal knowledge.

III.C. Why it Matters Now!

Now, the only reason the life insurance industry has been able to operate at this level of **complexity and sophistication** is the interconnected web of knowledge work it built around—and through it.

That web isn't confined to a single department or specialty. **It spans the entire supply chain** because the **complexity and sophistication** do too.

That operational knowledge web—ingenious in its construction, essential to the industry's function, and central to its resistance to change—**is now the target**. The judgment embedded in those human workflows—which once absorbed the industry's **complexity and sophistication**—is exactly what machine learning systems are now positioned to begin automating.

IV. "WE WILL NEVER ALLOW A MACHINE TO MAKE A RANDOM UNDERWRITING DECISION."

– Actuary panelist, 2023 Underwriting Innovations Symposium, in response to AI's impact on underwriting

There are some critical details I need to discuss before continuing. These details are crucial because they are so poorly understood, and I believe they shape how impactful people believe these capabilities will be. Of course, we would never let a machine make a random underwriting decision—that's illogical. Yet, many believe that's exactly what we're talking about.

IV.A. The LLM is a Tool

I see an article every few weeks about a lawyer—or pick your profession—botching a contract or some other piece of work because they used 'AI'. That's user error. **Full stop**.

LLMs make predictions. Predictions can be wrong. **If you use the tool, it's still your work.** No one accepts "I got it from the internet" as an excuse for an error. You're responsible for knowing your tools and how you use their output—this is no different.

IV.B. Randomness

While an LLM is a probabilistic prediction model at its core, its 'randomness' can be controlled. It can be set to provide the **best estimate answer** (temperature = 0), consistently giving the **same best estimate to the same input 100%** of the time (e.g. deterministic). Every time, all day, any day—for the same LLM model (e.g., Anthropic's Claude 3 Opus, claude-3-opus-20240229)

IV.C. Underwriting: Parameter Driven Classification vs. Interpretation

This one's big—and widely misunderstood. It goes to the heart of the quote: "We will never let a machine make a random underwriting decision."

Underwriting is a classification problem. A life insurance policy form through the underwriting manual, guidelines, etc. lay out the parameters an applicant must meet to qualify for a risk class like Preferred. For example, one parameter might be a maximum weight of 210 lbs.

To maintain the equitability already discussed, if two applicants are identical in every meaningful way but receive different ratings, you have a problem. So, you're never going to randomly give a 215 lb. applicant a Preferred risk. **Ever**.

But someone who weighs 215 lbs. might still get approved—if the underwriter reads the application and interprets the weight as 205. And that's the perfect segue to the next point.

IV.D. Human Error Fallacy and Bias

Humans overestimate their accuracy and underestimate their bias. I'm pretty sure that's been studied.

At that same underwriting symposium, someone asked a vendor who was presenting about the error rate of their tool—it was interpreting and analyzing some aspect of an Attending Physician Statement (APS), as I recall. The presenter said something like 3%, and the crowd reacted with clear discomfort.

That reaction made no sense. The task was hard, but the crowd was comparing against zero error—which is a common mistake when evaluating machine performance. But that's the wrong comparison.

I asked the presenter how it did against a human. Their answer: the machine was already winning, getting better every day—and that was two years ago.

Yet words like hallucination and bias get thrown around, and people—especially regulators—panic. But we're already using 'AI' in underwriting. Take something as basic as scanning a weight on an application. That process uses the same foundational machine learning methods—often neural networks—that underpin modern language models. It's been validated, tested, and shown to outperform humans. Depending on the structure of the source material, it's close to 100% accurate. Would you want a human doing that from an equality perspective? Absolutely not.

And while bias in every form should be taken seriously, **is there a more biased machine than a human**?

What happens when **you can evaluate every decision point in a human process**—and show that each one can be made more accurately and with less bias? That's next.

IV.E. Cognitive Decomposition at Scale

Often, knowledge workers believe their judgment is too complex to model—but that's just arrogance.

