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AI, Actuaries, and Education

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Abstract

Artificial intelligence (AI) is poised to revolutionise the actuarial profession, making it imperative to establish best practices for its integration into actuarial education. To ensure that future actuaries are well-prepared for the evolving demands of the field, it is essential to incorporate AI as both a powerful tool to enhance learning and a critical component of the curriculum. Best practices should focus on training actuaries to utilise AI efficiently and ethically, harnessing AI to enhance education delivery and assessment, and addressing the ethical and professional implications of AI in actuarial work. By proactively integrating AI, actuarial education can be aligned with the technological advancements shaping the profession.

Keywords: *artificial intelligence; actuarial education; best practices; professional development; ethics*

1. Introduction

The emergence of artificial intelligence, particularly in the form of generative AI systems such as large language models, represents a transformative force in professional practice across all industries. For the actuarial profession, AI presents both unprecedented opportunities and significant challenges. As AI systems increasingly demonstrate capabilities that overlap with traditional actuarial functions, from data analysis and modelling to communication and decision-making, we face a critical inflection point in educating and preparing future actuaries.

The actuarial profession has historically evolved alongside technological advances. From the adoption of calculators to the widespread use of spreadsheets, actuaries have consistently integrated new tools that enhance their analytical capabilities. However, AI represents a qualitatively different kind of technology that not only augments computational power, but possesses capabilities in domains previously considered uniquely human, such as pattern recognition, language understanding, and even certain forms of judgment.

This paper examines the implications of AI for actuarial education and proposes best practices for its integration. The fundamental premise is that banning or restricting the use of AI in education creates a dangerous disconnect between how students learn and how they will apply their knowledge in their professional lives. Instead, actuarial education must embrace AI as both a subject of study and a tool for learning, while simultaneously refocusing educational priorities on the skills and competencies that remain distinctly human.

The sections that follow explore the challenges AI poses to traditional educational models, analyse use cases for AI in both actuarial practice and education, examine assessment approaches in an AI-enabled world, and propose comprehensive guidelines for integrating AI into actuarial education. By addressing these considerations proactively, the actuarial profession can ensure that its educational frameworks remain relevant, ethical, and forward-looking in the age of artificial intelligence.

2. The Challenge: AI's Impact on Traditional Learning Models

AI and Cognitive Processing

Artificial intelligence is fundamentally altering our relationship with thinking, much like the internet has transformed our relationship with knowledge. As Krakauer (2016) observed, AI is not merely a tool but a potential paradigm shift in how we conceptualise thinking itself. This technological revolution challenges traditional notions of creativity and originality, with profound implications for education and professional practice.

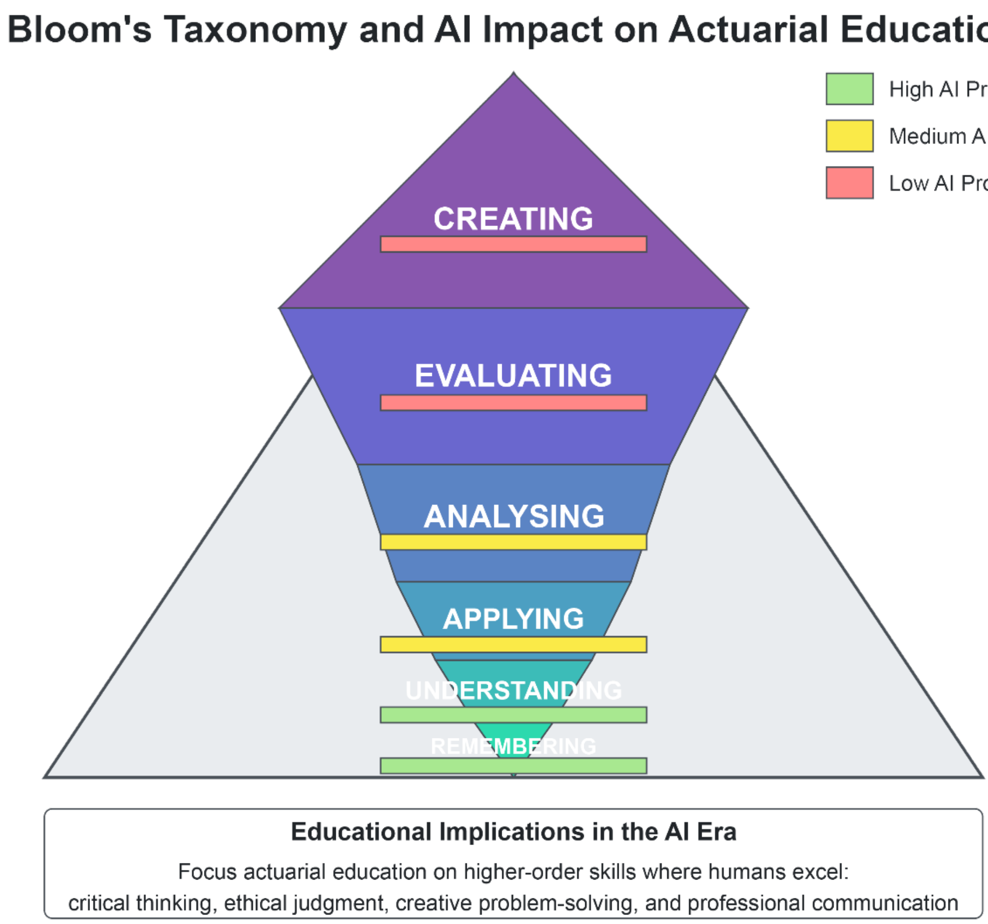
The impact on writing and cognitive processing is particularly significant. AI can now produce sophisticated analyses and essays that were once the exclusive domain of humans. This capability potentially undermines the traditional role of writing as a pedagogical tool for cognitive processing and learning. As Flower and Hayes (1981) noted, writing has historically served as a mechanism for students to clarify and refine their thoughts, a function now partially replicated by AI systems.

AI can be understood as a "cognitive artifact", a concept introduced by Donald Norman (1991) to describe tools that affect human cognitive performance. Norman and subsequent researchers, such as Krakauer, differentiated between complementary cognitive artifacts, which amplify human abilities even when the artifact is no longer present (e.g., Arabic numerals or the abacus), and competitive cognitive artifacts (e.g., GPS or calculators), which may diminish skills when unavailable. The critical question facing actuarial education is whether AI will function as a complementary or competitive cognitive artifact, whether it will enhance human capabilities or potentially atrophy certain cognitive skills.

Bloom's Taxonomy

Bloom's Taxonomy, a hierarchical framework that classifies educational learning objectives into levels of increasing complexity, provides a useful lens for understanding the educational impact of AI. Originally created by Benjamin Bloom and colleagues in 1956 and revised by Anderson and Krathwohl in 2001, this taxonomy organises cognitive processes from lower-order (remembering, understanding) to higher-order thinking skills (analysing, evaluating, creating). AI systems have demonstrated remarkable proficiency at lower levels of this taxonomy, capably handling tasks like recalling facts, explaining concepts, and even applying knowledge in certain structured contexts.

However, the creative capacities of AI remain a subject of debate. Many artists argue that AI-generated art lacks genuine creativity. For instance, artist Ben Templesmith contends that AI "has no ability to grow, no ability to understand emotion and expression," emphasising that AI outputs are devoid of the emotional depth and intentionality inherent in human-created art (Shankar, 2025). Conversely, some artists embrace AI as a collaborative tool that can enhance creativity. Artist David Salle has worked with AI to produce artworks that blend human intentionality with machine unpredictability, resulting in pieces that challenge traditional notions of authorship and creativity (The Guardian, 2025, April 15). Similar debates occurred when photography was first introduced in the 19th century, particularly about creativity, authorship, and the definition of art, yet photography is now generally accepted as a creative art form. For example, copyright law in most jurisdictions recognises photographs as original creative works, granting protections similar to other art forms. Although the diagram below reflects one viewpoint, it does not represent the position of this paper.



In actuarial education, Bloom's Taxonomy levels manifest distinctly. At the lower cognitive levels, students recall key risk factors and apply statistical methods (Remembering), then demonstrate understanding by explaining how mortality assumptions affect life insurance pricing

(Understanding). Moving higher, students apply these concepts by performing reserve calculations for specific products (Applying) and analysing how different economic scenarios affect long-term liabilities (Analysing). At the highest levels, students evaluate the appropriateness of different models for specific risk scenarios (Evaluating) and ultimately create novel approaches to emerging risks that lack historical precedent (Creating). As AI increasingly handles the lower cognitive levels, actuarial education must emphasise these higher-order skills.

This capability distribution creates an educational challenge: AI disrupts traditional approaches to teaching and assessing lower-order thinking skills, which have historically formed the foundation of educational practices. As Anderson et al. (2001) emphasised, educational objectives have traditionally been structured to build progressively from knowledge acquisition to higher cognitive functions. AI's ability to perform knowledge and comprehension tasks necessitates a re-evaluation of this progression. How does one ensure that students obtain the higher levels of the taxonomy when AI use may lead them to skip the lower levels? Are the lower levels a prerequisite to master the higher levels?

Historical Precedents

The historical precedent of calculators in mathematics education offers instructive parallels. Like AI, calculators changed the educational landscape by rendering certain traditional skills (such as long division) less essential while simultaneously shifting the focus toward higher-order mathematical understanding (Young, 2017). The introduction of calculators prompted educators to reevaluate which mathematical skills remained essential and to articulate why those skills mattered, precisely the challenge facing actuarial education today with the advent of AI. Educators need to articulate why certain skills remain essential in the age of AI.

Similarly, the internet has fundamentally changed our relationship with knowledge, shifting us from a world where knowledge was scarce but reliable to one where information is abundant but of variable quality. Early attempts to ban web-based tools like Wikipedia and Google ultimately failed, suggesting that prohibition-based approaches to managing AI in education may prove equally ineffective (Roll & Wylie, 2016).

Raising the Standard

As AI capabilities continue to improve, actuarial education must adapt by focusing increasingly on higher-order thinking skills that remain distinctly human - the ability to critically analyse, evaluate complex situations, and create novel approaches to emerging problems. This requires a shift in educational content, assessment practices, and pedagogical approaches.

The integration of AI into educational and professional contexts is also driving a fundamental shift in standards and expectations. As Zawacki-Richter et al. (2019) suggest, AI assistance enables a new baseline for work quality and productivity that may recalibrate our collective expectations. Just as contemporary readers might view typewritten documents with manual corrections as archaic, future generations may perceive pre-AI writing styles, analytical approaches, and common errors as similarly outdated artifacts of a less technologically advanced era. This evolution necessitates new pedagogical approaches in actuarial education. Educators must be increasingly explicit in requiring students to articulate their thinking processes, document their research methods, and reflect on their writing and analytical decisions. As Kasneci et al. (2023) emphasised, there is growing recognition of the need to develop meta-cognitive skills that involve analysing and critiquing AI-generated responses rather than simply accepting them. This represents a crucial shift toward developing critical thinking capabilities in conjunction with AI use, a skill set essential for actuaries navigating complex professional environments where human judgment and AI-enabled analysis must be thoughtfully integrated. With its longstanding emphasis on rigorous analysis and professional judgment, the actuarial profession is uniquely positioned to develop educational frameworks that strike a balance between technological enhancement and human expertise.

3. The Case Against Banning AI in Education

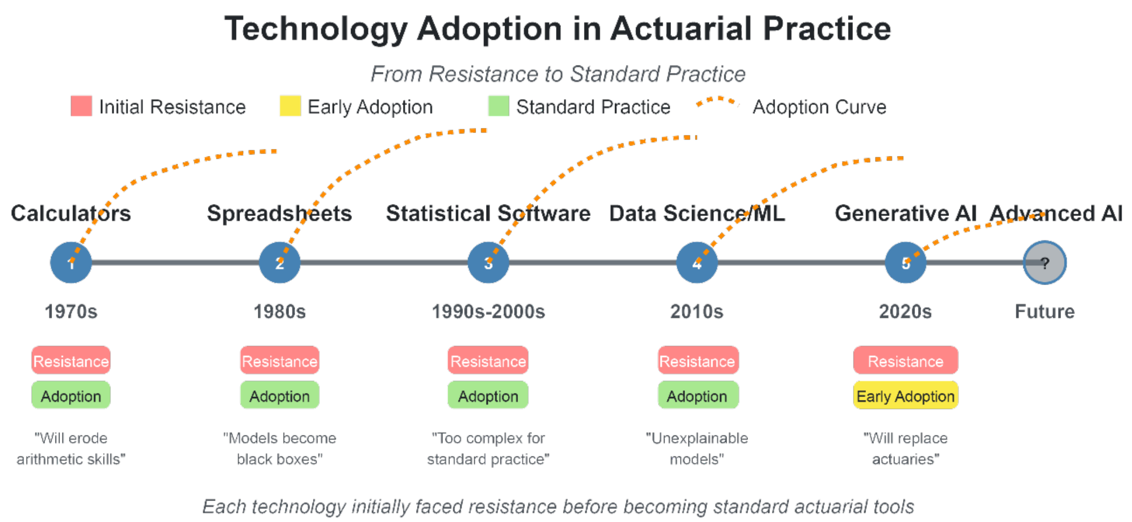
Artificial intelligence (AI) has rapidly emerged as a transformative force across industries, prompting intense debate about its role in education. Some stakeholders have called for banning AI tools such as chatbots in schools and universities, fearing negative impacts on learning and academic integrity. However, outright prohibition may exacerbate existing gaps between education and workforce needs, denying students valuable skills. This report presents a comprehensive analysis of why banning AI in education is counterproductive, drawing on evidence from workforce studies, historical technology adoption in classrooms, research on AI-enabled learning, enforcement challenges of bans, ethical and equity considerations, international policy responses, and relevant theories of technology adoption. The narrative builds the case that rather than bans, educators and policymakers should integrate AI into curricula to enhance learning and prepare students for future careers.

