Asian Actuarial Conference 2025 Bangkok

Navigating Model Risk Management in the Age of Artificial Intelligence

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Oliver Wyman

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NAVIGATING MODEL RISK MANAGEMENT IN THE AGE OF ARTIFICIAL INTELLIGENCE

NOVEMBER 2025

Chadwick Cheung, Kok Ern

Oliver Wyman Actuarial

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INTRODUCTION OF THE SPEAKERS

CHADWICK CHEUNG

FIA, FSA, FASHK

- Senior Manager at **Oliver Wyman Actuarial**, based in Hong Kong
- **14 years** of life insurance industry and consulting experience; in the UK, Hong Kong and Japan
- Leading **actuarial transformation** in OWA Hong Kong incl. analytics, automation and AI
- **International Actuarial Association** AI Task Force member - Governance (2024) and Adoption (2025)
- **Actuarial Society of Hong Kong** Innovation Committee member and AI Group member

KOK ERN

FIA, FSAS

- Principal at **Oliver Wyman Actuarial**, based in Singapore
- **18 years** of life insurance industry and consulting experience in APAC
- Diverse actuarial expertise spanning M&A, valuation, capital management and pricing
- Led **actuarial transformation** projects for clients

AGENDA

1 AI Model Risk Management

- Emerging Risks
- Considerations for MRM Framework

2 IAA AI Taskforce

- 2024 Governance Workstream
- 2025 Adoption Workstream

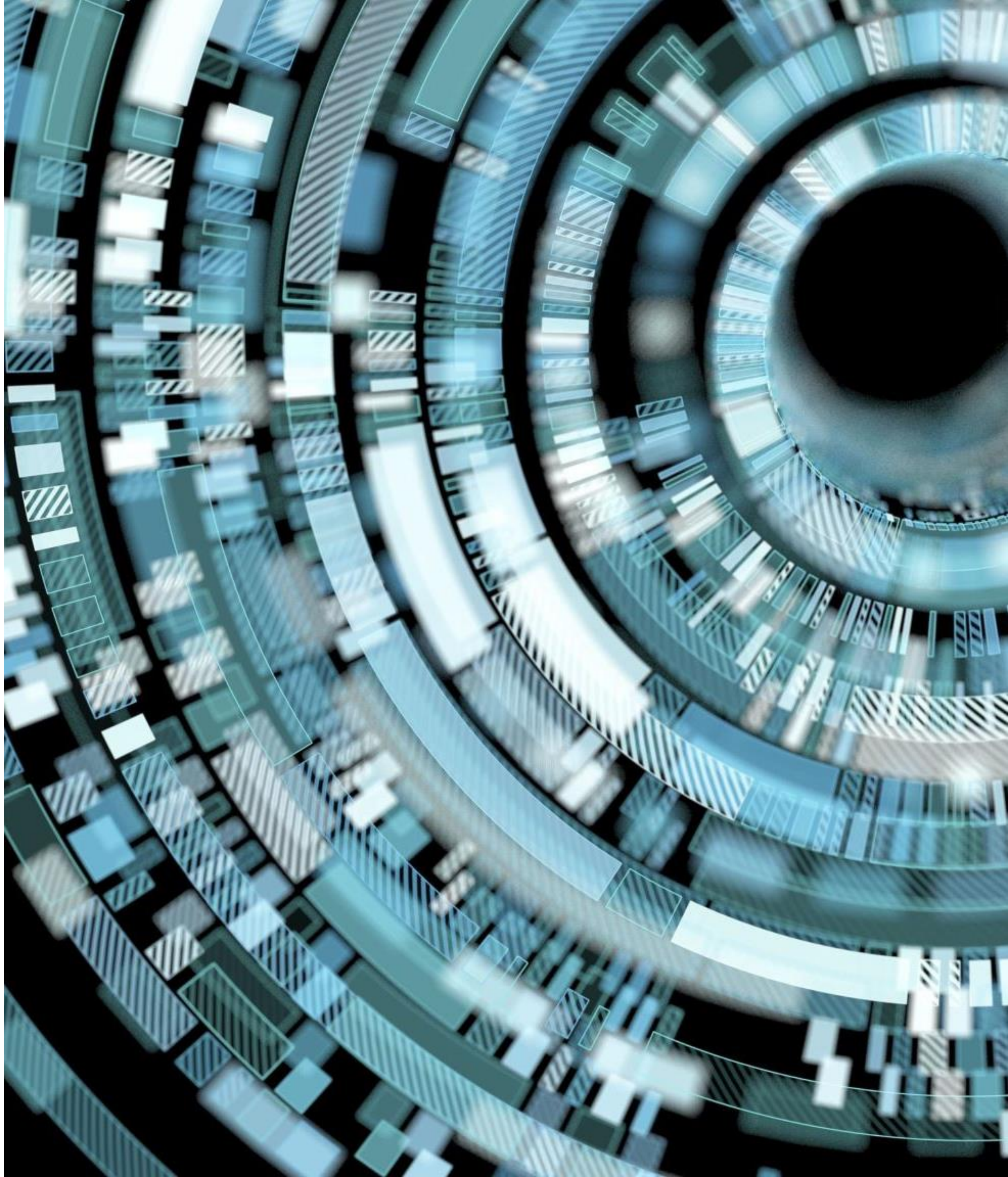
3 AI Governance in Action

- IAA Education Paper – Testing of AI Models
- Case Study – Model Validation of a Group Life Underwriting Model

AN INTERVIEW WITH CHADGPT ON AI AND ITS IMPACT ON INSURANCE AND ACTUARIES

1

AI MODEL RISK MANAGEMENT



A WAVE OF ARTIFICIAL INTELLIGENCE[1] MODELS HAS ARRIVED

Model Risk Management plays a crucial role in their safe deployment across the business

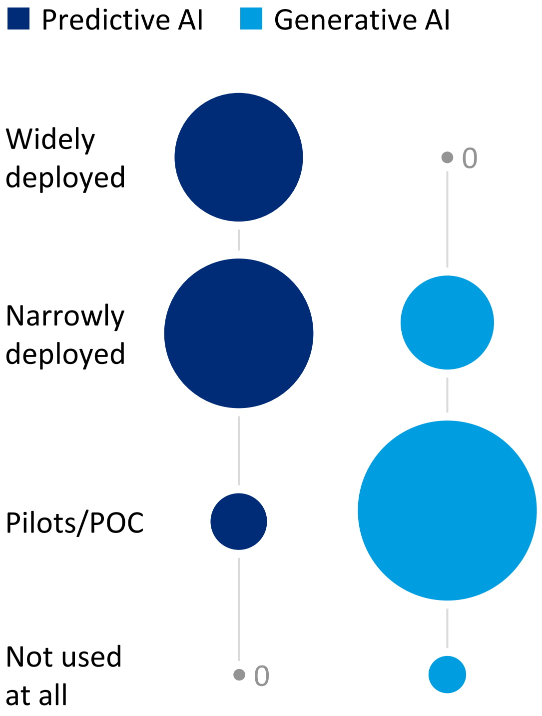
AI deployment areas

1 Growth and retention
- Marketing
- Sales
- Product distribution

2 Productivity and operations
- Process automation
- Claims automation
- Data usage and error detection

3 Risk management
- Underwriting
- Pricing
- Risk modelling

Current AI usage across business[2]



Predictive AI has an existing foothold within businesses while generative AI is growing

1. "AI" is used as an umbrella term for models with AI or Machine Learning algorithms such as Generalized Linear Models ("GLM"), Natural Language Processing ("NLP") models and Large Language Models ("LLM")
2. Source: Oliver Wyman 2023 survey with UK Finance, N=23 Global, EU and UK FIs