When you critically analyze any form of human knowledge work, you **can decompose it into a series of atomic units**—micro-decisions. You don't just "underwrite" a case. You first extract information from an application. Then you evaluate it through a sequence of discrete steps—each one a micro-decision that can be mapped and understood.

Even more complex tasks, like assessing the comorbidity of prediabetes and high blood pressure, follow the same pattern. You're breaking the problem down—interpreting the information based on learned mental models, applying rules, weighing relevance, drawing conclusions. It feels intuitive, but it's structured, and it can be modeled.

And these micro-decisions can be tested—at scale. The processes can be refined, and the decision logic can be trained to achieve greater accuracy, consistency, and fairness than any individual human—repeatable, auditable, testable, demonstrable.

IV.F. Human-In-The-Loop Progression

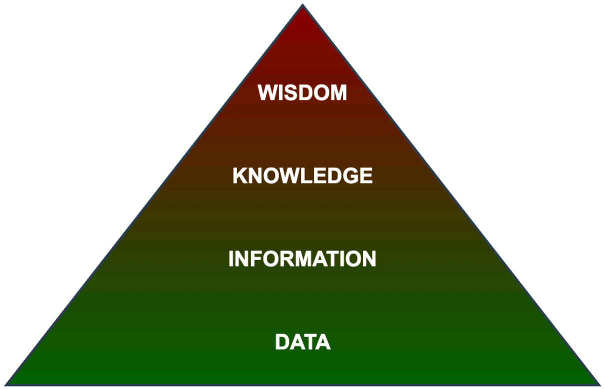
Lastly, you don't go from 0% to 100% automation overnight. Implementation advances through human-in-the-loop frameworks—validating each micro-decision until human involvement shifts from operational to supervisory.

V. HOW THIS IS GOING TO PLAY OUT

The mental model I've developed for how this transformation will unfold is the DIKW hierarchy—Data, Information, Knowledge, Wisdom—a foundational construct in information theory for decades. It was alluded to as early as 1938 by T.S. Eliot, who asked:

> *"Where is the wisdom we have lost in knowledge?*
> *Where is the knowledge we have lost in information?"*

The DIKW model is often represented as a pyramid because it reflects both quantity and complexity: data is plentiful but low in meaning, while wisdom sits at the top—rare, contextual, and built on layered interpretation. Each level compresses the one below it, requiring not just more structure, but more synthesis and judgment.



Machine learning doesn't just compress the vertical climb from data to wisdom—it expands your horizontal reach across domains, disciplines, and modalities. It widens the base, flattens the structure, and rewrites the ascent.

V.A. Immediately: Personal Productivity Skyrockets

The productivity gains you should be experiencing are astronomical. I've completed analyses in a couple of afternoons that would've previously taken months—just to gain the **expertise and confidence to trust the results**. That timeline collapses when you can ask an LLM to generate visual Python examples comparing biases across different normalization techniques and assumptions—as just one of countless examples.

Just consider this: right now, you have access to the knowledge equivalent of a **very smart college-level professor in any well-studied field—available 24/7, in your pocket or on your computer**. That's a nice thought partner to have around. You can say, "Let's debate—take the opposite position and push back." Or something simpler: "Ask me five questions to clarify what the hell I'm talking about."

And that professor doesn't stop at debate.

V.A.1. That Smart College Professor

That smart college professor scored a 1410 on the SAT (OpenAI's GPT-4, 2023)[5]. It doesn't sleep, doesn't get tired, and **doesn't mind doing clerical work at scale.**

It can write. It can edit. And—according to a University of Pittsburgh study—its poems were preferred 78% of the time over those of Shakespeare, Byron, and Emily Dickinson to name a few.[6] That's probably because it writes in a more contemporary style—but still, pretty good company to be in. In fact, it can make anyone a writer, just ask a college professor you know that grades college level essays.

