Insights from AI Use in Actuarial Practice

Prabhdeep Singh, FSA, MAAA, CERA, PMP

Any views and ideas expressed in the essays are the author's alone and may not reflect the views and ideas of the Society of Actuaries, the Society of Actuaries Research Institute, Society of Actuaries members, nor the author's employer.

Disclosure: At least some parts of this essay were written with the assistance of Gen AI.

This essay reflects on an exploratory two-month journey where the author engaged intensively with AI tools in actuarial contexts. The perspective is, therefore, one of experimentation rather than finished production.

Generative AI (GenAI) is altering actuarial work, not just through efficiency gains, but also by expanding the boundaries of what actuaries are willing to attempt. It reduces the friction of learning new methods and tools while demanding careful oversight and judgment. The key insight is that AI functions as an enabler of experimentation and professional growth, while human validation and reflection ensure outputs remain credible and relevant.

AI AS A PRODUCTIVITY ENHANCER

GenAI has proven especially effective for coding. Without AI, building a simple life valuation system in a new programming language might have taken several months of trial and error or extensive research. With AI, the same work can be completed in a matter of days. AI is particularly effective in programming classical actuarial functions because they build on one another. For example, once the formula for the present value of whole life benefits has been implemented, it takes only a plain-language description to generate accurate code for term, endowment, or deferred insurance. From there, AI quickly suggests additional functions, including annuities, net level premiums, reserves. These examples demonstrate the scale of productivity gain, often approaching tenfold improvements.

The agent is not perfect at discerning intent and will occasionally make mistakes. If left uncorrected, these mistakes propagate into other functions. Human oversight remains critical to ensure accuracy and coherence.

AI AS A LEARNING ACCELERATOR

When actuaries encounter new tools, AI can provide overviews and answer context-specific questions. Learning becomes tailored to individual needs rather than generic categories. For instance, the author used AI to learn Python, XML, and LaTeX as needed to implement actuarial functions, parse SOA mortality tables, and document formulas in proper notation — all within a two-month, part-time effort. Similar assistance proved useful in setting up research and writing workflows (Obsidian/Zettelkasten) and project management workflows (OneNote/GTD™).

Learning requires intent and discipline. Actuaries must choose whether to learn just enough to instruct AI or to build deeper expertise in the tools themselves. The most successful will be those who gain sufficient depth to combine human expertise with AI's capabilities, multiplying productivity. This observation aligns with trends in software engineering, where experienced developers using AI effectively are in highest demand.

LIMITATIONS AND RISKS

Despite its benefits, GenAI has important limitations:

- Performance: Chat interfaces slow down in extended sessions; integrated tools such as GitHub Copilot are better suited for iterative code development.
- Design Thinking: AI can generate code fragments or refactor codebases efficiently but does not solve higher-order design challenges — for example, how to structure documentation or apply different programming paradigms (functional programming for actuarial logic, object-oriented design for interfaces).
- Overconfidence and Credibility: AI can present flawed outputs with confidence, encouraging misplaced certainty. For example, in one exercise it confidently generated a LaTeX expression for an actuarial symbol that had to be corrected manually. No English prompt could produce the proper placement of the superscript. This example illustrates why validation is essential. AI's speed in generating answers must be balanced by actuaries' responsibility to check outputs against actuarial standards. Some may argue this undermines the thesis that AI enables courage, since overconfidence risks eroding critical thinking. Recognizing this tension is important: actuaries must pair AI's speed with rigorous testing, peer review, and professional skepticism to ensure that courage does not slip into misplaced confidence.

EMERGING SOLUTIONS FOR CREDIBILITY

Several technologies are beginning to address the credibility issue, though they are not yet fully mature for actuarial practice:

- Retrieval-Augmented Generation (RAG): Combines large language models with targeted document retrieval, grounding outputs in trusted sources. While promising regulatory or actuarial documentation, current implementations struggle with ongoing changes to actuarial knowledge and regulations.
- Knowledge Graphs: Structured networks of actuarial concepts, assumptions, objects and relationships (actuarial science ontology) that can help AI reason more reliably. Knowledge graphs could eventually improve explainability and reduce hallucinations, but they are not yet widely developed for actuarial science.
- Tooling: Another approach to improving credibility is augmenting LLMs with external tools. Instead of relying on generated text alone, the model can call APIs or calculators to ground outputs in verifiable data. For example, a weather API can provide authoritative real-time information, and an actuarial calculator written in Python can return exact present value or reserve calculations. This "tool use" paradigm reduces hallucination risk and helps ensure the accuracy of answers.

Each of these approaches provides incremental improvements, but actuaries must still supply the professional judgment, testing, and domain expertise to interpret results responsibly. Each of these solutions demonstrates the same underlying point: AI can accelerate experimentation, but only actuarial validation ensures credibility. Whether through retrieval, structured graphs, or external tools, technology provides the scaffolding; judgment remains the foundation.

CONCLUSION

AI should not be seen as a replacement for actuarial expertise but as an accelerator of experimentation and learning. It lowers barriers to learning and broadens participation in technical work, yet its confident errors and lack of design capability highlight the continued importance of actuarial judgment and external feedback. The profession's path forward lies in balancing AI's acceleration with disciplined validation — using the technology to expand horizons while maintaining core standards of rigor, humility, and clarity.

From this exploratory journey, three lessons stand out:

- Victories: AI accelerated coding of actuarial functions and expanded learning into new tools like Python, XML, and LaTeX.
- Frustrations: AI's confident mistakes, performance slowdowns, and lack of design judgment exposed its limits.
- Lessons Learned: AI lowers barriers to experimentation, but real progress requires human validation, peer review, and disciplined skepticism.

This essay is drawn from an exploratory journey rather than client deliverables. It illustrates the victories, frustrations, and lessons learned in early experimentation, which many actuaries will find valuable. By sharing candid reflections, actuaries can collectively shape how AI is integrated into professional practice, ensuring it becomes a tool for sound judgment rather than misplaced confidence.

* * * * *

Author Byline: Prabhdeep Singh, FSA, MAAA, CERA, PMP is an independent consulting actuary. He can be reached at prabhdeep.singh.actuary@gmail.com.