

# Actuaries

AI is speeding up actuarial modelling, data preparation and report drafting, while pricing, reserving and sign-off stay under professional control.

| EXPOSURE                                   | WINDOW                                           | ADOPTION TODAY         | READING                                                                                                                             |
|--------------------------------------------|--------------------------------------------------|------------------------|-------------------------------------------------------------------------------------------------------------------------------------|
| <div>45</div> <div>Elevated exposure</div> | <div>2–6 yrs</div> <div>until change lands</div> | <div>Medium-High</div> | <div>The role is being reshaped.</div> <div>Exposure is the share of today's work AI can plausibly take on within the window.</div> |

§ 01WHAT IS HAPPENING

## What is happening to actuaries

### Impact

Actuaries use Microsoft 365 Copilot and GitHub Copilot to write and document code in Excel, R and Python, and general assistants to draft reports, summarise regulation and explain model results to non-specialists. Machine-learning pricing platforms such as Akur8 fit and explain models that used to be built by hand in generalised linear modelling software, and data platforms automate the cleansing and reconciliation that preceded every valuation. Day to day, more time goes to interpreting results, validating models and communicating with underwriters, boards and regulators, and less to assembling the numbers.

## Risk

The role is being reshaped around modelling oversight and judgement; routine analysis automates, professional sign-off does not.

Occupation-level measures place actuaries in the highest official exposure tier because the work is quantitative and document-heavy, yet observed usage of AI assistants in the profession is still very low, and the measured task applicability is moderate. That gap reflects a regulated profession in which models must be explainable, validated and signed off by a qualified person, which slows adoption and limits what can be delegated. Over 2-6 years, data preparation, model coding, experience studies, standard reserving runs and first-draft reporting will become substantially automated, with machine-learning methods taking a larger share of pricing. Assumption setting, model validation, capital and reinsurance judgement, and the formal opinions a company relies on remain with qualified actuaries. The role shrinks at the trainee and analyst level and grows in demand for people who can govern models they did not build line by line.

## Sector readiness

### Medium-High Adoption, Constrained by Model Governance

Large insurers and consultancies have deployed machine-learning pricing, automated data pipelines and generative assistants for documentation, and most actuarial software vendors are adding AI features. Adoption is held back by model-risk governance, regulatory expectations of explainability and professional standards, so many teams use AI for productivity around the model rather than inside the formal valuation or pricing process.

## § 02 POSITION

## Where you stand

- i Position yourself as the actuary who validates and governs machine-learning models, because insurers need qualified people who can explain them to regulators.
- ii Build your reputation on judgement in assumption setting, capital and reinsurance decisions, where professional sign-off remains the product.
- iii Become the translator between actuarial models and the business, using AI to speed your drafting and spending the saved time with underwriters, finance and the board.

## § 03 ACTIONS

6 POINTS

## What this means for you

Concrete changes to how the work gets done, in the order you are likely to meet them.

- 01 **Let the code write itself.** Use GitHub Copilot and Microsoft 365 Copilot for routine scripting, documentation and spreadsheet work, and redirect the hours to validation and interpretation.
- 02 **Learn machine learning properly.** Pricing and claims models built with gradient boosting and similar methods are becoming standard; an actuary who can validate and challenge them is more valuable than one who only builds GLMs.
- 03 **Own model governance.** Regulators expect explainability and documented validation; make yourself the person who sets and applies those standards for AI-assisted models.
- 04 **Guard against quiet errors.** Generative tools produce plausible code and prose that can be subtly wrong; build checking into your workflow so you never sign off something you have not independently tested.
- 05 **Spend time with the business.** Explaining results to underwriters, product teams and the board is where an actuary's judgement is visible; AI frees time for it, so use it.
- 06 **Keep the professional credential central.** Qualification and the duties that come with it are the main reason the role is protected; progress through the exams and stay active in the profession.