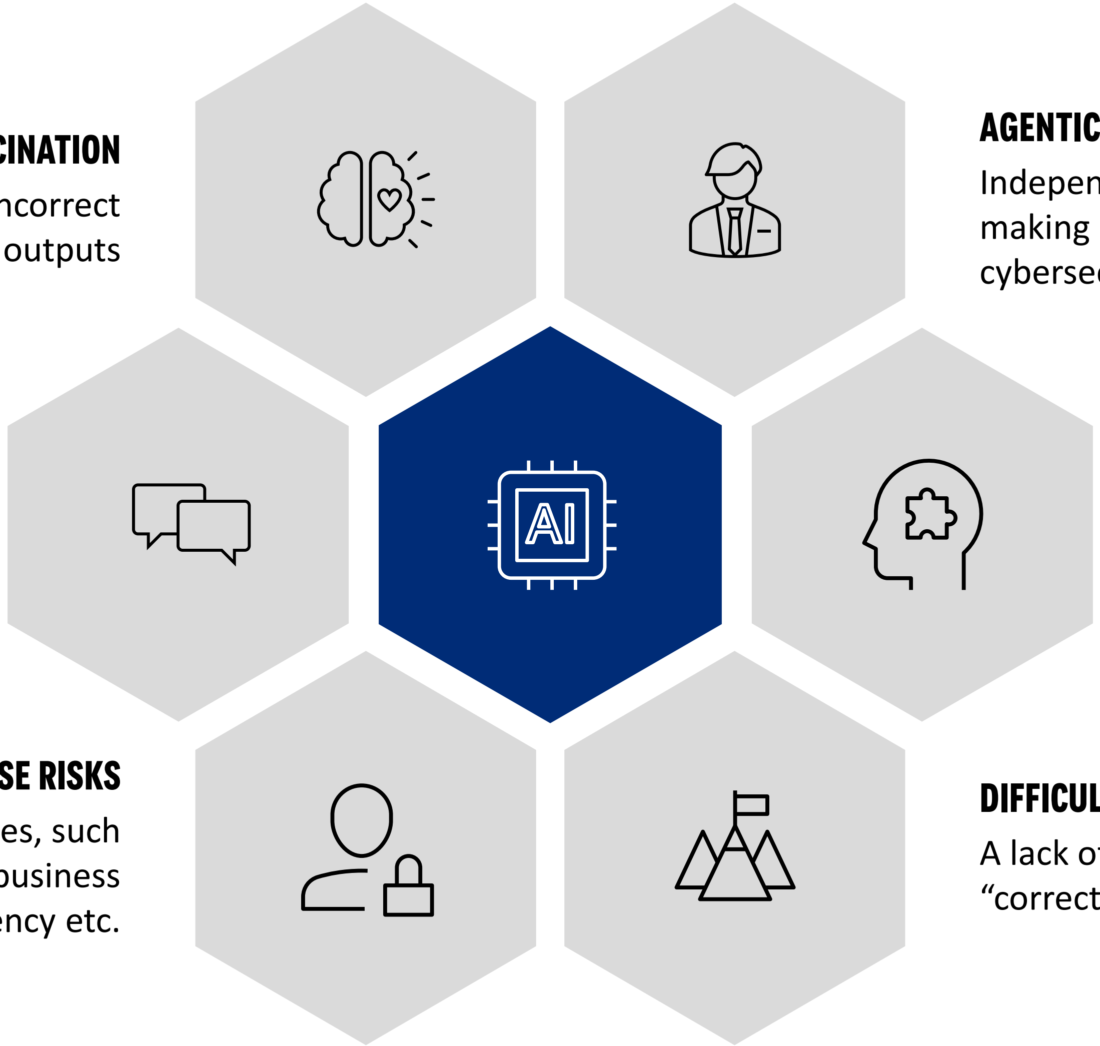
GEN AI MODELS ARE EXPOSED TO ADDITIONAL RISKS RELATIVE TO TRADITIONAL MODELS

HALLUCINATION

Gen AI models might give confident but incorrect outputs

AGENTIC BEHAVIOUR

Independently makes decision without oversight, making harmful/costly decision and additional cybersecurity vulnerabilities



PROMPT SENSITIVITY

It is fragile to input phrasing

NON-DETERMINISM

Outputs vary even for the same inputs

ENTERPRISE RISKS

Risks related to deployment by enterprises, such as cybersecurity risks, hacking, forming business dependency etc.

DIFFICULT TO BENCHMARK

A lack of ground truth, as there is no clear “correct” answer.