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[5] GPT-4 SAT: OpenAI. "GPT-4." OpenAI Research, March 2023. https://openai.com/index/gpt-4-research/

[6] Poetry Study: Porter, Brian, and Edouard Machery. "AI-generated poetry is indistinguishable from human-written poetry and is rated more favorably." Scientific Reports, November 14, 2024. https://pmc.ncbi.nlm.nih.gov/articles/PMC11564748/

V.A.2. Learning Has Changed & Best Practices

That smart college professor has helped me go deep into everything from statistics, stochastic mortality analysis, neural networks, the regulatory framework for energy incentives, impact of climate change on data center efficiency, and chemical composition of hormones, encryption algorithms, quantum computing, to name a few.

This kind of multidisciplinary exploration would have been nearly impossible just a few years ago—not because the information wasn't available, but because the learning curve made it prohibitively time-intensive. **Learning has undergone a fundamental transformation with the advent of Large Language Models**, creating an educational revolution through personalized tutoring at scale, particularly when combined with high-quality, low or no-cost educational content available through platforms like Coursera, Udemy, and MIT OpenCourseWare.

And best practices? The transformation is staggering. Need the latest privacy protection methods—differential privacy, homomorphic encryption, implementation frameworks? That smart college professor has them instantly.

V.A.3. Accuracy, Synthesis, and Interpretation

That smart college professor is also **precise**. In Anthropic's Needle in a Haystack benchmark, Claude 2.1 achieved near-perfect recall across a 200,000-token context window—roughly 500 pages. [7]

And that was 18 months ago.

I use it constantly for synthesis. Give it a topic, ask for 5, 10, or 50 categories that define the space. Add, subtract, challenge—it resynthesizes on the fly. This isn't recall. **It's thought structuring**.

[7] Long context prompting for Claude 2.1." Anthropic Blog, December 6, 2023. https://www.anthropic.com/news/claude-2-1-prompting

A 2024 JAMA Network Open study found that while physicians using LLMs performed similarly to those using conventional tools (76% vs. 74%), the LLM alone significantly outperformed both groups at 92%. The LLM alone scored 16 percentage points higher than conventional methods, completing cases faster with greater diagnostic reasoning.[8]

V.B. Shortly: Integration into Existing Processes

The next phase will be defined by 'AI' tooling bolted onto existing business processes, without any meaningful restructuring underneath. Some of these tools will be useless—but others **will be meaningful**, and some potentially very much so.

Of course, this is already happening—and happening quickly. Gemini's ability to semantically search my Google Drive, extract key information, and summarize documents has become a go to utility. Apple is making significant moves with Apple Intelligence, and Microsoft continues to expand Copilot across its ecosystem. Even tools like Notion follow the same pattern: intelligence layered on top of existing workflows, without changing the workflows themselves.

This is beginning in the life insurance industry as well. Take a life insurance illustration system, for example. Even without inside knowledge, I would have expected them to be exploring natural language prompts to semantically and structurally search illustrations. And come to find out—they are. Will it be useful and adopted? Maybe. But that's just the tip of the iceberg. There are plenty of cool and helpful tools you can 'bolt on,' so to speak.

This phase continues indefinitely—there will always be tools to bolt on—but what begins next is the onset of **cognitive decomposition.**

[8]Goh, Ethan, et al. "Large Language Model Influence on Diagnostic Reasoning: A Randomized Clinical Trial." JAMA Network Open, vol. 7, no. 10, October 28, 2024, e2440969. https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2825395

V.C. Emerging: Cognitive Architecture Revolution

This is where things take off, as people begin to cognitively decompose knowledge work processes and automate those micro-decisions using rapidly maturing cognitive architecture tooling. Development will take a minute to find its rhythm—but once the conceptual frameworks are in place and code agents begin to scale, things will start to get interesting.

I've seen firsthand how quickly the abstractions enabling this kind of development have progressed, and we are now entering what some are calling the beginning of "gen 2." What was once mostly accessible to larger players—who had the capability to build these abstractions—is now opening broadly. This is the phase that truly moves us up the DIKW pyramid—with increasing speed—as reliable, industrial-strength micro-decisions become the foundation for the next layer of automation.