## § 04 CAUSES

6 DRIVERS

## What is pushing this change

- 01 **Machine-learning pricing platforms.** Tools such as Akur8 fit, constrain and explain pricing models automatically, replacing much of the manual GLM building that defined personal-lines pricing.
- 02 **Code assistants.** GitHub Copilot and Microsoft 365 Copilot accelerate R, Python, SQL and spreadsheet work and generate documentation, reducing the analyst hours behind every model.
- 03 **Automated data pipelines.** Databricks and similar platforms clean, reconcile and version policy and claims data, removing the data-preparation phase that used to consume valuation cycles.
- 04 **Generative drafting and summarisation.** Large language models draft reports, summarise regulatory text and explain results, compressing the writing and review stages of actuarial work.
- 05 **Regulatory expectations on model risk.** Supervisors require explainable, validated models with clear accountability, which slows adoption inside the formal process and preserves demand for qualified sign-off.
- 06 **Low observed usage so far.** The profession has been slow to use AI assistants in daily work, so much of the measured potential has not yet landed, which spreads the change over the coming years.

## Impact by sector

The headline figure is an average. Where you work changes the picture.

|                                   |                                                                                                                                                       |
|-----------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------|
| Personal-lines general insurance  | Pricing is the most automated area, with machine-learning platforms and continuous repricing now mainstream and fewer analysts needed per product.    |
| Life insurance and pensions       | Long-term valuation and regulatory reporting remain governance-heavy, so AI is used for documentation and data work rather than the core valuation.   |
| Reinsurance and capital modelling | Complex, judgement-driven work with scarce data; AI assists with coding and scenario drafting but decisions stay with senior actuaries.               |
| Consulting                        | Consultancies use AI to speed research, drafting and model building, and are selling model-governance services to insurers adopting machine learning. |

## Skills to build

The skills that keep the human part of this work valuable as the routine part is automated.

- 01 **Machine-learning model validation.** Understanding how gradient boosting, neural and penalised models behave, and how to test them for bias and stability, lets you sign off work you did not build by hand; the profession's own ML courses are a good start.
- 02 **Programming with assistants.** Fluency in Python or R, combined with skilled use of code assistants, multiplies your output and lets you check generated code rather than trust it.
- 03 **Model governance and explainability.** Knowledge of regulatory expectations, validation frameworks and explainability techniques positions you where insurers most need qualified people.
- 04 **Communication with non-specialists.** Explaining uncertainty and model limitations to boards and underwriters is the actuary's distinct contribution; practise it deliberately.
- 05 **Data engineering awareness.** Knowing how pipelines, data quality checks and versioning work helps you judge whether the numbers entering a model can be trusted.
- 06 **Professional judgement in assumption setting.** Deciding what to assume about mortality, lapses, inflation or claims trends remains the core skill; build it through exposure to real decisions and peer review.

## Tools in use

### KINDS OF TOOL WORTH KNOWING

01

**AI features in actuarial modelling platforms.** The major valuation and projection software vendors are adding assistants and automation; know what yours offers and how it is governed.

### NAMED TOOLS ALREADY IN USE

|                                                                                                                            |       |
|----------------------------------------------------------------------------------------------------------------------------|-------|
| <b>Microsoft 365 Copilot</b>                                                                                               | VISIT |
| Assists with Excel formulae and analysis, drafts reports in Word and summarises long regulatory documents.                 |       |
| <b>GitHub Copilot</b>                                                                                                      | VISIT |
| Code assistant used by actuarial teams working in Python, R and SQL to write, explain and document modelling code.         |       |
| <b>Akur8</b>                                                                                                               | VISIT |
| Machine-learning pricing platform built for insurers that fits transparent models and is used in place of hand-built GLMs. |       |
| <b>Databricks</b>                                                                                                          | VISIT |
| Data and analytics platform used by insurers to prepare, govern and model policy and claims data at scale.                 |       |
| <b>ChatGPT</b>                                                                                                             | VISIT |
| General assistant used to draft explanations, check reasoning and summarise technical material for non-specialist readers. |       |

## In practice

Ways people in this role are already using AI, and what they get from it.