AI MODELS REQUIRE INSURERS TO REFINE MODEL RISK MANAGEMENT FOR NEW RISKS

Core objectives

- An AI-compatible model risk management framework to **manage risks associated with design, development, deployment and use of AI** within the organization
- Provide a **structured approach to identify, assess, mitigate, and monitor risks, incidents and issues**, ensuring responsible and effective utilization of AI technologies
- Consistently **applied to all AI systems and models** used within the organization, encompassing the entire model lifecycle
- Provide guidance for ongoing **control assurance** and testing requirements

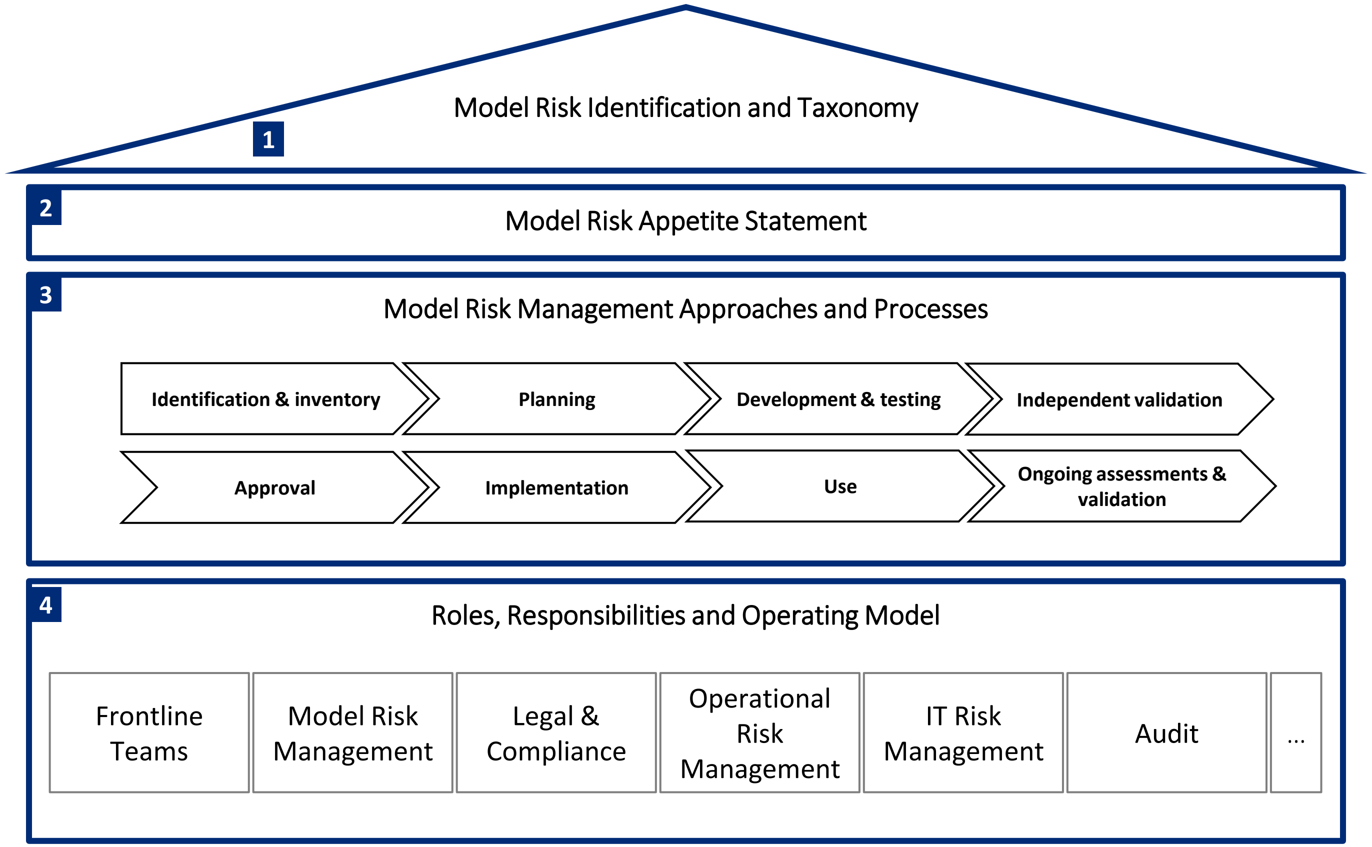
Key considerations for the model risk management framework