The Education-Employment Disconnect

Modern economies are exhibiting a growing disparity between traditional education and the skills demanded by an AI-driven workforce. Employers are increasingly seeking graduates who are proficient in data analytics, automation, and AI; however, many academic programs fall behind in updating their curricula. Graduates often lack relevant skills, forcing them to either take jobs outside their field of study or relocate for work (Coffey, 2024). In domains such as actuarial science and engineering, the disconnect is especially pronounced. Actuarial employers, for instance, place a high premium on programming and machine-learning skills in addition to classical mathematics (Actuaries Institute, 2023). If actuarial and STEM education fails to incorporate AI-based problem-solving, future professionals could be left behind in a rapidly changing labour market.

Recent research highlights the importance of updating educational curricula to accelerate the adoption of new technologies in industry. A Swiss study examining how newly introduced digital skills in vocational training impacted firms concluded that well-structured educational reforms “substantially shorten the time it takes for new technologies to arrive in firms’ workplaces” (Schultheiss & Backes-Gellner, 2024). In other words, once schools teach cutting-edge tools, businesses are quicker to adopt them, aligning their workforce capabilities with market innovations. More broadly, the World Economic Forum (2025) has warned of a “skills chasm,” arguing that workers risk displacement unless they develop competencies like AI literacy. It recommends harnessing “AI-powered educators” and adaptive learning platforms to future-proof the workforce (World Economic Forum, 2025). Consequently, aligning education with employment needs, rather than banning AI, can help reduce the risk of an ever-widening gap between academia and the labour market.

Lessons from Historical Technological Advances



History demonstrates that many new tools, from calculators to personal computers, initially faced resistance in educational contexts but ultimately gained acceptance. When hand calculators first became affordable, teachers and administrators worried that students' arithmetic skills would deteriorate (Banks, 2011). Critics argued that calculators would enable shortcuts and weaken foundational numeracy. Over time, however, empirical studies have shown that using calculators appropriately can enhance problem-solving skills rather than undermine them (Ellington, 2003). Educators developed strategies to ensure students still understood basic operations while leveraging calculators for more complex tasks (Johnson, 2023).

A parallel can be drawn to the introduction of spreadsheets in the 1980s. Spreadsheets transformed accounting, finance, and data analysis by automating manual calculations, sparking concerns that students would cease to grasp fundamental methods. Yet spreadsheets ultimately enabled more sophisticated exploration of data, freed learners from tedious arithmetic, and shifted focus to conceptual understanding (Davis, 1989). In domains such as business and actuarial education, teaching spreadsheet use has become synonymous with preparing students for professional environments that rely on data modelling (Actuaries Institute, 2023).

The emergence of data science and machine learning offers a more recent example of educational transformation driven by technological innovation. Initially confined to specialist fields like computer science and statistics, these tools have rapidly permeated disciplines such as economics, public health, and actuarial science. Early scepticism centred on their perceived complexity and the risk of students relying on opaque algorithms without understanding underlying principles (Jordan & Mitchell, 2015). However, as educational frameworks evolved, machine learning became a gateway to teaching applied reasoning, critical data interpretation, and probabilistic thinking. Integrating tools like Python, R, and open-source libraries into coursework has empowered students to engage with real-world datasets, build predictive models, and evaluate algorithmic fairness. Rather than displacing foundational knowledge, data science has expanded what students can achieve, mirroring how prior technologies reshaped both pedagogy and practice. As with calculators and spreadsheets, the key to successful integration lies not in resisting the tools, but in teaching students how to use them responsibly and insightfully.

These precedents, calculators, spreadsheets, and computers, reveal a consistent pattern: technological adoption in education, though initially contentious, tends to enhance learning outcomes once integrated with the right pedagogical approach. AI appears poised to follow the same trajectory.

Why Prohibition Approaches Are Unlikely to Succeed

Attempts to ban AI tools are often impractical. Students already have ready access to AI applications on personal devices and off-campus networks, making enforcement nearly impossible (Johnson, 2023). Past efforts to restrict resources, such as Wikipedia or open-source libraries, have largely failed because prohibitive measures ran counter to the ubiquitous availability of these tools and the ease of finding guides on how to circumvent filters (Nina, 2019). The rapid innovation cycle in AI, with new tools continually emerging, compounds the difficulty of maintaining comprehensive bans.

From an education policy standpoint, blanket prohibitions can undermine trust and may inadvertently encourage covert misuse (Torrey, 2023). Rather than eliminating cheating, bans often prompt students to use AI in unethical or unsupervised ways. By contrast, integrating AI into formal curricula can demystify its functions, highlight its limitations, and guide students in applying it responsibly. Drawing parallels to plagiarism detection software, many institutions now incorporate AI detection tools within existing academic honesty frameworks, treating AI assistance as a resource that requires correct attribution (Cotton, Cotton, & Shipway, 2023). Research suggests that such transparent approaches better instil ethical norms and technical competence than blanket prohibitions (Rogers, 2003).

AI Integration in Education as a Tool, Not a Threat

A substantial body of peer-reviewed research suggests AI can be a powerful learning tool if properly incorporated. Applications range from intelligent tutoring systems that adapt to learners' needs in real time to AI-driven writing assistants and coding tools (University of San Diego, n.d.). When thoughtfully embedded in curricula, these applications can provide personalised feedback, automate repetitive tasks, and allow teachers to focus on higher-level mentoring (Rogers, 2003). UNESCO (2025) has emphasised that AI offers unprecedented opportunities to address learning gaps, manage large class sizes, and foster inclusive education, provided ethical and equitable frameworks are in place.

Within STEM fields, pilot studies have demonstrated that AI-based tutoring in subjects such as mathematics and computer science can substantially enhance problem-solving skills and motivation (Torrey, 2023). Early research on AI-driven tools suggests they may help students practice and refine their skills with continuous, instant feedback, thereby increasing self-efficacy (Davis, 1989). In actuarial programs, the introduction of AI-based statistical software and coding assistants has the potential to deepen the conceptual understanding of complex risk models by offloading some of the more mechanical tasks (Actuaries Institute, 2023). This approach echoes earlier lessons from calculators and spreadsheets: by delegating routine computations to technology, learners can devote more energy to reasoning, interpretation, and real-world applications.

Ethical and Equity Considerations

Banning AI raises several ethical questions, particularly regarding equity and access. When schools prohibit the use of AI in the classroom, more privileged students may continue using it elsewhere, benefiting from the extra practice and guidance, while others are left behind (Smith et al., 2025). As a result, prohibitions can widen the digital divide, undermining the principle of equal educational opportunity. By contrast, structured access to AI can level the playing field, ensuring all learners receive comparable exposure and skill development (World Economic Forum, 2025).

Academic integrity is also a factor in the ethical argument. Critics worry that generative AI tools, such as chatbots, could facilitate automated cheating (Torrey, 2023). However, educators and researchers note that outright bans do not resolve this issue. A more ethical long-term strategy is to teach students when and how to cite AI-generated content, to design assessments that focus on authentic demonstrations of understanding, and to highlight the risks of overreliance on AI's sometimes inaccurate outputs (Johnson, 2023). Moreover, educators can use AI itself to detect AI-generated submissions, just as they use plagiarism detection software, thus establishing reciprocal measures of accountability (Quinn & Burns, n.d.). Viewed in this light, AI becomes not just a potential vehicle for dishonesty but also a resource for promoting transparency.

Additionally, equity concerns extend to learners with special educational needs or language barriers. For some students, AI can serve as an assistive tool, for instance, offering real-time translation, reading assistance, or step-by-step problem-solving guidance (UNESCO, 2025). Banning AI universally overlooks these potential benefits and may inadvertently disadvantage students who stand to gain the most. An inclusive framework thus acknowledges that AI, if properly regulated and supported by teacher training, can help bridge persistent educational gaps.

4. Actuaries are Human

The previous sections have explored AI's impact on learning models and the case for embracing these tools rather than banning them. However, to properly shape actuarial education, we must first understand what aspects of actuarial work will remain inherently human even as AI capabilities advance. This section examines how professional standards across actuarial societies worldwide emphasise the human actuary as the source of advice—a critical consideration that must inform how we prepare future professionals.

Actuaries Institute (Australia): Individual Actuaries as Source of Advice

The Actuaries Institute of Australia explicitly requires that actuarial advice be given and owned by individual actuaries, not by corporations or automated systems. In its professional Code of Conduct (historically known as the Institute of Actuaries of Australia Code), the Institute states: "All actuarial advice must be, and be seen to be, the responsibility of one or more individual actuaries." This means that any formal actuarial report or advice must have a named actuary (or actuaries) taking personal professional responsibility. The Code further defines "actuarial advice" as advice an actuary gives and relies on because of an actuary's expertise. In practice, only natural persons can be members of the Actuaries Institute. Therefore, only individuals (Fellows or Associates) can provide recognised actuarial advice, not a company or a software program. The Institute's rules also require actuaries to disclose their role when giving advice (e.g., whether they act as an employee or consultant), reinforcing that the member actuary is accountable for the work, rather than a corporate entity.

Importantly, if an actuary uses input from other experts or machines, the actuary must still assume responsibility for the final advice. The Code of Conduct permits limited reliance on the expertise of others. Still, even then, the actuary must document the expert's input and take responsibility for the overall advice unless responsibility for that part truly cannot be assumed. Nowhere do the Institute's professional standards permit a machine or AI to be the provider of "actuarial" advice on its own – the human actuary must oversee and sign off on the work. This principle is rooted in the profession's emphasis on accountability and ethics: an algorithm cannot be held to the Code of Conduct or disciplined for misconduct, but an Institute member can. Recent Actuaries Institute discussions on AI reiterate that while actuaries can leverage advanced models, the actuary's judgment and accountability remain paramount (i.e. the actuary must understand and take responsibility for model outputs, rather than abdicate responsibility to a "black box").

CAS and SOA (United States): Personal Responsibility in Actuarial Services

The Casualty Actuarial Society (CAS) and the Society of Actuaries (SOA) in the U.S. have very similar policies, as both organisations subscribe to the Code of Professional Conduct promulgated by the U.S. actuarial profession (through the American Academy of Actuaries). Under this Code, an *“Actuary”* is explicitly defined as an individual professional – *“an individual who has been admitted to a class of membership to which the Code applies”*. Likewise, *“Actuarial Services”* (which includes providing actuarial advice or opinions) are defined as professional services provided by an individual acting in the capacity of an actuary. In other words, only an individual person can perform actuarial services under the Code; a corporation itself cannot be an “actuary.” Both the CAS and SOA restrict membership to individuals, so any official actuarial advice must come from a human member actuary, not from a company or an AI system alone.

The U.S. Code of Professional Conduct also contains provisions to ensure the responsible actuary is identified in any work product. Precept 4 of the Code (on communications and disclosure) requires that actuarial communications clearly identify the actuary responsible for the work. Annotation 4-1 states: *“An Actuary who issues an Actuarial Communication shall ensure that the Actuarial Communication clearly identifies the Actuary as being responsible for it.”* When a report or advice is given, the actuary's name (and credentials) should be on it – for example, when signing an actuarial opinion for an insurance reserve or pension valuation. The actuary cannot remain anonymous or hide behind a firm’s name, nor can a report be issued solely under a firm’s letterhead without pinpointing an individual actuary. In regulatory contexts, this is reinforced by requirements that a qualified appointed actuary sign certain actuarial opinions. Again, while CAS and SOA encourage the use of tools (including predictive models and AI) in actuarial work, their standards make it clear that the actuary using those tools must apply professional judgment and remain accountable. There is no provision in the CAS/SOA code for a machine to independently provide “actuarial advice” – any such advice must be vetted and delivered by a credentialed actuary who takes responsibility for it.

Institute and Faculty of Actuaries (UK): Actuaries’ Personal Sign-Off

The Institute and Faculty of Actuaries (IFoA) in the UK similarly insists that actuarial advice is the responsibility of individual actuaries. The IFoA’s ethical code, known as the Actuaries’ Code, requires members to act honestly, competently, and with care – implicitly meaning they must take ownership of their work. More directly, the IFoA has issued guidance that when actuarial advice is given, the actuary must be personally identified as the source. For example, the IFoA’s *Advice on Professional Conduct* guidance notes that if a report contains advice that only an actuary can provide (such as funding advice for a pension scheme), “it must be personally signed by the actuary (or actuaries, if it is a joint report) taking professional responsibility for that advice.”. Generally, *“reports should be personally signed by the actuary ... taking professional responsibility for the advice.”* This requirement ensures that the accountable expert is an individual named actuary, not just a company. Even when working in a team or within a firm, the actuary’s signature (or names of the responsible actuaries) must appear on actuarial advice given to clients or the public.

As with the other societies, the IFoA does not allow corporate membership – only individuals can be members (Associates or Fellows). The IFoA’s standards (including Actuarial Profession Standards, “APS”) often reinforce that one or more individual members must take responsibility for actuarial work. For instance, in areas like pension scheme funding or insurance valuations, typically, a “Scheme Actuary” or “Signing Actuary” must be an IFoA member who certifies the results. The IFoA has also examined the role of automation and AI. Their guidance and research (e.g., recent risk alerts or papers on algorithms) emphasise that while automation can aid analysis, professional judgment and oversight by an actuary are critical – an algorithm alone cannot fulfil the role of a “professional actuary” bound by ethical standards. The IFoA’s focus is on members maintaining accountability: even if calculations are automated, the actuary must ensure the outputs are reasonable and must communicate the advice, with their name attached, to the user of that advice.