|                                                       |      |                                                                                                                                                                                       |
|-------------------------------------------------------|------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Machine-learning pricing with governance<br>EXAMPLE 1 | HOW  | A pricing team builds motor models in a platform that fits and constrains the model automatically, then the actuary reviews factor behaviour, fairness and stability before approval. |
|                                                       | GAIN | Repricing cycles shorten while the actuary's time is spent on judgement rather than fitting.                                                                                          |
| Assisted model documentation<br>EXAMPLE 2             | HOW  | A code assistant generates explanatory comments and a draft methodology note from the model code, which the actuary corrects and expands.                                             |
|                                                       | GAIN | Validation and audit documentation is completed faster and more consistently.                                                                                                         |

|                                                      |      |                                                                                                                                                      |
|------------------------------------------------------|------|------------------------------------------------------------------------------------------------------------------------------------------------------|
| Regulatory summarisation<br><small>EXAMPLE 3</small> | HOW  | An actuary uses a language model to summarise a new supervisory statement and list its implications, then checks each point against the source text. |
|                                                      | GAIN | Regulatory change is absorbed quickly without replacing professional reading of the primary document.                                                |

§ 09    CONTEXT

## How this role compares

Three neighbouring roles chosen to show the direction of travel.

|                                                             |               |                                                                                                                                                      |
|-------------------------------------------------------------|---------------|------------------------------------------------------------------------------------------------------------------------------------------------------|
| Insurance Underwriters<br><small>MORE EXPOSED</small>       | AI IMPACT     | Automated underwriting engines decide a growing share of standard risks directly, so routine underwriting is being substituted rather than assisted. |
|                                                             | WORK MOVES TO | Actuaries retain the model-governance and sign-off role that underwriters are losing; stay on the governance side.                                   |
| Data Scientists<br><small>DIFFERENT SKILLS, GROWING</small> | AI IMPACT     | AI writes much of the code, but demand for people who build and validate models on business data continues to rise.                                  |
|                                                             | WORK MOVES TO | Broader modelling and engineering skills; a realistic parallel path for actuaries who deepen their machine learning.                                 |
| Risk Managers<br><small>COMPLEMENTARY, LESS EXPOSED</small> | AI IMPACT     | Risk management uses AI for monitoring and reporting, but the judgement about appetite, controls and accountability stays human.                     |
|                                                             | WORK MOVES TO | Enterprise risk, governance and board communication; an established progression for senior actuaries.                                                |

§ 10    VERDICT

## Closing judgement

Actuarial work is one of the few quantitative professions where a qualified person must still put their name to the result, and that is why your score sits in the middle of the range rather than the top. The parts of your job that are being automated, the data wrangling, the coding, the routine runs and the drafting, were never the parts that justified the qualification. Use the tools to do them faster, learn enough machine learning to validate models built that way, and invest in the judgement, communication and governance skills that make you the person a board trusts when the model says something surprising.

## Evidence and revisions

What the exposure figure rests on, what changed when it was last revised, and the published work cited for this role.

SCORE

45

WINDOW

2-6 years (unchanged)

The 5 October 2026 review held the score.

Exposure Index v2. Inputs: task applicability 32/100 (Microsoft AI applicability score 0.16 for Actuaries); observed usage 7/100 (Anthropic observed exposure 0.05); official exposure tier 100/100 (BLS: very high); labour-market trajectory not yet mapped for this occupation, so its weight was spread across the other inputs; published adoption rating 55/100 (medium-high adoption). Weighted base 45.3. Final score 45. New report: the window of 2-6 years is set from the score band.

HOW THE FIGURE IS BUILT (EXPOSURE INDEX V2)

|                                                                       |              |      |
|-----------------------------------------------------------------------|--------------|------|
| Task applicability — Microsoft Research, AI applicability score       | 32 × 39%     | 12.3 |
| Observed usage — Anthropic Economic Index, observed exposure          | 7 × 22%      | 1.6  |
| Official exposure tier — US BLS AI-exposure category                  | 100 × 22%    | 22.2 |
| Labour-market trajectory — US BLS projected employment change 2025–35 | not measured | —    |
| Published adoption rating — This report’s adoption level              | 55 × 17%     | 9.2  |
| Weighted base                                                         |              | 45.3 |
| Exposure score                                                        |              | 45   |

MEASURES BEHIND THE SCORE

**US Bureau of Labor Statistics** · *Employment Projections 2025–35 and AI Exposure Categories* (27 August 2026)  
AI-exposure tier: Very high. Projected employment change not yet mapped for this occupation. Matched to Actuaries.