Principles for the use of AI	Principles typically need to be established and should articulate the stance that organization has when it comes to the use of AI, including social, societal, ethical and fair use.
A clear **definition** of AI	To qualify what is considered AI vs. other software and technologies, and when the policy does or does not apply.
Governance and **authorization** of AI	Consider establishing an AI risk council to support central governance and decisions for AI. Consider which core 'pre-trained' AI models should be allowed within the organization and which developed and enhanced models require governance and endorsement before use.
Heightened and **New AI Risks**	Understand the heightened and new risks introduced by AI and Large Language Models, and how these impact the current treatment of risks and controls within the organization.
Assessment of AI Systems and Models	Clarify how an AI system or model should be assessed, and against what parameters. E.g., accuracy, hallucination, traceability. Assess which industry frameworks can be used (e.g., NIST).
Minimum **Control Requirements**	A risk-based classification of AI systems and models should be conducted, further suggesting the minimum controls requirement and the level of human intervention required.
AI Risk **Taxonomy**	Understand the risk levels of AI models and establish AI Risk Taxonomy spanning current risks and potentially new treatments that may be required.
AI **Regulation** and Legal Obligations	With increasing regulatory oversight, consider scanning, updating and maintaining the AI obligations backlog.
Alignment with current policies	Align how AI will be managed under current Risk Management Framework, and how it will use Incident and Issue management, Data, Privacy, Security, 3rd Party Risk Policies.
AI Skills / Talent Management	Operationalizing the AI risk framework will likely require upskilling / reskilling and refinement of talent management practices.

An AI-compatible model risk management framework should be established before AI models are scaled and productionized

INSURERS CAN BUILD ON EXISTING MRM FRAMEWORK TO MANAGE AI RISKS

Model risk management framework



Example AI risk elements to be incorporated into existing standards

1

- AI definition
- AI risk definition
- AI risk taxonomy

Technical understanding of **risk definition** and **risk taxonomy** is critical*

2

- AI risk appetite statement (e.g., considering ethical, regulatory, financial, reputational factors)
- AI risk appetite metrics

3

- AI risk tiering approach
- Development standards and requirements
- Validation and independent testing requirements
- AI on-going monitoring metrics and thresholds
- Third party AI risk management

A well-defined and measurable **risk tiering policy** informs the model **development** and **validation** requirements*

4

- Team-specific testing requirements throughout AI lifecycle (e.g., validation, compliance testing, data privacy assessment, code review)
- Hand-offs and SLAs
- Board and management reporting and escalation
- Processes and operating model
- Skills and training

Regulations such as **Colorado Reg 10-1-1** and **NY DFS Circular Letter No. 7** provide detailed requirements

A clear understanding of AI model risks and required governance standards is essential for establishing a robust MRM framework.

2

IAA AI TASKFORCE

GOVERNANCE WORKSTREAM – RECAP ON ACHIEVEMENTS IN 2024

KEY FOCUS AREAS

1 Monitor and evaluate **existing AI governance frameworks, policies, and regulations**, identifying gaps and areas where **actuarial expertise** can contribute

2 Participate in **policy discussions, consultations, and industry forums** related to AI governance, emphasizing the **actuarial profession's perspective** and advocating for **fair and transparent** AI practices

3 Engage with **regulators, standard-setting bodies, and policymakers** to contribute actuarial insights to the development of AI governance frameworks, ensuring the **profession's perspectives are considered**

TARGET/GOAL

- Help actuaries understand the scope and impact of AI regulations
- Develop principles of AI for adoption by actuaries
- Develop a governance framework on AI (e.g., Data | Model | Implementation)
- Create practice notes (e.g., Validation | Testing | Auditing | Documentation)
- Facilitate the dialogue with the relevant regulators (following IAAs approach)