Key Similarities and Differences Among the Societies

All these actuarial bodies share the fundamental principle that only individual qualified actuaries can provide actuarial advice under the banner of the profession. In practice, this means Actuaries must take personal responsibility for their work. Every society's code or standards make clear that actuarial advice is ultimately the actuary's responsibility – not that of an employer, corporation, or machine. For example, Australia's Institute says, *"actuarial advice must be... the responsibility of one or more individual actuaries"*, and the U.S. Code requires identifying the responsible actuary on any communication. None of the organisations permit corporations to be members or to act as "actuaries." The term *Actuary* is defined as an individual professional (as explicitly defined in the US Code and used similarly by the other bodies). So, a company cannot present itself as an actuary independent of the individual professionals it employs. Likewise, an automated system (AI or software) is considered a tool, not an actuary – it cannot sign reports or assume professional responsibility. All encourage or require that actuarial opinions or reports include the name/signature of the actuary who prepared them. This is to ensure clarity about who is accountable. The IFoA and Actuaries Institute explicitly mandate personal sign-off for actuarial advice, and the CAS/SOA Code's communication standards effectively require the same by saying the actuary must be identified as responsible. Ethical Codes and Standards: Each society binds its individual members to a professional code of conduct or standards of practice. These codes converge on the idea that an actuary cannot shirk responsibility – e.g. one cannot claim "the computer/AI made this decision, not me." The human professional is always responsible for ensuring the advice is sound and ethical.

While the core principle is consistent, the form and emphasis of the rules differ slightly among the organisations. The Actuaries Institute (Australia) was very explicit about individual responsibility for advice in older codes. The IFoA's requirement for personal signing of advice is also very direct. In contrast, the CAS and SOA rely on the definitions within the general Code of Conduct and communication rules to enforce the concept. The U.S. Code doesn't outright say "corporations or machines cannot give advice," because it implicitly covers that by defining an actuary as an individual and requiring actuary identification on communications. The outcome is the same, but the Australian and UK materials are more explicit on this point, likely due to their detailed guidance notes. The IFoA often uses separate guidance or Actuarial Profession Standards to drive home how advice should be delivered (for example, the IFoA's guidance note explaining how reports must be signed). The Actuaries Institute included the principle in its Code of Conduct itself. The CAS/SOA embed the requirement in the Code of Professional Conduct (Precepts and Annotations) that all members must follow. So, the structure differs: in the U.K., a member might refer to both the Actuaries' Code and supplementary guidance; in Australia, it was right in the Code; in the U.S., it's in the Code and also reinforced by Actuarial Standards of Practice (e.g., ASOP 41 on communications) rather than a separate "guidance note."

Comparison of Human Actuary Requirements Across Professional Bodies

Aspect	**Actuaries Institute (Australia)**	**CAS and SOA (United States)**	**Institute and Faculty of Actuaries (UK)**
Definition of Actuary	Individual professionals only; only natural persons can be members	Explicitly defined as "an individual who has been admitted to a class of membership"	Individual members only; corporations cannot be members
Responsibility for Advice	"All actuarial advice must be, and be seen to be, the responsibility of one or more individual actuaries"	"An Actuary who issues an Actuarial Communication shall ensure that the Actuarial Communication clearly identifies the	Actuarial advice must be "personally signed by the actuary taking professional responsibility for that advice"

Aspect	Actuaries Institute (Australia)	CAS and SOA (United States)	Institute and Faculty of Actuaries (UK)
		Actuary as being responsible for it"	
Corporate Limitations	Corporations cannot provide recognised actuarial advice	A corporation itself cannot be an "actuary"	Companies cannot be presented as actuaries independent of individual professionals
Documentation Requirements	Actuaries must document expert input but take responsibility for overall advice	Actuary must be identified as responsible on any communication	Reports must be personally signed by the responsible actuary
AI/Automation Guidance	Emphasises that while actuaries can leverage advanced models, the actuary's judgment and accountability remain paramount	Updated standards (e.g., ASOP 56) guide actuaries on using modelling techniques responsibly	Guidance and research emphasise that while automation can aid analysis, professional judgment and oversight by an actuary are critical
Enforcement Mechanism	Embedded in the Code of Conduct	Through the Code of Professional Conduct and reinforced by Actuarial Standards of Practice	Through the Actuaries' Code and supplementary Actuarial Profession Standards
Uniqueness in Approach	Very explicit about individual responsibility for advice in older codes	Relies on definitions within the general Code of Conduct and communication rules	Uses separate guidance or Actuarial Profession Standards to emphasise how advice should be delivered

These bodies have acknowledged the rise of machine learning and AI in recent years. The messaging is consistent in that tools don't replace the need for an actuary's oversight, but there may be some differences in emphasis. The Actuaries Institute has published *information notes on AI* (e.g., avoiding discrimination) and emphasises the importance of appropriate human oversight. The IFoA has issued risk alerts about the limitations of models. The CAS and SOA (often through the American Academy's standards) have updated or created Actuarial Standards (like ASOP 56, etc.) to guide actuaries on using modelling techniques responsibly. While these aren't differences in allowing machine advice (none allow machine-only advice), they show different approaches to guiding members on how to integrate technology. However, all approaches circle back to the idea that the actuary is accountable for the advice provided.

In summary, all four professional actuarial bodies require that actuarial advice comes from qualified human actuaries who are individually accountable. The similarities far outweigh any differences: an actuary's professional judgment and personal ethical responsibility cannot be outsourced to a company name or an algorithm. The differences lie in how the rules are articulated or enforced – with the Actuaries Institute (Australia) and IFoA (UK) providing very explicit statements in their professional guidance, and the CAS/SOA (US) embedding the principle in their unified Code of Conduct and standards – but the fundamental principle of personal responsibility is universal across these actuarial societies.

5. The Actuarial Profession in the AI Era

The actuarial profession is at a pivotal turning point as AI technologies rapidly transform the way financial services operate. While the integration of AI into actuarial education has gained significant momentum (Actuaries Institute, 2023; Society of Actuaries [SOA], 2021), it is equally important to examine how these technologies are reshaping the profession's core competencies and future direction. This article analyses the intersection of traditional actuarial skills with emerging AI capabilities, identifies areas where human actuaries maintain distinct advantages, and outlines a vision for the profession's evolution in an increasingly automated world.

Core Actuarial Skill Domains

The actuarial profession has traditionally been built upon three interconnected skill domains that together form the foundation of actuarial expertise (Poon et al., 2023; Taylor, 2019).
The first domain encompasses specialised industry knowledge across multiple sectors. Actuaries develop deep expertise in insurance markets spanning life, general, and health categories. Their knowledge encompasses investment management principles and practices, as well as superannuation and pension systems. Many actuaries also cultivate an understanding of banking and broader financial services, while all must navigate complex regulatory frameworks and adhere to professional standards and guidelines. This contextual understanding enables actuaries to apply their technical skills within appropriate industry frameworks and constraints (Australian Actuaries Institute, 2022).

The second domain consists of rigorous technical competencies that form the analytical backbone of actuarial work. The profession is grounded in advanced mathematics and statistical theory, with practitioners skilled in applying stochastic processes and predictive modelling to complex problems. Actuaries integrate economic principles and financial mathematics into their analyses while developing comprehensive risk management frameworks. The field increasingly demands proficiency in programming and software development, as well as sophisticated data management and analytics capabilities. These technical foundations have evolved significantly over time, with the most recent addition being machine learning techniques, as identified in the International Actuarial Association's revised education syllabus (IAA, 2024a).

The third essential domain encompasses interpersonal abilities that translate technical insights into business value. Successful actuaries develop exceptional communication and presentation skills to convey complex concepts to diverse stakeholders. They cultivate stakeholder management strategies that build trust and facilitate decision-making across organisational functions. Ethical reasoning and professional judgment underpin all actuarial work, requiring practitioners to balance competing interests while maintaining integrity. As actuaries advance in their careers, leadership and strategic influence become increasingly important, complemented by strong teamwork and collaboration skills. Negotiation and persuasion abilities round out the modern actuary's toolkit, enabling them to drive meaningful change within their organisations. As Cervi et al. (2021) noted, these "soft skills" have become increasingly crucial as actuaries expand their influence beyond traditional calculation-focused roles into broader business advisory positions.

How AI Affects Each Actuarial Skill Domain

The integration of AI technologies, particularly generative AI (GenAI) and large language models (LLMs), has differential impacts across the actuarial skill domains.

In domain knowledge, GenAI tools have demonstrated impressive capabilities in synthesising public information about insurance, finance, and related industries. However, these systems face notable limitations in actuarial contexts. Their training data often skews toward US-centric information, resulting in a weaker understanding of Australian and other international markets (Actuaries Institute, 2023). They lack access to enterprise-specific or proprietary information, limiting their ability to provide contextualised insights that reflect organisational realities rather than generic industry knowledge (Poon et al., 2023). While LLMs can offer general industry perspectives, achieving truly valuable domain-specific applications requires either fine-tuning or Retrieval-Augmented Generation (RAG) with internal knowledge bases, consistently implemented under strict data security protocols to protect sensitive information (Liu & Hartog, 2024). As the IAA (2024b) notes in its scenario analysis, actuaries who understand both their domain and AI capabilities will maintain significant advantages over either non-actuarial AI specialists or actuaries who fail to embrace technological change.

The technical knowledge domain reveals both remarkable strengths and significant limitations in AI. Generative AI (GenAI) tools often outperform non-specialist humans in mathematical and statistical reasoning, code generation, and pattern recognition within large datasets, enabling rapid analysis of complex information (Poon et al., 2023). However, domain experts remain indispensable for validation and contextual judgment for sophisticated actuarial models or edge cases requiring nuanced interpretation. While LLMs can efficiently "write code to solve the math," they occasionally produce erroneous or "hallucinated" outputs, reinforcing the critical need for human review of AI-generated content, particularly in high-stakes financial applications where errors could have significant consequences (Actuaries Institute, 2023). Specialist actuaries consistently outperform GenAI tools in terms of quality and technical accuracy, although machines hold clear advantages in processing speed and computational throughput. Data privacy presents another challenge, with potential risks that proprietary information might inadvertently be incorporated into training datasets, potentially compromising confidential client or company information (IFoA, 2023). These findings align with the IFoA's 2022 thematic review, which found that actuaries are increasingly using AI as a complement to, rather than a replacement for, their technical expertise (IFoA, 2021).

The impact of AI on interpersonal aspects of actuarial work reveals a more distinct division between human and machine capabilities. GenAI tools demonstrate strong proficiency in language processing, writing, and basic comprehension, sometimes exceeding average human performance in these areas, particularly for routine communication tasks (Poon et al., 2023). However, substantial components of stakeholder management, ethical decision-making, leadership, and teamwork involve interpersonal dynamics and emotional intelligence that current AI systems cannot replicate in real-world settings. The nuances of reading body language, building authentic relationships, and navigating organisational politics remain beyond AI's reach (IAA, 2024b). While GenAI may understand theoretical ethics and articulate ethical frameworks, it cannot be trusted to make ethical judgments aligned with organisational values and professional standards, especially considering potentially problematic training data drawn from the broader internet. Most importantly, professional judgment and accountability, core tenets of actuarial practice that require balancing multiple factors in uncertain conditions, cannot be delegated to automated systems without compromising the profession's value proposition (Australian Actuaries Institute, 2022; IFoA, 2021). These observations support Cervi et al.'s (2021) conclusion that actuaries must leverage AI for routine tasks while developing their uniquely human capabilities for higher-value activities that require judgment, creativity, and interpersonal connection.

Actuarial Skills: Human Uniqueness vs. AI Augmentation

Understanding the complementary relationship between human actuaries and AI tools helps identify where the profession retains its greatest value and where technology can provide enhancement.

Human actuaries maintain distinct advantages in several critical areas that resist automation. They bring moral reasoning, professional ethics, and value judgments that extend beyond rule-following to nuanced ethical decision-making in complex situations where competing interests must be balanced (IFoA, 2023). Building genuine trust, demonstrating authentic empathy, and navigating complex interpersonal dynamics remain exclusively human, allowing actuaries to influence and collaborate effectively across organisational boundaries (Society of Actuaries. (n.d.)). While AI can generate variations based on existing patterns, creating genuinely novel concepts or approaches, it has been argued that true creativity that breaks new ground rather than recombining established ideas, remains a human strength that drives innovation in actuarial methods (Actuaries Institute, 2023). Human actuaries excel at applying practical common sense and contextual reasoning across diverse scenarios in ways that AI systems struggle to replicate, particularly when confronting unprecedented situations or integrating disparate knowledge domains (IAA, 2024b). Perhaps most crucially, the informed, experience-based judgment that underpins actuarial value cannot be automated; this professional judgment represents the synthesis of technical knowledge, domain expertise, and ethical awareness refined through years of practice and reflection (SOA, 2023). These uniquely human capabilities align with the "positive scenario" described in the IAA's (2024b) forward-looking research, where actuaries leverage AI while developing their distinctive professional strengths.

Conversely, AI technologies demonstrate clear advantages in computational domains that complement human capabilities. These systems can process calculations and generate analyses at scales impossible for human actuaries, handling vast datasets and complex simulations in seconds rather than days or weeks (Poon et al., 2023). The scalability of AI solutions represents another significant advantage; once developed, AI models can be deployed across multiple contexts with minimal marginal cost, enabling efficient standardisation of routine analyses and reports (SOA, 2024). The capacity to process both structured and unstructured data, including text-based information from regulatory documents, research papers, and market reports, allows AI to analyse volumes of information beyond human capability, identifying patterns and correlations that might otherwise remain hidden (Cervi et al., 2021). The ability to synthesise insights from massive text and data repositories represents an emerging "superpower" of LLMs, enabling them to connect concepts across disparate sources and generate novel combinations of ideas based on existing knowledge (Actuaries Institute, 2023). As demonstrated in the IFoA's Certificate in Data Science program, actuaries who develop skills in harnessing these AI capabilities gain significant competitive advantages in the marketplace while expanding their professional impact (IFoA, 2021).

Actuarial Education's Response

The actuarial profession has already begun adapting its educational frameworks to prepare practitioners for this AI-augmented future.