Assume you need to assess the comorbidity of a diabetic smoker. Let's further assume you need to evaluate the applicant's blood sugar compliance and decide that reviewing an Attending Physician Statement (APS) is required. You don't just drop a 1,200+ page APS into a HIPAA-compliant LLM. Instead, you first embed the content using an embedding strategy.

This turns the APS into semantically searchable chunks, organized into sections. Each section is tagged based on your ontology, taxonomy, and canonical definitions. The sections stay small to manage the context window you'll feed into. From there, you could send an agent to systematically search those embeddings for specific information—say, all content related to blood sugar readings, extract those readings, structure them, and then algorithmically assess them.

Or, you might dispatch a team of agents, each focused on a different aspect of the 1,200-page APS. Once the infrastructure and agents are in place, your marginal cost is compute time not human time. You could also supplement those LLM calls with additional context—such as specific policyholder data or guidance on how to make the assessment. The consultants I previously referenced would call this a RAG (Retrieval-Augmented Generation) model—the fancy way to say you add information to the model call.

A few other points are worth noting. You'd likely train the LLM on additional corpora to improve accuracy. In the comorbidity case, the underlying framework is relatively mature. Based on blood sugar compliance and other extracted factors, your agents might assign a standard tobacco mortality adjustment, a 150% multiplier for diabetes, and an additional 50% for the combined presence of both—representing the comorbidity effect. You could build that analysis engine independently or expose it as a tool the LLM can invoke dynamically.

Now, you might say that's a relatively simple comorbidity to model—and you'd be right. That's why I chose it. But let's make it harder: introduce coronary artery disease. The comorbidity framework for that case might not be as well-defined, but it exists. Otherwise, you'd be leaving the underwriter to wing it every time—and that's not what knowledge work is about. Of course you can deconstruct it. **The human can learn it. So can the system.**

V.D. Not too Distant Future: Disruption Begins

As you begin decomposing and building foundational components—embedding the APS, structuring comorbidity assessments, or deploying agents around decision points—you start to see how climbing the DIKW pyramid becomes self-reinforcing. Each tool, each agent, each micro-decision doesn't just solve a problem—it becomes reusable infrastructure.

Then something else starts to happen. Anyone with a programming mindset—or even basic operational instincts—naturally asks: **how do I improve this process?** At first, that looks like optimization: making the current system faster, cheaper, or more consistent.

Eventually, the question shifts: **What if I started from a white piece of paper?** If I had today's tools from the beginning, how would I design this from scratch?

That's the inflection point—where cognitive decomposition becomes cognitive re-architecture.

And that re-architecture won't just come from one direction. Incumbents will push inward, using these tools to rethink processes they already own. But the same shift will invite disruptors—those with no legacy constraints—who can redesign the supply chain from the outside in.

Rearchitecting from a blank page is no longer constrained by human knowledge work—either structurally or economically. For the last 30 years, if you were going to redesign the life insurance industry from a white piece of paper, it wouldn't look anything like it does today. But it didn't happen—because the only way to manage the complexity and sophistication was through that intricate web of human knowledge work.

That constraint is gone. So now the real question is: What would you disrupt—if you could start from a blank piece of paper?

We're going to find out.

VI. WHEN, NOT IF

As you read this conclusion and predictions, consider a quote I've always attributed—rightly or wrongly—to Bill Gates:

> *"People overestimate what can be done in two years and underestimate what can be done in ten."*

Whether or not that's the exact phrasing, it has mostly proven true in my life. And even now, that truth sits in the back of my mind as I write what follows.

But at its core, I don't believe that quote holds for the future. Things are moving faster than I ever imagined. From the moment I first sat down with ChatGPT to now, these tools have driven repeated, stepwise leaps in productivity.

The progress over just the past year has been breathtaking. The cognitive architecture enabled by the code generation agents I've been working with is phenomenal. It's the blueprint for how knowledge work is going to be rewritten.