KEY DELIVERABLES / SUB-WORKING GROUPS

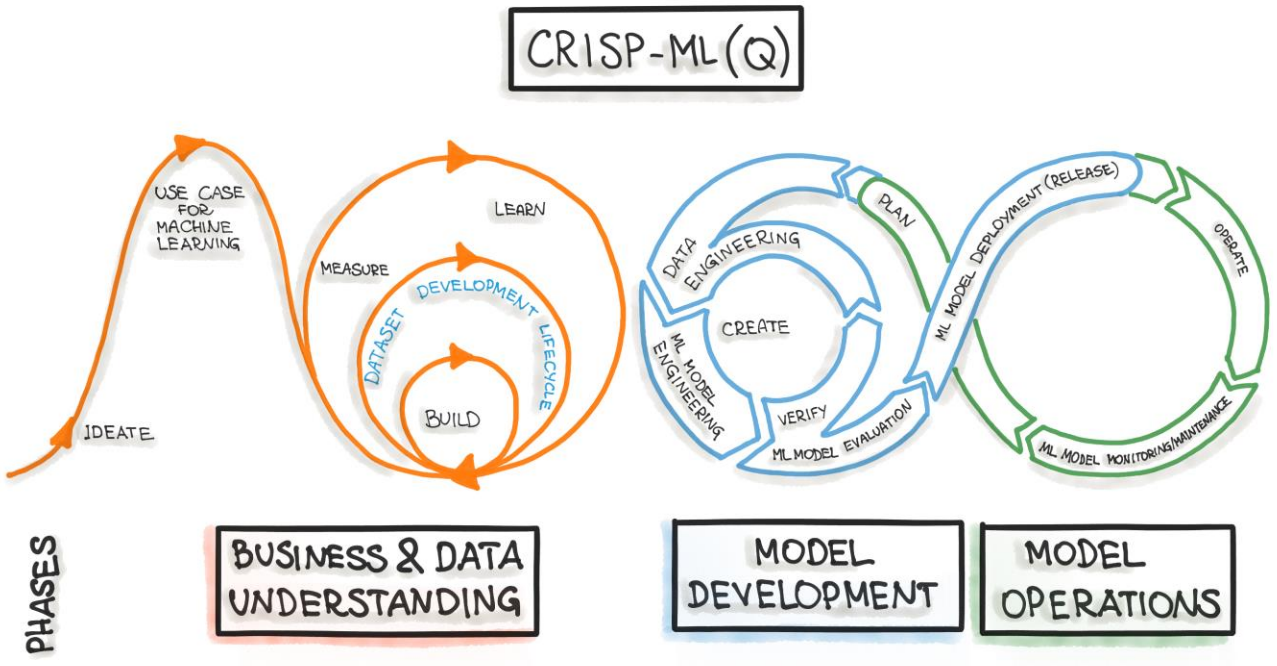
DELIVERABLE 1	A **comparative study on AI regulations and guidelines** worldwide
DELIVERABLE 2	Identifying **challenges of existing AI regulations/guidelines vs actuarial relevance**
DELIVERABLE 3	Develop a **comprehensive governance framework**
DELIVERABLE 4	Develop **practice notes on Documentation, Testing, Validation and Auditing**

ADOPTION WORKSTREAM – 2025 OBJECTIVES

OBJECTIVE 1	Provide actuaries with a **framework** that helps them **evaluate adoption strategies**
OBJECTIVE 2	The framework should include considerations such as **best practices, professionalism, governance, ethics**, as well as **practicality**.

Sub-goals:

- Materialize on products from 2024
- End-to-end comprehensive framework
- Address topics that were not addressed yet
- Responsible and sustainable AI
- Cross-country and FMA importance (regulation and adoption strategies)



ROADMAP: CURRENT STATUS & NEXT STEPS

Decide on initial structure
Draft
Delivery

2025-Q3 | 2025-Q4 | 2026

LINK-UP 2024 DELIVERABLES
Review/Adapt/Update

Initial focus was on a set of 3 papers:
Governance framework | Documentation | Testing

Second batch of 3 papers:
Professional Considerations | Risk Taxonomy | Prompt Engineering

Drafting new content and aligning with Group 2

INTERACTIVE FRAMEWORK
End-end to case study;
Structural design of an AI implementation process

Deciding on initial structure:
A sub-group has been set-up, focusing on areas to address

Aligning current products:
Existent reviewed and produced content to be linked to the framework.