Educational institutions and professional bodies worldwide have implemented significant curriculum changes to incorporate competencies related to artificial intelligence (AI). The Australian Actuaries Institute introduced Data Science Principles and Applications subjects to ensure graduates possess relevant analytical skills for contemporary practice (Aitken, 2022). These courses provide foundational knowledge in machine learning techniques, data visualisation, and computational methods that complement traditional actuarial education. The International Actuarial Association revised its global syllabus to incorporate machine learning and AI concepts, establishing worldwide standards for AI literacy among actuarial professionals (IAA, 2024a). This harmonised approach ensures consistent preparation across national boundaries while recognising AI as a core competency rather than a specialist skill. The Society of Actuaries established a Predictive Analytics exam as a core requirement for certification, signalling the profession's commitment to quantitative methods beyond traditional actuarial mathematics (SOA, 2021). These reforms collectively reflect the profession's recognition that AI literacy has become an essential actuarial competency rather than an optional specialisation.

The practical implementation of AI in actuarial education continues to accelerate through innovative approaches to teaching and learning. Students are increasingly leveraging AI tools like ChatGPT to support exam preparation and enhance concept comprehension, utilising these systems to explain complex topics in accessible language or provide alternative perspectives on challenging material (Actuaries Institute, 2023). This represents a significant shift in learning strategies, with AI functioning as an always-available tutor that adapts to individual learning needs. The IFoA's Certificate in Data Science program has demonstrated strong adoption rates and practical applications in workplace settings, with graduates reporting immediate benefits, including increased efficiency and enhanced analytical capabilities (IFoA, 2021). This practical orientation ensures that educational programs deliver tangible professional value rather than theoretical knowledge alone. Educational institutions have begun exploring AI for content development, automated feedback mechanisms, and personalised learning pathways that adapt to individual student needs and learning styles (Poon et al., 2023). These innovations illustrate how AI is not just changing what actuaries learn, but fundamentally transforming how they learn it, creating more responsive, personalised educational experiences.

Research bodies across the actuarial profession continue to advance understanding of AI's implications through comprehensive studies and thought leadership initiatives. The SOA's "Emerging Technologies and Their Impact on Actuarial Science" report highlighted the transformative potential of AI while emphasising the need for expanded education to prepare practitioners for changing role expectations (Cervi et al., 2021). This research identified specific competency gaps and recommended targeted interventions to address them, providing a roadmap for educational reform. Complementing this, Ronald Richman’s recent publications have provided detailed guidance on integrating AI, particularly deep learning, into actuarial practice and education. His work advocates for curriculum reform to include machine learning, interpretability, and ethical model design, arguing that actuaries must evolve into "AI-enhanced professionals" to remain relevant and effective (Richman, 2023; Harris et al., 2024). The IAA's AI Summit and Education Workstream have established global frameworks for AI competencies, providing consistent standards while allowing for regional adaptation (IAA, 2024a). This international coordination ensures that actuaries worldwide develop comparable skills while avoiding the fragmentation of professional standards. The IFoA's thematic reviews and leadership initiatives have systematically mapped the changing landscape of actuarial skills, tracking how technological developments reshape practice requirements across financial sectors (IFoA, 2021). This ongoing research provides the theoretical foundation for practical educational reforms and professional development initiatives, ensuring that educational changes respond to genuine market needs rather than technological hype.

The Future Actuary in an AI World

As AI capabilities advance, the actuarial profession faces challenges and opportunities that will reshape its future trajectory.

Generative AI will inevitably automate certain actuarial tasks, particularly routine calculations, standardised data processing, and templated reporting functions (SOA, 2023). These developments may initially create anxiety about professional displacement, but historical precedent suggests more nuanced outcomes. This transition parallels previous technological shifts in the profession, such as the widespread adoption of calculators and spreadsheet software, which ultimately expanded actuarial capabilities rather than diminishing them by freeing practitioners from mechanical tasks to focus on higher-order analysis (Divine, 2024). Just as electronic spreadsheets have eliminated manual calculation, creating new analytical possibilities, AI tools may automate routine aspects of actuarial work while enabling more sophisticated risk modelling and business insights.

Developing proficiency with AI tools is rapidly becoming a fundamental requirement for actuarial practice rather than an optional specialisation or competitive differentiator (Actuaries Institute, 2023). Contemporary actuaries must understand not only traditional statistical methods but also machine learning approaches, natural language processing, and the strengths and limitations of various AI systems. This expanded technical literacy represents an evolution of the profession's quantitative foundation rather than a departure from its essential nature.

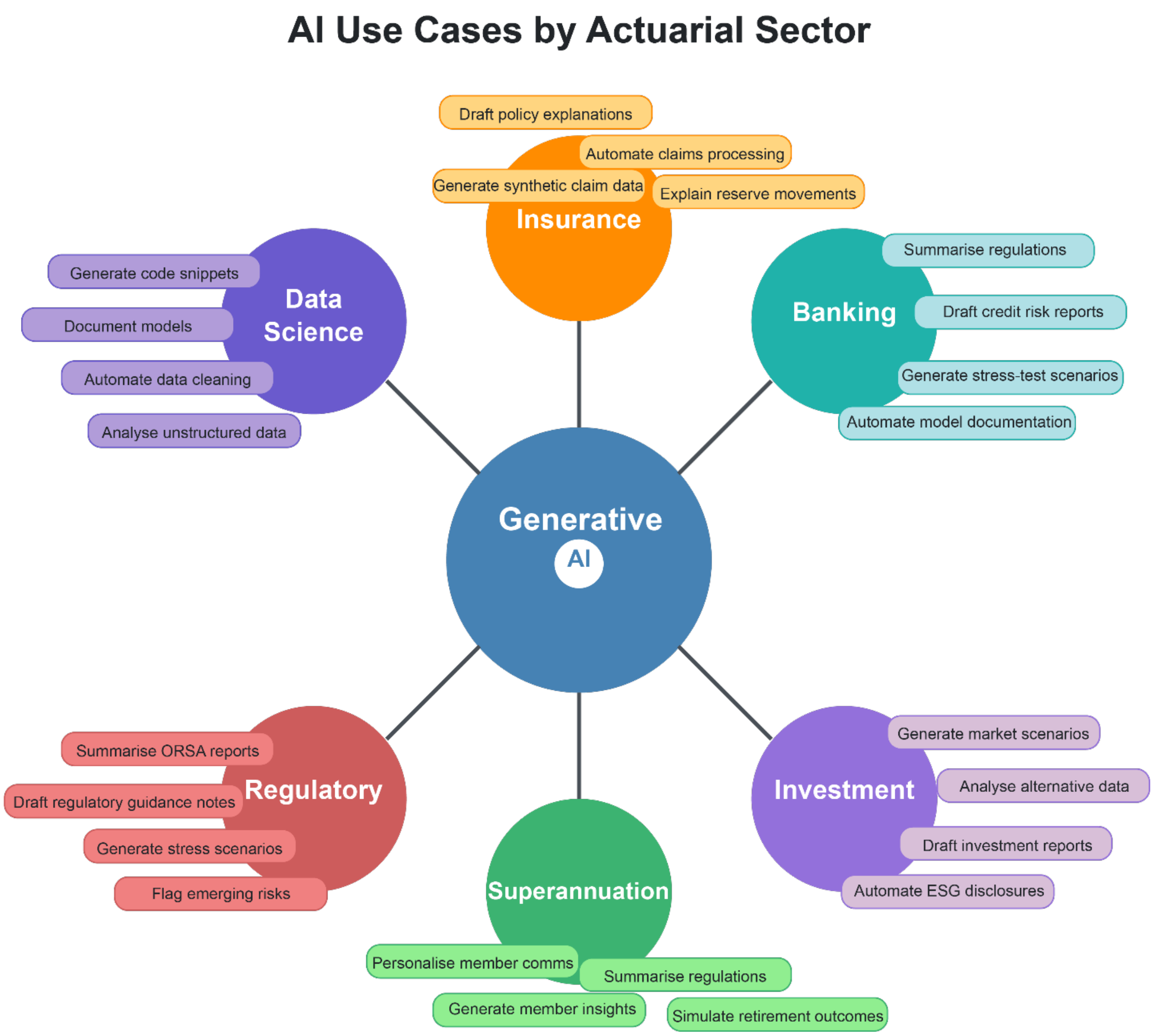
The greatest opportunities will emerge for actuaries who learn to effectively "co-pilot" with AI, using automated systems for data exploration and initial calculations while applying human judgment and technical review to finalise results and develop strategic recommendations (IAA, 2024b). This collaborative approach recognises the complementary strengths of human and machine intelligence, with AI handling computationally heavy lifting while humans provide contextual understanding, ethical oversight, and creative problem-solving. The most successful actuaries will likely view AI as a powerful tool to amplify their capabilities rather than a threat to their professional identity.

This human-AI partnership could shift actuarial focus toward higher-value activities like strategic risk management, scenario planning, and integrated risk modelling, while routine tasks are increasingly automated (Poon et al., 2023; IFoA, 2023). Rather than performing standardised calculations, actuaries may spend more time interpreting model outputs, communicating insights to stakeholders, and developing innovative approaches to emerging risks. This evolution would represent not a diminishment of the profession but an elevation of its impact and value proposition.

The Australian Actuaries Institute (2022) has insightfully observed, "The future belongs not to those who fear technology, but to those who harness it while developing their uniquely human strengths." The actuarial profession's longstanding adaptability suggests it will successfully navigate this latest technological revolution, emerging with enhanced capabilities while maintaining the professional judgment and ethical foundation that has always defined actuarial work. By embracing AI as a complement to human expertise rather than a replacement, actuaries can redefine their roles for the digital age while preserving the essential value they bring to financial decision-making.

6. AI Use Cases for Actuaries

Generative AI (GenAI) is rapidly transforming actuarial work across multiple financial services industry sectors. As language models and other AI technologies become more sophisticated, they are being deployed to augment actuarial tasks ranging from routine documentation to complex risk modelling. This section examines how actuaries are currently utilising GenAI in five key sectors: insurance, banking, superannuation, investment, and regulatory functions, as well as how it's enhancing data science capabilities within actuarial teams. While implementation approaches vary by domain, common themes emerge: GenAI is helping actuaries process information more efficiently, generate higher-quality reports and communications, and shift their focus from repetitive tasks to higher-value analytical work. However, human oversight remains essential, with actuaries applying professional judgment to validate outputs and ensure compliance with industry standards.



Insurance

Actuaries in the insurance industry are exploring GenAI to streamline traditionally labour-intensive tasks in underwriting, claims, and communication. For example, Zurich Insurance has experimented with using ChatGPT to extract information from lengthy documents and even to write code for statistical models, with its digital officer expecting "a huge amount of efficiency" gains from such tools (Insurtechworld.org, n.d.). Early applications include automating routine correspondence and summarising claim files, helping claims actuaries process cases faster without sacrificing accuracy. GenAI's strength in language enables it to craft clear, plain-language explanations of complex policies or results for clients and regulators, thereby enhancing transparency. Zurich's Head of AI noted that insurance operations – from policies and underwriting to customer interactions and claims – are heavily language-driven, and there are "many, many opportunities" for GenAI to support teams in handling documents and extracting insights, ultimately making work more efficient and enhancing customer experience (Zurich.com, n.d.). Future uses under development include generating synthetic data or new risk scenarios to complement sparse historical datasets (e.g. for rare claims), which can broaden the range of analyses available to pricing and reserving actuaries (Soa.org, n.d.). While GenAI is not yet embedded in core financial modelling (actuaries aren't looking for "creative" financial results), it shows promise in adjacent tasks like explaining reserve movements or drafting model documentation (Theactuarymagazine.org, n.d.). Overall, the benefits for insurance include faster processing, more personalised communications, and offloading administrative workload, allowing actuaries to focus on higher-value analytical work. However, practical challenges, such as ensuring outputs are accurate and compliant, mean adoption has been cautious, mainly in pilot stages (Theactuarymagazine.org, n.d.). Actuaries report that human oversight and robust validation remain essential when using GenAI in insurance, to manage risks like hallucinated content while reaping efficiency gains.

Banking

In banking, GenAI offers actuaries and risk managers new tools to enhance risk assessment, compliance, and customer service. Given the massive volume of regulatory text and reporting requirements, banks have begun using large language models to serve as virtual assistants for risk and compliance teams (McKinsey.com, n.d.). For instance, generative models can instantly answer queries about complex regulations or compare policy documents, which helps actuaries in risk and compliance roles ensure alignment with the latest rules (McKinsey.com, n.d.). GenAI is also being piloted to generate first drafts of credit risk reports and stress-test scenarios. McKinsey reports that some financial institutions use GenAI to summarise borrower financials and draft credit memos or contracts, speeding up the credit approval process and letting humans finalise decisions (McKinsey.com, n.d.). Likewise, actuaries in banking, who often work on balance sheet management and capital stress testing, could use GenAI to generate plausible economic scenarios beyond historical data, thereby improving strategic risk modelling. Another emerging use case is automating model documentation and validation reports, a traditionally tedious task, by having GenAI produce initial drafts that actuaries then review (McKinsey.com, n.d.). The anticipated benefits for banking include efficiency gains of 10–20% in risk and finance operations, achieved through faster reporting, improved risk transparency, and partial automation of policy and procedure drafting (Bcg.com, n.d.). This enables risk actuaries to spend more time on strategic analysis rather than rote documentation. However, the implementation needs to be balanced with strong governance. Studies note that deploying GenAI in banking risk functions requires new skill sets and careful model monitoring, and many banks are still in proof-of-concept stages due to concerns around data privacy, accuracy, and integration with legacy systems (Theactuarymagazine.org, n.d.). Actuaries in banking, therefore, see substantial potential in GenAI, from automated fraud detection and narrative generation to AI-driven scenario analysis – but are proceeding pragmatically, ensuring that any GenAI-generated insights are thoroughly vetted and comply with regulatory standards.