And just as I saw immediately, there's no reason that acceleration should stop. In fact, the pace of those leaps has only increased—because every problem you solve makes the next one easier, even if the next problem is harder. **The snowball effect.**

I.A. Input Assumptions

I promised predictions, so let me outline some of the input assumptions I'm starting from:

VI.A.1. The Snowball Effect

I'm assuming the stepwise gains in personal productivity will continue—and may even accelerate—but the real compounding will occur at the industry level.

Every semester, new computer science graduates are entering the workforce, while experienced software developers are being displaced by this technology. And they are only life insurance domain expertise away from being able to architect meaningful systems.

And of course, alongside them, the industry incumbents will also begin moving quickly—adopting these tools, learning the frameworks, and participating in the transformation directly.

As foundational tools are built and new methodologies are tested, this dynamic will drive the pace of transformation sharply upward.

VI.A.2. Regulatory Impact

I'm assuming that regulation at the industry level does not get ahead of a proper understanding of the technology.

I'm also assuming we don't see societal-level regulation aimed purely at "preserving jobs."

That last point carries risk. But either way—whether through industry-specific action or broader societal policy—such regulation would only slow the transformation, not stop it.

VI.A.3. Middle of the First Inning

I believe the life insurance industry is still in the nascent stages of this shift—roughly the middle of the first inning, and perhaps only an inning behind other industries.

We don't know how this transformation will play out. We don't know which breakthroughs are coming, or in what innings they'll begin to unfold—or how fundamentally they'll change the game.

One example already discussed: the development of a new underwriting model—capable of traversing a medical knowledge graph, classifying condition severity, and trained on synthetic data at scale, constrained only by compute cost. This isn't theoretical. It's a logical extension of what's technically possible today—and when that breakthrough lands, we may not even be playing baseball anymore.

VI.A.4. Capital Markets, Consumer, and the Disruptors

I assume that anyone—or any combination—of capital markets, consumer expectations, or strategic advantage will force this transformation. Together, they create conditions where resistance is not viable.

The capital markets argument is easy. If it costs the industry $300 today to digest an APS—and that same outcome can be achieved tomorrow for a few cents of compute—someone will do it. Change becomes inevitable.

The consumer expectations argument is more nuanced—but no less consequential. And I say this with absolutely no pleasure: the life insurance industry is fighting to maintain relevance. This transformation may not just be inevitable—it may be necessary for the industry's survival. For decades, its players have been fighting for their share of a shrinking pie.

Across the supply chain—whether it's the insured, the distributor, the insurer, the vendor, or even the employee—every participant is demanding change. That pressure is mounting. And maybe that's not a bad thing. Because the current model isn't just under strain—it's clearly not the model for the next 50 years.

And last—but certainly not least—back to the disruptors.

There's massive strategic advantage for the next disruptor. The human knowledge web that once resisted change now functions as a structural tax they don't have to pay.

VI.B. The Predictions

Here's the first prediction I'll offer—and I'll do so with both a caveat and an important clarification.

I see human involvement in the life insurance *new business* underwriting process **gone within the next 5 to 10 years**.

Now, the caveat: maybe it's 10 to 15.

But here's the important part: It's not 20.

I've always believed this would eventually happen. The benefits are simply too overwhelming—and I'm not even talking about cost savings.

The biggest impact will be the potential for a material reduction in risk-adjusted capital requirements. Eliminate human error, bias, and inconsistency, and you increase decision accuracy. Increase accuracy, reduce uncertainty, and you know how that story unfolds.

While I've always believed this was inevitable, I never thought I'd see it. For most of my career, it was perpetually 20+ years away—never getting any closer. Even today's automated underwriting systems didn't change that view. They're just evidence-waiver programs with a cost structure that's unsustainable in a hyper-competitive market.

But once the **Dawn** came for me, **I knew I would see it**.

And that's the most important point: As you consider these predictions, I'm willing to debate when—**but no longer if**—the industry will fundamentally transform. That's not a position I would've taken before.