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**Microsoft Research** · *Working with AI: Measuring the Applicability of Generative AI to Occupations* (10 July 2025)  
AI applicability score 0.16 for SOC 15-2011; scaled to 32/100 as the task-applicability input.

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**Anthropic** · *Anthropic Economic Index report: Cadences* (26 June 2026)  
Observed exposure 0.05 for SOC 15-2011; scaled to 7/100 as the observed-usage input.

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## UK Department for Science, Innovation and Technology · *Assessment of AI capabilities and the impact on the UK labour market* (28 January 2026)

UK context: around 70% of UK workers are in occupations with tasks AI could perform or enhance, above the US average; a one-standard-deviation rise in exposure was associated with a 3.9% fall in UK job postings.

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<https://www.careerguard.ai/sources>

### § 12   APPENDIX

## Method and sources

Each report was written from a large body of published research. The exposure score itself is computed, not written: it is the CareerGuard Exposure Index, a weighted average of occupation-level measures from the US Bureau of Labor Statistics (AI-exposure classification and 2025–35 projections), Microsoft Research (AI applicability scores) and Anthropic (observed exposure), together with the adoption rating published on the report. The organisations and publications below are the standing literature behind the narrative sections. Every source, with dates, licences and archived copies where we are permitted to hold them, is catalogued in the research library.

Exposure Index v2 (October 2026). Each input is scaled to 0–100 and weighted: task applicability 35% (Microsoft AI applicability score ÷ 0.5), observed usage 20% (Anthropic observed exposure ÷ 0.75), official exposure tier 20% (BLS very high = 100, high = 70, moderate = 40, low = 10), labour-market trajectory 10% ( $50 - 2.5 \times \text{projected \% employment change}$ ), published adoption rating 15% (very high = 85, high = 70, medium-high = 55, medium = 40, low-medium = 25, low = 10). Inputs not measured for an occupation are dropped and the remaining weights renormalised. An editorial adjustment of at most  $\pm 12$  points is allowed only for automation channels the measures cannot see (robotics, self-service, machine vision, medical imaging, RPA/OCR, generative video) and is always logged with its reason. Scores are whole numbers, not rounded to five. The change window shifts one notch (a year at each end) per ten points of movement.

### I   GLOBAL AND MACROECONOMIC IMPACT OF AI ON WORK

#### World Economic Forum

*The Future of Jobs Report series* — Employer survey of expected job growth and decline, skill shifts and technology adoption (2020, 2023 and 2025 editions); *Artificial Intelligence and the Future of Entry-Level Work* (2026).

*AI governance and transformation reports* — Frameworks on ethical AI, talent strategy and industry transformation.

#### McKinsey Global Institute

*AI, Automation and the Future of Work series* — Research quantifying automation potential by task, sector and demographic, from "Jobs Lost, Jobs Gained" to "Agents, robots, and us" (2025).

*Industry-specific reports* — Financial services, healthcare, manufacturing and others.

#### PwC

*Global AI Jobs Barometer* — Annual analysis of job postings and productivity by AI exposure (2024–2026 editions).

*Upskilling Hopes and Fears survey* — Employee perceptions and readiness.

#### Microsoft Research and Anthropic

*Working with AI* (2025); *Anthropic Economic Index* (2025–2026) — Occupation-level usage data from Copilot and Claude conversations, the two observed-usage measures behind the 2026 revision.

**Stanford Digital Economy Lab and Stanford HAI**

*Canaries in the Coal Mine? (2025–2026); AI Index Report (annual)* — Payroll evidence on early-career employment in exposed occupations; annual measurement of AI capability, investment and adoption.

**Deloitte**

*Human Capital Trends series* — Workforce, talent and HR technology trends.

*Tech Trends series* — Emerging technologies and their business implications.