Superannuation

Superannuation (pension) funds have begun experimenting with GenAI to enhance member engagement and fund management. A primary use case is personalised member communication. Australia's largest super funds serve millions of members, and GenAI offers a way to have a "unique conversation with every single member" through AI-powered chatbots and tailored content (Superreview.com.au, n.d.). For example, generative models can draft individualised retirement benefit explanations or answer member queries in natural language, at a scale that human advisors cannot match. This has clear benefits during periods of high member inquiry (such as legislative changes or market events), as the AI can handle volume while providing consistent, high-quality information (Superreview.com.au, n.d.). According to industry experts, member communications will see the greatest impact from GenAI, enabling super funds to deliver more relevant guidance and education to each person (Superreview.com.au, n.d.). Beyond communications, superannuation actuaries are exploring the use of GenAI to support compliance and analysis. The technology can rapidly review and summarise new regulations or lengthy trust deeds, helping actuaries ensure fund policies and products remain compliant with changing laws. It can also scan member data and disclosures to flag inconsistencies or potential risks, adding a layer of quality assurance in reporting. One case study highlights that Australian super funds are seeking AI-driven efficiencies in processes and member segmentation – for example using AI to segment membership for targeted services or to identify trends in member behaviour – while being mindful of data privacy and ethical considerations (Superannuation.asn.au, n.d.). In the investment aspect of superannuation, GenAI is being explored to generate market commentary and insights for portfolio managers, or to simulate economic scenarios that inform strategic asset allocation. The benefits expected in this sector include improved member satisfaction (through timely, personalised interactions), cost savings in administration, and more informed decision-making by leveraging AI's ability to distil complex information quickly. Still, super funds are cautious. There is recognition that, in Australia, adoption has lagged due to concerns about potential risks and regulatory uncertainty around AI (Superreview.com.au, n.d.). Actuaries emphasise the need for robust AI governance in superannuation – ensuring transparency, fairness, and oversight – so that GenAI augments the work of fund professionals without undermining trust. When implemented responsibly, GenAI could significantly enhance how actuaries manage retirement outcomes, from member advice to fund risk monitoring, by providing powerful tools for personalisation and analysis.

Investment

Investment analysts and actuaries are leveraging GenAI to enhance portfolio management, research, and decision support. In asset management, generative AI has been used to simulate thousands of market scenarios, allowing investment teams to explore a wider range of potential outcomes and stress test portfolios against varied conditions (Actuarialpost.co.uk, n.d.). This capability enables actuaries and financial engineers to design portfolios more closely aligned with an investor's risk profile and time horizon by examining how strategies might unfold under various hypothetical scenarios. GenAI has also expanded the use of alternative data in investing – for instance, processing unstructured data like news, social media, or satellite images – and summarising insights that would be hard to extract manually (Actuarialpost.co.uk, n.d.). Case studies in asset management have shown that AI can identify patterns in vast amounts of historical and real-time data, thereby enhancing trend forecasts and risk assessments. According to a senior executive at Mapfre Asset Management, AI (broadly defined) is being integrated at various stages of the investment process, and recently, this has included deploying generative AI in report generation and risk management tasks (Actuarialpost.co.uk, n.d.). This integration has begun automating routine analyses and client reporting, freeing analysts' time for more strategic, higher-level decisions. Generative AI can draft sections of investment reports or performance commentaries in seconds, which investment actuaries or portfolio managers then refine – speeding up a process that traditionally took many hours. It can similarly produce first drafts of compliance reports or climate-risk disclosures based on underlying data. The benefits cited for investments are greater operational efficiency, faster and more data-driven decision-making, and the ability to offer more personalised services to clients. In fact, 75% of asset management CEOs in a 2024 survey view generative AI as a top investment priority, underscoring its perceived strategic importance to the industry (Actuarialpost.co.uk, n.d.). Key improvements include the faster identification of market opportunities and risks through real-time data processing, personalised client insights at scale (e.g., customised portfolio recommendations), and the automation of internal processes such as portfolio rebalancing and documentation (Actuarialpost.co.uk, n.d.). These advances can enhance agility – for example, quickly reallocating assets in volatile markets – and enable extreme personalisation in wealth management. Nonetheless, firms are proceeding with care. Challenges such as staff training on AI tools, integrating new systems with legacy investment platforms, and ensuring the interpretability of AI-driven insights remain significant (Actuarialpost.co.uk, n.d.). Actuaries in investment roles stress that human judgment and oversight remain crucial – AI-generated scenarios and recommendations must be vetted for reasonableness and aligned with fiduciary standards. Overall, GenAI is poised to augment the investment process by handling data-heavy tasks and presenting actionable intelligence, with actuaries playing a key role in supervising these models and interpreting their output for portfolio strategy and risk management.

Data Science

Across all sectors, many actuaries now operate as data scientists, and GenAI has quickly become a valuable assistant in data-centric actuarial work. One immediate application is in coding and model development. Actuaries often build models in Python, R, or other languages, and tools like ChatGPT can generate code snippets, help debug errors and translate logic from one programming language to another (Actuaries.blog.gov.uk, n.d.). The Government Actuary's Department (UK) reports that using ChatGPT for programming tasks can speed up development

– it's "quicker and less burdensome to check the outputs" from the AI than to write code from scratch, provided thorough testing is in place (Actuaries.blog.gov.uk, n.d.). This co-coding approach has allowed actuarial data scientists to prototype models and analytical tools more efficiently. Likewise, GenAI aids in documenting models by explaining what a complex block of code or an actuarial formula is doing in plain English, and creating draft documentation for model governance purposes (Theactuarymagazine.org, n.d.). Data preparation is another area that benefits from this approach. Actuaries can utilise GenAI to automate data cleaning and feature engineering tasks – for example, by describing a data formatting task in natural language and allowing the AI to suggest the transformation script. This natural language-to-code capability accelerates tasks such as reformatting datasets or merging large tables, which would otherwise consume considerable time. GenAI can also assist with analysing unstructured or semi-structured data. Actuaries working with text-heavy data (such as insurance claims descriptions or customer feedback) traditionally had to manually categorise and interpret this information; now an LLM can summarise key themes or even flag anomalies in textual data (Actuaries.blog.gov.uk, n.d.). In one case, analysts at GAD used ChatGPT to extract specific provisions from a lengthy pension scheme document and were able to get accurate answers along with references to the source text, turning a time-consuming lookup into a quick Q&A task (Actuaries.blog.gov.uk, n.d.). The benefits in data science applications are clear: productivity gains, fewer coding errors, and more accessible insights from complex data. GenAI effectively serves as a junior analyst, handling tedious tasks (such as writing boilerplate code or scanning documents), allowing actuaries to concentrate on interpreting and validating results. Moreover, GenAI can enhance knowledge sharing and model transparency within teams by automating documentation and providing natural language explanations. On the flip side, actuaries recognise the practical limitations. AI-generated code or analysis still requires rigorous review – ChatGPT can make mistakes or inefficient suggestions, especially for intricate problems, so every output must be tested and validated by a human expert (Actuaries.blog.gov.uk, n.d.). There are also constraints with current GenAI tools around data privacy and the volume of data they can handle at once (token limits), which can require careful engineering to work around (Theactuarymagazine.org, n.d.). Nonetheless, the trend is that actuaries with data science skills are rapidly adopting GenAI as a productivity tool. It has proven effective at accelerating the analytical pipeline from data ingestion to model deployment, essentially augmenting the actuarial toolkit with conversational coding, automated documentation, and deeper text analytics. As with other areas, maintaining professional standards (e.g., robust model validation and compliance with data confidentiality) is key; however, when used judiciously, GenAI can significantly enhance the efficiency and scope of actuarial data science projects.

Regulatory

In regulatory and risk oversight roles, actuaries are increasingly applying GenAI to manage large information flows and complex analyses. Regulators and appointed actuaries must digest vast amounts of data – including financial statements, detailed actuarial reports, and compliance documents – and GenAI offers assistance in summarising and interpreting this content. For instance, a generative model can swiftly summarise an insurer's Own Risk and Solvency Assessment (ORSA) report or a pension fund's funding valuation, highlighting key risks and changes for the regulator's review. This kind of application is akin to the "virtual expert" described in banking: an AI assistant trained on regulatory codes and past filings that can answer questions or flag inconsistencies in submissions (McKinsey.com, n.d.). Early experiments show GenAI can also draft sections of regulatory reports and consultation papers. Actuaries at regulatory bodies have used LLMs to parse new legislation and produce initial drafts of guidance notes, which experts refine, accelerating the policy development cycle. Generative AI is also being tested for scenario analysis in regulatory stress tests. By simulating economic or insurance-specific scenarios (e.g., a pandemic with specific characteristics), GenAI can help regulators and risk officers explore a broader range of "what-if" situations beyond those seen historically, which is valuable for systemic risk assessment. The potential benefits in the regulatory arena include more efficient analysis (regulators can cover more ground in the same time), improved detection of emerging risks, and enhanced consistency in the review process. A recent blog by the UK's Government Actuary's Department illustrated how their analysts use

GenAI to boost quality and efficiency – from checking complex spreadsheets to retrieving information from pension scheme rules – all under strict human oversight (Actuaries.blog.gov.uk, n.d.). They found that ChatGPT could accurately answer certain technical questions (with sources), turning what might be hours of document review into minutes, although it struggled with more complex multi-source queries (Actuaries.blog.gov.uk, n.d.). This underscores how GenAI can act as a force multiplier for actuarial regulators, handling straightforward queries so humans can focus on deeper judgment calls. Regulators, however, are acutely aware of the risks. Professional bodies have issued guidance to ensure AI use does not compromise actuarial standards – for example, the Institute and Faculty of Actuaries in the UK released a risk alert highlighting concerns around data confidentiality, model error, and accountability when using AI tools (Actuaries.blog.gov.uk, n.d.). In Australia, reviews have found that while financial institutions (including super funds and insurers) are cautiously exploring AI, many have been slow to update governance and risk frameworks to address AI's challenges (Superannuation.asn.au, n.d.). Thus, a key part of any GenAI deployment in regulatory work is establishing strong governance, which involves defining the tasks the AI can perform, setting checks (such as requiring human sign-off on AI-generated analysis), and continuously monitoring outputs for biases or inaccuracies. Actuaries in regulatory roles are well-placed to do this, given their expertise in risk controls. In conclusion, GenAI has begun to assist in the regulatory and compliance sector by accelerating data analysis and document drafting for actuaries, with notable productivity benefits. However, the sensitive nature of regulatory work means the emphasis is on augmentation rather than automation – using GenAI to support actuarial judgment, not replace it. With prudent oversight, regulators and their actuarial teams can harness GenAI to keep pace with growing data demands and complex emerging risks, while upholding the rigorous standards required to protect the public interest.

7. AI Use Cases in Education

In tertiary education and professional accreditation contexts, generative AI (GenAI) tools are increasingly integrated into teaching and learning activities. A helpful way to examine their role is through a simplified Bloom's Taxonomy framework, focusing on the Knowledge, Comprehension, and Application levels. Each level represents a distinct cluster of cognitive skills, ranging from basic recall to more advanced understanding and problem-solving. GenAI applications align with these levels for both instructors and learners. Below is a discussion of past and emerging GenAI applications at each level, highlighting relevant case studies in STEM and business education, alongside a balanced evaluation of their benefits and limitations. Finally, the prototype AI tools developed for this paper are described, including their functionality and support for the educational process.

Knowledge

At the knowledge level, teachers have used GenAI to create and refine content that helps students acquire and remember information. Common examples include having AI simplify complex explanations in course materials, enhance lecture presentations, or generate quiz items that test factual recall. GenAI can also assist in drafting a bank of practice questions and flashcards tailored to a curriculum, allowing teachers to save time and focus on higher-order teaching tasks.

Students at this level typically use GenAI for study support, leveraging interactive chatbots as "AI textbooks" to clarify ideas or generate flashcards for self-quizzing. They may also rely on AI tools to produce quick summaries of assigned readings, which can be especially beneficial when reviewing large volumes of material. More advanced adaptive study coaches could create personalised study plans in the future, automatically generating mnemonic aids and quizzes based on learners' performance metrics.

Research in medical education compared multiple-choice questions generated by ChatGPT to those written by professors (Cheung et al., 2023). The AI-produced questions performed similarly to the instructor-authored set in terms of clarity and appropriateness, although human review remained necessary to ensure curricular alignment. Notably, ChatGPT generated these questions much faster than faculty members, suggesting that GenAI can serve as a significant timesaver. This potential similarly extends to professional accreditation settings, where a constant need for fresh test questions often challenges instructors.

GenAI reduces the workload for teachers, who can offload time-consuming tasks such as creating quizzes or summarising textbooks, and it provides students with immediate, on-demand study materials. Survey data indicate many students appreciate how GenAI saves time in gathering and organising information (Kyaw, 2023). AI can also offer students abundant practice opportunities by generating multiple variations of quiz questions or flashcards.

Despite these advantages, the reliability of AI-generated content remains a concern. Hallucinations or inaccuracies can arise, making human oversight indispensable, especially in high-stakes contexts such as medical training. Students risk depending too heavily on AI summaries without truly engaging in deeper learning. Academic integrity issues are also relevant: if students simply copy and paste AI-generated answers, they lose out on meaningful practice and risk violating course policies. In sum, GenAI excels as a quick reference and test generator at the knowledge level, but it cannot replace verification by human educators or learners.

Prototype Tools – Knowledge Level

1. Mnemonics Generator. This prototype generates catchy acronyms or phrases for lists or sequences of key facts. By prompting a large language model to create memorable hooks, it saves teachers the effort of coming up with mnemonics themselves. Students can also tailor the output to their personal interests, thereby boosting engagement. The main benefit is improved recall, though the AI's suggestions sometimes require human refinement to ensure clarity.
2. AI Flashcard Creator. This tool uploads course content, such as a textbook chapter, and automatically generates question-and-answer flashcards. It may also include brief images or diagrams for visual reinforcement. This speeds up the production of study materials and allows for content to be tailored to the precise topics a student needs to review. Users should still validate the accuracy of each flashcard before sharing.