WITH THAT A FEW PREDICTIONS

Operations

The operational supply chain will transform more quickly. The work is more structured, less judgment-dependent, has largely already been cognitively decomposed, and the state-of-the-art operational platforms are already orchestrated in layers that can directly support the introduction of LLM model calls. For new policies issued, I expect full automation—from policy issuance through claim—**within five years**. As with underwriting, I'm defining this transformation specifically in the context of *new business;* the automation timeline for the hundred years of legacy cohorts already in force is an entirely different question—and one I am **not** going to speculate on.

Finance and Actuarial

As I think back to my days pricing products—and the modeling work I've done since—once the tools are wired to a semantic understanding of inputs and their downstream effects, the heavy lift at the modeling layer disappears. That work doesn't vanish; it moves up the chain—toward higher-level judgment, interpretation, and system design. But given how structured and repeatable those processes already are, I see routine modeling work disappearing within the **next five years**.

The Rise of the **Super Learner**

I don't believe '**Super Learner**' is a broadly adopted term—at least not yet—but I heard it once and immediately knew what it referenced. It perfectly describes a new archetype of knowledge worker that is already emerging—and **within the next 24 months**, we **will all see** direct examples.

The **Super Learner** isn't defined by credentials or a fixed domain, but by range. They move across disciplines without abandoning depth—compressing the learning curve through this new technology. They operate with semantic fluency, build tools instead of requesting them, and integrate reasoning, synthesis, and execution into a continuous loop. They work at a level of productivity and speed that simply wasn't possible before—often outpacing entire teams. They don't wait for handoffs or coordination. They don't file a ticket to solve the problem—they write the tool to solve the problem.

In a machine-native future, the **Super Learner** becomes the center of gravity in this transformation.

Two Years from Now

Two years from now, we're going to be having a very different conversation.

In that window, we won't just see the rise of the **Super Learner**—we'll begin to see cognitive architecture take hold. It may not be many processes, but we'll see concrete examples of entire workflows eliminated—processes that, until now, were widely assumed to be impossible to automate.

Those examples will matter. Not because of their immediate operational impact, but because they will mark the break from the legacy model—and the beginning of a new question: What will we become?

Maybe it takes four years—there are a lot of moving parts. Or maybe it's 18 months, driven by a new disruptor with a superior business model.

The earlier disruptors weren't wrong about the opportunity. They just didn't understand the **complexity and sophistication** of this industry.

The next one will have the tools to address it.

VI.C. A Few Final Thoughts

As I wrap this up—and this manifesto approaches 50 pages—I'm struck by how much more there is to say. Just a few examples:

- **Distribution** has built business models around managing operational inefficiencies. Remove that friction, and the focus will shift toward revenue-generating activities like lead generation, recruitment, and training.
- **Reinsurers** are well positioned for this shift—for a variety of reasons.
- The **legal domain** must be fascinating right now. It has something most industries don't: a massive, well-structured, well-defined corpus.

- **Voice**. Try ChatGPT's voice mode, and tell me it's not impressive. Once voice becomes wired into workflows, it will be wired into everything.

Of course—my favorite—learning. For those who've embraced this technology, learning has already been transformed. I could talk about learning and the rise of the **Super Learner** all day long—after all, I read E.D. Hirsch for fun. And there's still more to come.

I see this transformation everywhere. Walk up and down the supply chain and you'll find endless examples—all pointing to the same conclusion: This technology will change everything.

And that is the opportunity.

Epilogue

The life insurance industry has been good to me. It's good for society. I wish it continued success, and I hope my words are taken in the spirit they were offered. That said, the industry does carry structural weaknesses—most notably, its longstanding acceptance of inefficiency as a cost of doing business.

I believe that inefficiency will have to be stripped out for the industry to stay relevant. Maybe I'll play some small role in that—but that's not the goal.

This technology is just too fun to ignore. The ability to learn anything and build anything—it's Christmas morning, every morning.

Now: back to executing the-plan.