**Accenture**

*Technology Vision series* — Forward-looking analysis of emerging technology, with emphasis on AI.

*Fjord Trends* — Design, innovation and human experience in a digital world.

**Boston Consulting Group**

*AI/ML insights and industry solutions* — "The AI Revolution in the Workplace" and related research.

**EY**

*AI and workforce reports* — Adoption, talent strategy and ethics.

**IBM Institute for Business Value**

*AI and automation studies* — Business models, workforce evolution and leadership.

**OECD**

*AI Policy Observatory* — International data and policy on AI, labour markets and skills.

*Employment Outlook* — Labour-market trends including technological impact (2023–2026 editions).

**International Labour Organization**

*Generative AI and Jobs: A Refined Global Index of Occupational Exposure (2025)* — Task-level exposure gradients for every ISCO occupation; successor to the 2023 global index.

**International Monetary Fund**

*Staff Discussion Notes on AI and work (2024, 2026)* — Complementarity framing: where AI augments and where it substitutes.

**UK Department for Science, Innovation and Technology**

*Assessment of AI capabilities and the impact on the UK labour market (2026)* — UK occupational exposure and job-posting evidence.

**Brookings Institution**

*AI and automation research* — Economic and social implications, displacement and skills.

**Yale Budget Lab and Goldman Sachs Research**

*Tracking the Impact of AI on the Labor Market; AI and the US labour market (2026)* — Aggregate labour-market monitoring; macro displacement estimates.

**Oxford University (Oxford Martin School)**

*The Future of Employment* — Frey & Osborne and subsequent research on susceptibility to automation.

**MIT Technology Review**

*AI & Work* — Reporting on AI research and its implications for industries and jobs.

**Gartner**

*Hype Cycle for Artificial Intelligence* — Maturity and adoption of AI technologies.

*Future of Work reports* — Workplace models and talent strategy.

**U.S. Bureau of Labor Statistics**

*Employment Projections 2025–35; AI Exposure Categories; Occupational Outlook Handbook* — Ten-year employment projections and, from the 2025 cycle, an AI-exposure tier for every detailed occupation.

**Indeed Hiring Lab**

*AI at Work Report (2025) and posting-market updates* — Skill-level transformation estimates and job-posting trends by occupation.

**II CORE AI AND MACHINE-LEARNING RESEARCH**

**OpenAI***Research papers, blog and API documentation* — Large language models, generative AI, safety and societal impact.**Google DeepMind***Research papers and blog* — Reinforcement learning, AI for science, AGI and ethics.**Meta AI***Research papers and blog* — Large language models, computer vision, AI for social good.**Hugging Face***Transformers library and model hub* — Open-source state-of-the-art NLP models.**TensorFlow and PyTorch***Documentation and community forums* — Core frameworks illustrating practical capability.**arXiv***cs.AI, cs.LG, cs.CV, cs.CL* — Pre-print research.**NeurIPS and ICML***Conference proceedings* — Top-tier academic research.**ACM and IEEE***Journals and proceedings* — ACM Computing Surveys; IEEE Transactions on AI.**Kaggle***Datasets and competition solutions* — Applied machine learning on real-world problems.**The Alan Turing Institute***Research and reports* — Responsible and applied AI.**III ETHICAL AND RESPONSIBLE AI DEPLOYMENT****NIST***AI Risk Management Framework* — Voluntary framework for managing AI risk.**European Commission***AI Act* — Risk-tiered legal framework for AI.*Ethics Guidelines for Trustworthy AI* — Principles for responsible development.**Partnership on AI***Research and best practice* — Responsible AI development.**AI Now Institute***Annual reports* — Social implications: power, inequality, rights.**ACM FAccT***Proceedings* — Fairness, accountability and transparency.**Data & Society***Publications* — Social implications of data-centric technology.**WIPO***Conversation on IP and AI* — Intellectual-property implications of AI.**IEEE Global Initiative on Ethics of AI/IS***Ethically Aligned Design* — Recommendations for ethical AI design.**Center for AI and Digital Policy***Policy briefs* — Accountable AI policy.

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