Comprehension (Understand and Explain in One's Own Words)

GenAI helps educators promote deeper understanding at the comprehension level by generating explanations and examples and checking for conceptual grasp. Teachers commonly use AI to rephrase complex ideas, brainstorm analogies, or construct open-ended questions that probe whether students can restate content in simpler terms. Moving forward, advanced AI might serve as an interactive companion that periodically quizzes or challenges students while they read course texts.

Students often rely on GenAI as an on-demand tutor to clarify concepts. For example, they can request "an explanation like I'm five years old" on confusing topics or ask the AI to summarise complex material. Some learners also engage in dialogue-style study sessions, where they explain a concept to the AI and receive immediate prompts or corrections, mimicking the exchanges of a human tutor.

One study examined how ChatGPT and Bing Chat (subsequently renamed to Microsoft Copilot) could be "objects to think with" for STEM students, helping them verbalise and refine their reasoning (Vasconcelos & dos Santos, 2023). Students worked on math and science problems with AI hints or paraphrases, which prompted reflective thinking and encouraged self-explanation. Although inaccurate AI responses occurred, students learned to verify and correct errors. The researchers concluded that AI's ability to provide various ways of framing a concept increased both engagement and understanding, especially when combined with peer discussion.

By offering alternative explanations, analogies, and immediate feedback, GenAI scaffolds learning for students who might otherwise feel too intimidated to ask classmates or instructors for help. For teachers, it saves time on creating multiple rephrases of the same concept. Studies in undergraduate courses show that students gain confidence and comprehension when they can “talk through” material with an AI, which continually prompts them for clarifications.

AI lacks genuine insight into what each learner truly misunderstands; it can only address queries the student explicitly raises. Oversimplified explanations also risk omitting critical nuances. Students might become dependent on AI to clarify every minor confusion, missing out on the constructive struggle that often cements understanding. Moreover, erroneous or misleading AI explanations can cause misunderstanding if taken at face value. Educators must, therefore, guide students to use AI feedback as a springboard rather than a substitute for active learning.

Prototype Tools – Comprehension Level

1. ELI5 Tutor. This tool specialises in simplifying complicated material into plain-language explanations. It helps users establish a baseline understanding before moving on to more advanced texts. The risk is excessive simplification, so it offers an option for requesting a “more detailed explanation” after the user grasps the basics.
2. Own Words Quiz. Here, students write short-answer explanations, which the AI evaluates for clarity and correctness. After receiving the AI’s feedback, students can revise their work. This encourages iterative self-assessment. Though AI effectively highlights missing or unclear parts, human instructors remain important in confirming nuanced or alternative explanations.

Application (Solve Problems or Analyse Situations)

At the application level, GenAI assists educators in creating realistic problem-solving exercises or case studies that require students to go beyond memorisation. In the past, teachers dedicated considerable time to creating novel scenarios, especially in fields such as engineering, data science, or business. Now, AI can generate multiple hypothetical datasets or situation-based prompts with unique parameters for students to work on. Future possibilities include AI-driven, dynamic problem simulations where variables change in real-time, challenging students to adapt their strategies.

Students employ GenAI as a “co-pilot” in coding tasks, data analysis, or business-case scenarios, asking the AI for potential solution outlines or partial drafts. Many refine or debug the AI-generated output, which can improve both their efficiency and their critical thinking. In business or professional programs, learners sometimes ask GenAI to propose a preliminary case study analysis and then build upon or critique the AI’s solution. Future courses may expand into simulation-based learning, where students role-play with AI chatbots serving as clients, patients, or stakeholders.

An article discussing the use of AI in case-based business programs noted concerns about students obtaining complete case solutions from chatbots (Lafkas, 2024). However, some faculty members found that learning can actually deepen if they ask students to critique AI-produced analyses or push discussions toward more complex or ethical questions that extend beyond the AI’s generic approach. Rather than eliminating case discussions, AI can free up time for exploring nuanced, real-world factors that AI tools might overlook.

Another investigation explored the use of ChatGPT as a coding assistant in graduate-level machine learning projects (Yoo & Kim, 2024). Students who viewed the AI as a “knowledgeable partner” benefited the most, taking the AI’s generated code as a draft to analyse and improve.

Those who merely copy-pasted faced problems when asked to explain underlying logic. The researchers concluded that while AI can handle routine tasks, human judgment remains irreplaceable for verifying correctness and contextual relevance.

GenAI can enhance productivity at the application level by automating routine tasks, such as generating sample datasets or drafting solutions. This frees learners to focus on higher-order problem-solving and reflection. It also provides a risk-free and accessible environment for practicing real-world scenarios, an advantage for professional accreditation, where candidates must apply technical skills in realistic contexts. GenAI can increase the amount and variety of application-level practice by acting as a tireless simulator.

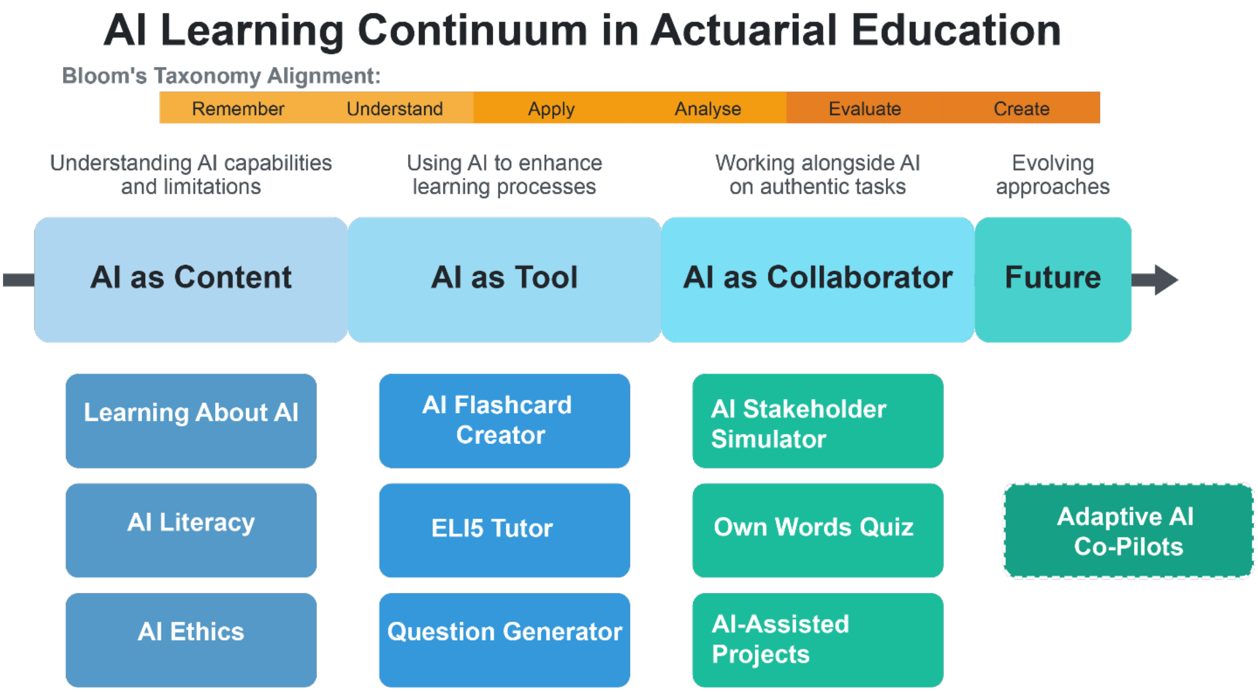
Reliability and correctness remain major concerns, given that flawed AI solutions can be more harmful than no solutions at all. Students risk stunted skill development if they let AI handle too much of the problem-solving process. In high-stakes fields such as actuarial science or engineering, overreliance on AI-generated outputs without careful validation can lead to serious errors. Ethical issues also arise when summative assessments are meant to measure individual competency, but AI is involved in producing key steps.

Prototype Tools – Application Level

1. Question Generator & Evaluator. Intended primarily for instructors, this prototype automatically generates scenario-driven questions (such as finance or engineering cases) and provides model answers or rubrics. It reduces preparation time by quickly generating variations on a single theme. Educators must still verify complexity and accuracy. The tool has been particularly valuable in professional courses that demand a large volume of realistic practice questions.
2. AI Stakeholder Simulator. This prototype enables students to practice explaining solutions to a simulated client or stakeholder. The AI role-plays by asking questions, requesting justification, or expressing confusion, compelling the student to clarify or reconsider their approach. This technique is especially beneficial in disciplines such as accounting, law, and consulting, where communicating complex ideas to non-expert audiences is crucial. Although the simulator helps students hone professional communication, it is not a flawless human emulation; occasionally, it over-simplifies issues or provides unintended hints.

Conclusion – AI Educational Use Cases

The diagram below illustrates an AI Learning Continuum in Actuarial Education, aligned with Bloom's Taxonomy. It describes a progression from foundational understanding ("Remember" and "Understand") to higher-order thinking ("Analyse," "Evaluate," and "Create"). Initially, AI is introduced as content, emphasising fundamental AI literacy, ethical considerations, and an understanding of AI capabilities. The next stage depicts AI serving as a tool, where learners use AI-driven applications such as flashcard creators, simplified (ELI5—Explain Like I'm Five) tutoring, and question generators to enhance learning. The continuum progresses further with AI becoming a collaborator, assisting in authentic actuarial tasks like stakeholder simulations, quizzes promoting self-expression (own words quizzes), and AI-assisted projects. Finally, the diagram indicates a future direction characterised by evolving educational methods, specifically the integration of adaptive AI co-pilots that dynamically support students' learning journeys.



Across knowledge, comprehension, and application levels, GenAI has emerged as a powerful ally in tertiary education and professional accreditation. The tools discussed, ranging from AI-generated study aids to interactive role-play simulators, illustrate how human teachers and learners can harness GenAI to streamline tasks, deepen conceptual grasp, and enrich experiential learning. Case studies in medical education (Cheung et al., 2023), STEM (Vasconcelos & dos Santos, 2023), data science (Yoo & Kim, 2024), and business courses (Lafkas, 2024) highlight tangible advantages, including time savings, personalised feedback, and expanded practice scenarios.

However, a balanced perspective reveals that AI can introduce errors, oversimplifications, or temptations to take shortcuts. It also lacks the authentic judgment and empathy required to fully replace human expertise. Educators must incorporate safeguards: verifying outputs, clarifying academic integrity policies, and designing assignments that foster genuine engagement. In short, GenAI is best understood as a potent but imperfect tool. When employed thoughtfully and with critical oversight, it can complement human capabilities and potentially transform both tertiary and professional education for the better.

8. Assessment in the Age of AI

AI will not only transform the way students learn but also significantly impact how their learning is assessed. Actuarial science is an accredited profession; therefore, it is essential that assessment methods effectively verify that qualified actuaries possess the requisite knowledge, skills, and judgement to uphold professional standards.

Limitations of AI Detection Tools

The rapid integration of AI tools in education has prompted the development of various detection mechanisms, but these tools have significant limitations. Based on empirical research, AI detection tools face several challenges:

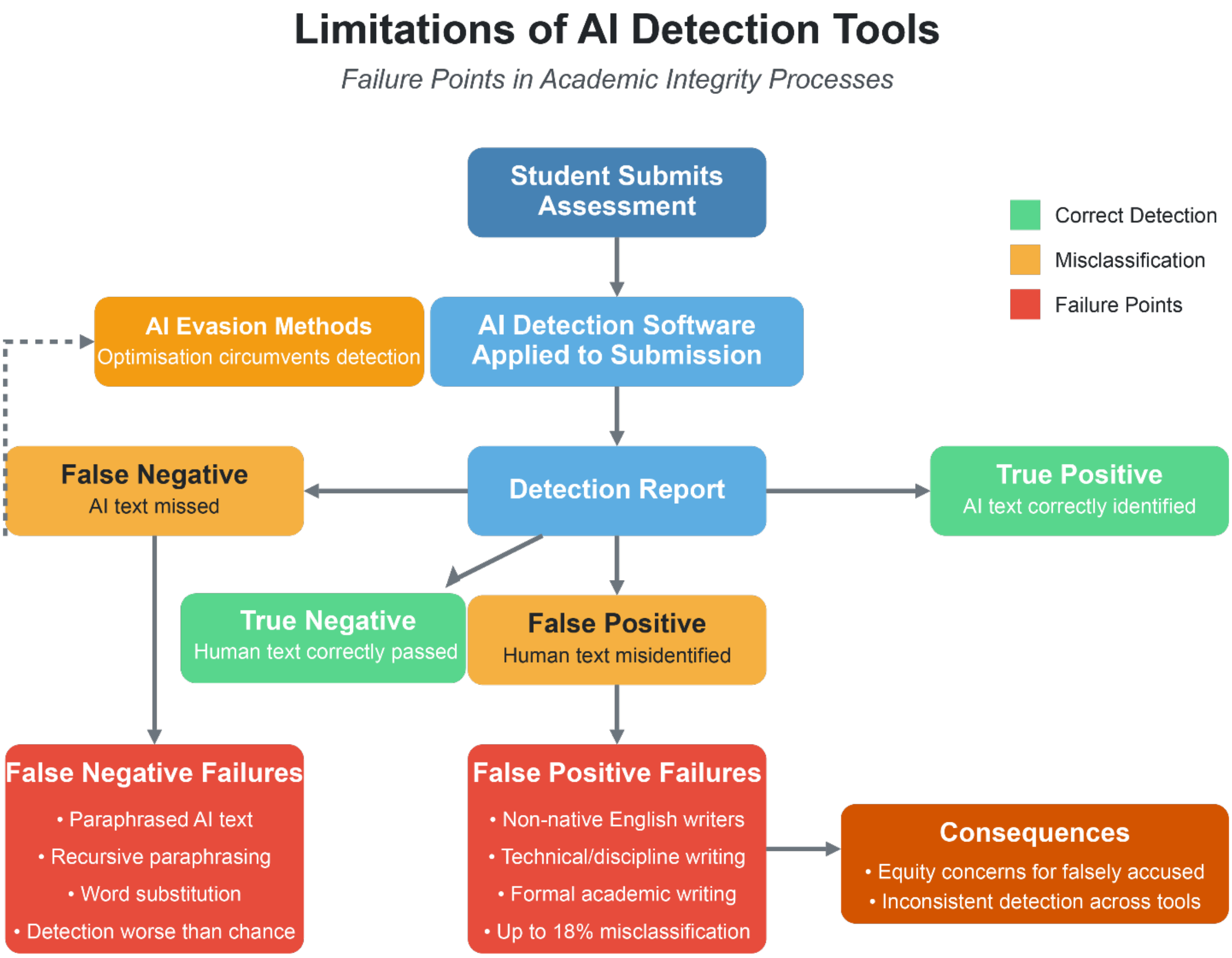
AI detection tools frequently misclassify human-written content as AI-generated. Turnitin, one of the most widely used plagiarism and AI detection platforms in higher education, initially claimed a 1% false positive rate but later revised that to 4% (Bowen & Watson, 2024). This led institutions, including Vanderbilt and Michigan State, among others, to disable Turnitin's AI detection feature (Bullock, Stone, & Supra, 2024, 2023).

Research by Liang et al. (2023) found that seven popular AI detectors, including GPTZero and ZeroGPT, disproportionately flagged work by non-native English writers. Their study revealed that over 50% of TOEFL essays from Chinese educational sources were misclassified as AI-generated. This raises significant equity concerns about the use of these detection tools in diverse educational environments.

GPTZero, another widely used detector, has been shown in some trials to misclassify up to 18% of human-written text as AI, missing nearly a third of genuinely AI-generated text. When paraphrasing tools are employed, detection misses can increase to even higher levels (Ibrahim et al., 2023).

Desaire et al. (2023) demonstrated enormous variability among detectors; a specialised detector trained on chemistry journals correctly identified 298 of 300 GPT-3.5 and GPT-4.0 documents as AI-generated, while ZeroGPT correctly identified only 27. This inconsistency makes it difficult for educators to rely on a single detection solution.

Detection tools are locked in a technological race with increasingly sophisticated AI systems. Weber-Wulff et al. (2023) examined fourteen different detectors against various text types and found that while some performed well at identifying purely human-written text, they were significantly less accurate at identifying AI-text, especially when it had been edited by humans or paraphrased.



Research by Sadasivan et al. (2023) demonstrated that recursive paraphrasing significantly reduces detector accuracy. Students can easily circumvent detection by running AI-generated text through paraphrasing tools or by instructing AI models to incorporate more intentional errors or stylistic variations.

Lu et al. (2023) tested an "optimization" technique where they asked ChatGPT to iteratively substitute words and phrases in academic essays. When tested against six detection methods, the detection results were worse than random chance.

Further complicating matters, certain detection algorithms disproportionately flag the work of multilingual students, raising serious equity issues. As a result, academic staff are strongly advised not to rely solely on the outcome of a single AI-detection tool; rather, they should treat these tools as only one piece of evidence in an academic integrity inquiry (Perkins et al., 2023). In the professional education context, including actuarial training, these limitations raise serious questions about the viability of relying on detection as a primary strategy for maintaining assessment integrity.

Australian Case Studies: Tertiary Students Falsely Accused of Plagiarism Using AI

In mid-2023, several Australian universities reported cases where students were incorrectly flagged for AI-generated content by Turnitin's AI detection tool. The University of Queensland was among the institutions that identified this issue (Flaherty, 2023). The problem occurred when Turnitin's AI detection feature began flagging legitimate student work as potentially AI-generated, particularly affecting non-native English speakers and students writing in technical disciplines. Some students who had never used AI tools were called to academic integrity hearings based solely on these algorithmic determinations (Dawson et al., 2023).

In one specific instance, a postgraduate engineering student at an Australian university submitted a technical report flagged with an "AI likelihood" score above 80%. Despite the student providing comprehensive notes and drafts, and explaining their research methodology, they were initially presumed guilty. After a lengthy appeals process and faculty review of their work process, the plagiarism charge was eventually withdrawn (Lancaster, 2023).

These false plagiarism accusations led to negative publicity and legal considerations for Australian universities, though not all cases resulted in formal litigation (Ross, 2023). One of the more notable instances occurred when a group of international students at a major Australian university went public with their experiences after being falsely accused based on Turnitin AI detection results. This received coverage in Australian higher education media, such as The Australian and Campus Morning Mail, as well as some mainstream news outlets, resulting in reputational damage for the institution involved (Baker, 2023).

Several key repercussions included:

1. Public relations damage: Universities faced criticism for over-reliance on automated systems and insufficient human oversight in academic integrity processes (Tertiary Education Quality and Standards Agency, 2024).
2. Threatened legal action: Although most cases were resolved through internal appeals processes, some students consulted with education lawyers and threatened legal action, citing procedural unfairness and discrimination (Mylne, 2023).
3. Student advocacy group involvement: Organisations such as the Council of International Students Australia (CISA) and the National Union of Students have issued statements condemning the practices and advocating for affected students (National Union of Students, 2024).
4. Regulatory scrutiny: The Tertiary Education Quality and Standards Agency (TEQSA) expressed concern about potential procedural fairness issues in some institutions' handling of these cases (Tertiary Education Quality and Standards Agency, 2024).

Following these incidents, several Australian universities revised their academic integrity policies to ensure that AI detection tools would be used only as one piece of evidence rather than as definitive proof of academic dishonesty (Dawson et al., 2023). Many universities subsequently implemented changes to require multiple forms of evidence beyond AI detection tools and to ensure proper appeals processes were in place. Some institutions also issued public statements acknowledging the limitations of AI detection technologies and committing to more balanced approaches to academic integrity investigations (University of Queensland, n.d.).

"Dead" vs. "New" Assessment Styles

Several traditional assessment formats, now considered "dead" in the age of AI, are becoming increasingly problematic. Standard take-home essays and reports with generic prompts focusing primarily on summarising existing knowledge have become particularly vulnerable to AI generation. Research by Mollick and Mollick (2023) found that standard essay prompts are easily handled by AI tools, producing work that is often indistinguishable from average student submissions. This is especially relevant for actuarial education, where case study analyses and policy evaluations can now be readily generated by AI tools with minimal human input. Multiple-choice questions for factual recall and simple assessments testing factual recall or basic applications of formulas have diminished value, as AI can readily process and answer such questions. These assessment formats are particularly vulnerable in actuarial education, where standard formulas and applications are frequently tested (Fyfe, 2022). Even traditional closed-book exams with standardised questions are becoming obsolete as AI capabilities advance. Mobile AI applications can easily process standard actuarial problems, and unless stringent device restrictions are enforced, such assessments may no longer reliably measure student knowledge or skills (Ibrahim et al., 2023). Basic data analysis tasks, a substantial component of actuarial education, can now be completed by AI tools that can write code, perform statistical analyses, and interpret results with minimal human guidance (Noy & Zhang, 2023). Formulaic responses and low-challenge tasks, such as summary essays or straightforward take-home questions that ChatGPT or other models can easily produce, risk allowing "AI for hire," effectively undermining authentic learning (Bharadwaj et al., 2023).

The emergence of AI has necessitated new assessment strategies that either incorporate AI tools or are designed to resist AI-generated responses. AI collaboration assessments have been introduced by several institutions where students explicitly collaborate with AI. University of British Columbia’s Centre for Teaching, Learning and Technology provides guidelines on integrating generative AI into assessments. They suggest that students might use AI tools to receive instant feedback on their draft essays or identify areas of improvement in their writing. This process involves students documenting how they use AI to refine their work, thereby promoting transparency and critical evaluation of AI-generated content. (Centre for Teaching, Learning and Technology. (n.d.)). This approach could be particularly valuable in actuarial education, where model selection and interpretation are critical skills. The Massachusetts Institute of Technology has implemented AI-assisted project development with process documentation, where students utilise AI to develop complex projects while documenting their decision-making processes (Grush, 2023). Students must justify why specific AI suggestions were accepted or rejected, focusing assessments on critical thinking rather than production capabilities. Harvard Business School has pioneered AI tool evaluation assignments that require students to assess the strengths and limitations of various AI tools for specific business tasks (Davenport & Miller, 2022). This assessment approach is particularly relevant for actuarial education, where model selection and validation are essential skills.

AI-specific tasks teach students to evaluate, question, and refine output from AI tools. Instructors might ask students to compare multiple AI-generated essays, identifying stylistic or factual errors, and verify the consistency and accuracy of citations provided by ChatGPT, Claude, or Copilot. They should also disclose how they utilised AI (such as prompt engineering versus final copy), with explicit annotations to reinforce academic honesty.

AI-aware tasks accept that students can access tools; instead of banning them, faculty design assessments that embed AI usage meaningfully. For instance, prompting students to generate a first draft via AI, but requiring an extensive revision log to highlight improvements and personal insights, using in-class or synchronous critiques so AI alone cannot complete the entire assignment, and asking students to reflect on ethical or discipline-specific responsibilities surrounding AI use, as recommended in new TEQSA guidelines (Tertiary Education Quality and Standards Agency, 2024).

Assessments can be designed to be AI-resistant through various approaches. In-person presentations and defences of written work have gained renewed importance. Several universities have implemented systems that require students to defend their written work, explaining their reasoning and responding to questions in real time. This approach, often called viva voce or interactive oral assessment, enhances academic integrity and assesses students' understanding more authentically. (Cribb, n.d.). Authentic, personalised assessments based on personal experiences or requiring application to specific, unique contexts are more resistant to AI generation. Stanford University's engineering program has implemented personalised problem sets where students must apply principles to specific, individualised scenarios (Stanford University, 2020, 2023). In-class and oral assessments demand real-time demonstration of knowledge, which is more difficult to fake with AI assistance. Annotated bibliographies with reflective commentary enable students to offer personal reflections on AI-generated references, demonstrating a deeper engagement with the material. Iterative, project-based tasks require personalised data, creative problem-solving, or step-by-step documentation of the student's thought process, driving higher-order skills such as analysis, synthesis, and metacognition.

While in-person and oral examinations are often promoted as effective tools to counter AI-driven academic dishonesty, their practicality in contemporary higher education warrants scrutiny. Universities are increasingly moving away from resource-intensive assessment methods due to concerns over cost and scalability. For instance, institutions like the University of Cambridge have indicated a shift from traditional three-hour written exams to more flexible assessment formats (McKie, 2021), influenced by lessons learned during the COVID-19 pandemic. Similarly, the University of South Australia has adopted viva voce examinations to address issues arising from AI and digital exams (Doherty, 2024), though this method presents challenges for scaling up to large groups.

Given these constraints, it's pertinent to question whether reverting to labour-intensive assessment formats is necessary. Instead, exploring alternative assessment methods that align with the digital age and the prevalence of AI tools may be more practical. Such methods could include AI-assisted project development with process documentation, where students utilise AI to develop complex projects while documenting their decision-making processes, as implemented by institutions like the Massachusetts Institute of Technology (Jisc, 2025). These approaches not only address concerns about academic integrity but also promote critical thinking and adaptability, skills essential in the age of AI.

AI Guidelines and Practices in 2025

For actuarial education specifically, the Society of Actuaries has begun exploring supervised computer-based testing environments that allow access to computational tools but prevent access to generative AI systems (Society of Actuaries, 2023). In Australia, the Actuaries Institute has taken a similar approach.

The University of New South Wales (UNSW) has developed a comprehensive framework for categorising and designing assessments in the age of AI. Their approach classifies assessments into four categories. First, AI-free assessments, which explicitly prohibit the use of AI, are designed to be completed in controlled environments without access to artificial intelligence. UNSW recommends these for foundational knowledge and skills that students must master independently, particularly where original thought or data privacy is paramount (UNSW, 2024). Second, AI-assisted assessments (controlled AI use) enable students to utilise AI tools as resources, but they require substantial human input. Students must document their AI interactions and explain how they evaluated and incorporated AI input. This category is recommended for specific learning outcomes, such as referencing or brainstorming (UNSW, 2024). Third, AI-evaluated assessments use AI tools to evaluate student work, providing immediate feedback. UNSW has implemented this approach in programming courses, where AI provides instant code reviews (UNSW, 2024). Fourth, AI-integrated assessments (full AI integration) explicitly require students to leverage AI tools as integral components of the assessment process. The focus is on students' ability to effectively direct, evaluate, and integrate AI capabilities. This is particularly appropriate for advanced contexts, including courses that teach AI prompt engineering or rely on AI data analytics (UNSW, 2024).

UNSW's guidelines also emphasise several important aspects. Disclosure requires students to clarify when and how AI is used. Equity and accessibility considerations ensure that AI usage guidelines are explicit, so that students without reliable access to AI are not disadvantaged. Staff preparedness is supported through workshops and resources to help staff design tasks that value reflection, manual calculation, or creativity beyond AI's "easy wins."

UNSW provides specific guidance for each category, including recommended implementation strategies and considerations for academic integrity. Their approach emphasises transparency in assessment design and clear communication with students about AI expectations (UNSW, 2024).

The University of Sydney has adopted a more centralised approach to AI integration in assessments. Their framework, outlined in "Aligning our assessments to the age of generative AI" (Educational Innovation, 2024), prioritises clear policy directives through university-wide policies that specify where and how AI can be used, technical solutions through investment in institutional-level detection tools, and standard practices with consistent implementation across faculties.

The University of Sydney also emphasises academic integrity by design, focusing on creating assessments that inherently discourage inappropriate AI use rather than relying primarily on detection (Educational Innovation, 2024).

However, recent reporting suggests a shift toward more nuanced, pragmatic teaching with AI, updating guidelines and relaxing earlier bans ("Sydney Uni's U-turn on AI is pragmatic teaching," 2024). In contrast to UNSW's more formal categorisation, Sydney University now appears to grant individual faculties and teaching staff greater discretion to decide how AI should be applied or restricted.

Australia's Tertiary Education Quality and Standards Agency (TEQSA) has published various resources on good practices for integrating AI in higher education. Their emphasis includes encouraging universities to adopt transparent policies on permissible AI usage, promoting staff and student training around AI ethics, referencing, and academic integrity, and advising robust instructional design that values creativity, original thinking, and student interaction, reflecting best practices in TEQSA's "Higher Education Good Practice Hub – Artificial Intelligence" (Australian Tertiary Education Quality and Standards Agency, 2024).

TEQSA also underscores the importance of authenticity in assessment, ensuring that AI is a skill-enabling tool rather than a means to bypass learning altogether.

A hybrid approach may be most suitable for actuarial education, which necessitates both technical knowledge and professional judgment. The technical elements of actuarial training might benefit from the structured, consistent approach favoured by the University of Sydney. In contrast, the professional judgment aspects could benefit from UNSW's more flexible, AI-integrated assessment models. Professional bodies, such as the Institute of Actuaries of Australia, could develop assessment frameworks that address how AI tools can be appropriately incorporated into various aspects of actuarial training, ranging from technical calculations to professional ethics considerations (Institute of Actuaries of Australia, 2023).

As AI continues to transform the workplace, particularly affecting entry-level positions that have traditionally served as training grounds for actuaries, educational institutions and professional bodies must adapt their assessment approaches to ensure that graduates can effectively demonstrate value beyond what AI can provide.

Assessments in the AI Era

The table below summarises assessment approaches in the AI era.

Assessment Approach	**Description**	**Examples & Considerations**
"Dead" Approaches	*Traditional assessments vulnerable to AI*	
Standard Take-Home Essays	Generic prompts focusing on summarising existing knowledge	Case study analyses and policy evaluations easily generated by AI tools
Factual MCQs & Formula Tests	Tests of recall and basic application of formulas	Standard actuarial problems with straightforward applications
AI-Assisted Approaches	*Explicitly incorporating AI as a tool*	
AI Collaboration Assessments	Students explicitly collaborate with AI and document interactions	Documenting prompt refinement, evaluating AI responses
AI-Assisted Projects with Documentation	Using AI while documenting the decision-making process	Justifying why AI suggestions were accepted or rejected
AI-Resistant Approaches	*Designed to minimise AI assistance*	
In-Person Presentations & Defences	Oral defence of written work, explaining reasoning in real-time	Requires deeper understanding beyond what can be generated by AI
Authentic, Personalised Assessments	Based on personal experiences or unique contextual application	Personalised problem sets, supervised real-time assessments

9. Recommended AI Usage Guidelines for Actuarial Education

This section outlines recommendations for integrating AI into actuarial education while preserving and enhancing the distinct human value that actuaries bring to their organisations and clients.

Balanced Integration

AI tools should not be banned from actuarial education. Just as calculators and statistical software became essential tools for actuaries in previous technological transitions, AI represents the next evolution in actuarial tooling. However, balance is crucial. Components of education and assessment that relate to human-specific capabilities, such as face-to-face communication, ethical decision-making, and interpersonal influence, should be carried out without student access to AI tools. This approach ensures that students develop both technological competence and uniquely human skills that extend beyond automation.

Example 1: Designate specific "AI-assisted" and "AI-free" components within the same course. For instance, in a pricing course, allow AI use during premium calculation exercises but require independent work during ethical case study discussions about rate fairness.

Example 2: Design a capstone project where students first complete analysis with AI assistance, then defend their conclusions in an AI-free oral examination, explaining which parts of their work relied on AI and why.

AI as a Tool, Not a Practice Area

It is essential to frame AI appropriately within the profession: AI is no more an actuarial practice area than spreadsheets are. Instead, like other software tools, AI should be integrated into education across all actuarial domains. Students should learn how to effectively use AI tools for data analysis, report generation, and complex calculations, while understanding their limitations. This requires teaching students when to apply AI tools, when to rely on traditional methods, and how to verify the accuracy of AI-generated outputs.

Example 1: Create assignments that require students to apply the same actuarial concept (e.g., reserving methodology) across different tools—first using traditional spreadsheets, then using statistical software, and finally using AI assistance—and reflect on the strengths and limitations of each approach.

Example 2: Develop exercises that require students to identify and correct errors in AI-generated actuarial reports, emphasising that verification remains a human responsibility, regardless of the tool used.

Elevating Assessment Standards

As AI essentially represents the new "C-grade" capability in actuarial tasks, educational standards must rise accordingly. Assessments should avoid memorisation, rote learning, and straightforward calculations that AI can easily perform. Instead, they should emphasise higher-order abilities, including critical thinking and analysis, professional communication, application of common sense to mathematical results, complex problem-solving, ethical reasoning, and professional judgment in ambiguous scenarios. This transition requires reimagining course content and assessment methodologies to target distinctly human and professionally valuable capabilities.

Example 1: Replace exams that ask students to calculate insurance reserves with assessments that require them to evaluate and compare the appropriateness of different reserving methods for novel product features.

Example 2: Design case studies where students must recommend and justify appropriate actuarial approaches for emerging risks with limited historical data (e.g., cyber insurance for quantum computing vulnerabilities).

Enhancing Educational Efficiency

AI tools present significant opportunities to enhance educator efficiency and improve learning outcomes. Potential applications include automated grading of routine assignments, personalised learning pathways for students based on performance data, generating practice problems with varying difficulty levels, providing immediate feedback on student work, and creating realistic case studies and simulation exercises. These efficiency gains allow educators to devote more time to high-value student interactions, such as mentoring, guided critical thinking exercises, and professional development conversations.

Example 1: Implement an AI-powered practice system that generates personalised pricing exercises based on each student's performance, automatically increasing complexity when students master basic concepts.

Example 2: Develop virtual simulation labs where AI generates realistic client scenarios for students to practice stakeholder communication, with automated feedback on both technical accuracy and communication effectiveness.

Developing Critical AI Literacy

Actuaries must develop advanced data literacy skills to critically evaluate the outputs of artificial intelligence (AI). This includes understanding statistical limitations, identifying potential biases in AI systems, and recognising when outputs require further validation. Students should be taught frameworks for assessing AI-generated analyses' reliability, validity, and applicability to specific actuarial problems.

Example 1: Provide students with intentionally flawed AI-generated mortality analyses and require them to identify statistical issues, data biases, and inappropriate assumptions.

Example 2: Create workshops where students compare multiple AI-generated solutions to the same actuarial problem, evaluating differences in approaches and identifying which solution best addresses the business context.

Ethical Frameworks for AI in Actuarial Work

Educational programs should incorporate clear guidelines on the ethical use of AI in actuarial work. This includes transparency with clients about AI usage, maintaining professional responsibility for AI-assisted work products, and ensuring appropriate human oversight of critical decisions. Case studies that address ethical dilemmas in AI applications offer valuable learning opportunities.

Example 1: Develop a certification module requiring students to complete case studies on ethical AI use, such as determining appropriate disclosure when AI systems assist in underwriting decisions.

Example 2: Develop role-playing exercises that require students to explain complex AI-assisted actuarial analyses to simulated non-technical stakeholders, emphasising transparency and the appropriate representation of limitations.

Creating Effective AI-Human Workflows

Students need to learn efficient workflows that incorporate AI tools into actuarial processes. This includes developing skills in crafting appropriate inputs, critically evaluating outputs, and integrating AI-generated content into broader actuarial work products. These workflows should emphasise the complementary relationship between human expertise and technological capabilities.

Example 1: Design practical labs where students develop and document end-to-end workflows for common actuarial tasks (e.g., experience studies), specifying which components can be assisted by AI and which require human oversight.

Example 2: Create templates for AI prompting in actuarial contexts, teaching students effective techniques for directing AI tools to produce useful outputs for different actuarial applications.

Navigating Regulatory Requirements

As regulatory bodies develop standards around AI usage in financial and insurance contexts, actuarial education must prepare students to navigate these requirements. This includes understanding documentation requirements, explainability standards, and compliance frameworks related to AI-assisted actuarial work.

Example 1: Develop compliance exercises that require students to audit AI-assisted actuarial work against specific regulatory frameworks, such as ASIC's Regulatory Guide 274 (RG 274) for product design and distribution.

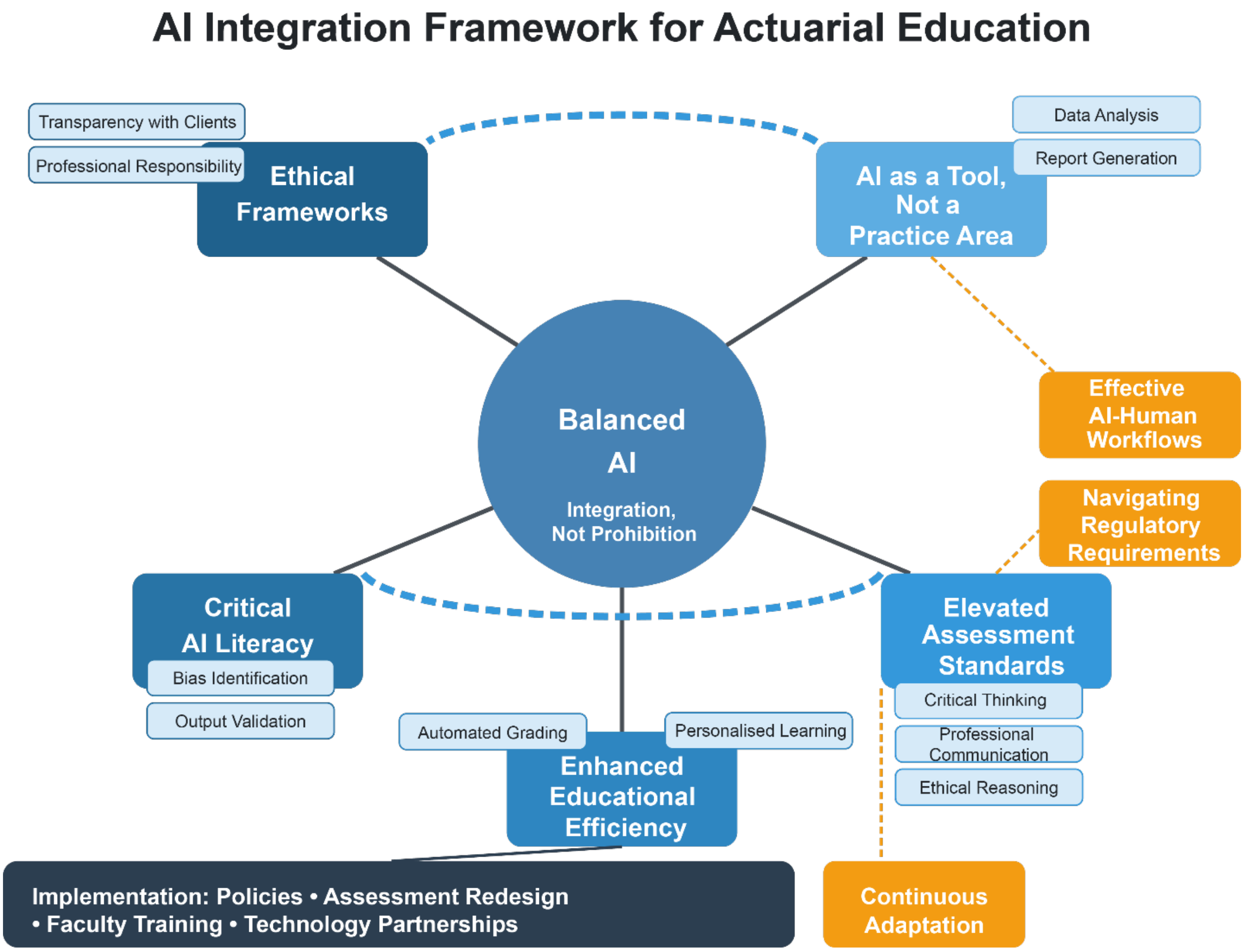
Example 2: Develop documentation templates that align with regulatory expectations, teaching students how to accurately record AI contributions in actuarial reports.

Fostering Continuous Adaptation

Actuarial education should prepare students for continuous adaptation as AI capabilities evolve. This means developing a mindset of technological flexibility, a commitment to lifelong learning, and the ability to identify emerging opportunities for AI application in actuarial work.

Example 1: Establish a "Technology Horizon" component in courses where students research emerging AI capabilities and create presentations on potential actuarial applications.

Example 2: Implement regular "AI update" sessions where faculty and industry partners demonstrate new AI capabilities relevant to actuarial work, keeping the curriculum aligned with rapid technological developments.



Practical Implementation Recommendations

Effective AI integration in actuarial education requires the development of clear policies on appropriate AI use in coursework and assessments, redesigning assessments to focus on higher-order skills, providing faculty training on effective AI integration in teaching, creating dedicated modules on ethical and effective AI usage, establishing partnerships with technology providers to ensure students have access to industry-relevant AI tools, and regularly updating curriculum to reflect evolving AI capabilities.

Example 1: Develop a staged implementation plan that begins with pilot courses, gathers feedback from both students and faculty, and then expands to the full curriculum.

Example 2: Develop faculty communities of practice where instructors share successful AI integration strategies specific to different actuarial domains, creating a repository of proven approaches.

10. Conclusion

In conclusion, artificial intelligence is fundamentally transforming both actuarial practice and education. Analysis reveals that embracing AI as a tool for learning and a subject of study offers a powerful means to enhance cognitive skills, streamline operations, and bridge the gap between academic preparation and industry needs. By integrating AI into the curriculum, we can better equip future actuaries with the advanced analytical and critical thinking skills required to navigate increasingly complex risk environments.

My recommendations call for a balanced approach that leverages AI's computational strengths while preserving the uniquely human elements of creativity, empathy, and ethical judgment. Rather than replacing traditional skills, this approach advocates for incorporating AI literacy, rigorous validation processes, and dynamic assessment methods that reinforce academic integrity and foster a deep, genuine understanding of actuarial science. This strategy prepares practitioners for the evolving technological landscape, ensuring that the core values of the actuarial profession remain intact.

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