Address new areas
New content to be created.
Technical infrastructure | Document to be decided

LINKAGE OF REGULATION
Expand existing products
Connect with IAA committees

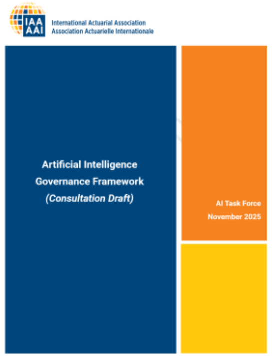
Regulation related products from 2024 were shared with the IRC

Expanding and updating regulatory related matters, with new insights and needs as identified through other deliverables

COMMUNICATION AND ENGAGEMENT

Several presentations have been done with several stakeholders. More webinars and knowledge sharing activities to be planned.

PHASE 1: LINK-UP THE 2024 DELIVERABLES | ARTIFICIAL INTELLIGENCE GOVERNANCE FRAMEWORK



ARTIFICIAL INTELLIGENCE GOVERNANCE FRAMEWORK

"...to provide educational material that helps actuaries in **safeguarding responsible Artificial Intelligence (AI)**, while raising awareness of the risks that need to be managed when **designing, developing, implementing, and using AI models and AI systems**."

Key Components of AI Governance Framework:

- Roles and Responsibilities
- Board of Directors
- Committees & Policies
- Key Functions
- Model Owner
- Model Risk Ratings
- Key Governance and Risk Management Processes
- Independent Validation of an AI model
- Applicability of Framework to Third Party Vendor AI Models and Data
- Human Supervision and Oversight

Definitions

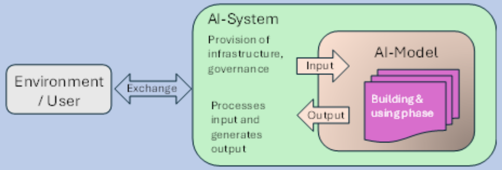
AI System

"An AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment."

AI Model

"An AI model is a core component of an AI system used to make inferences from input to produce outputs."

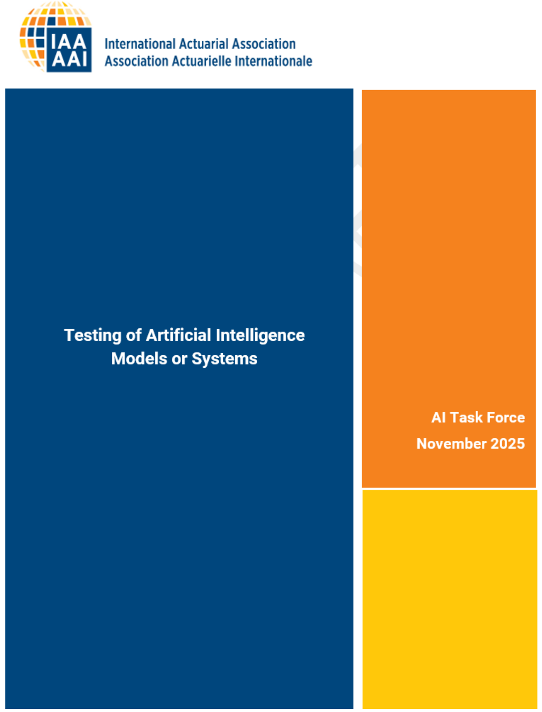
An AI model is distinguished from a traditional model by having adaptive and autonomous features.



PHASE 1: LINK-UP THE 2024 DELIVERABLES | TESTING OF ARTIFICIAL INTELLIGENCE MODELS

TESTING OF ARTIFICIAL INTELLIGENCE MODELS:

"…the paper is structured to offer an overview of the **key considerations and methodologies involved in testing AI models**. It begins by outlining the **core principles of ethical AI models**, followed by a discussion of the **testing methods and metrics** that could be used."


International Actuarial Association
Association Actuarielle Internationale

Testing of Artificial Intelligence Models or Systems

AI Task Force
November 2025

Key Components of documentation:

- Setting up the foundations such as defining objectives, criteria, test cases and Data
- Testing the core principles of ethical AI Models: accuracy, fairness, explainability etc.
- Broader Fairness and Ethical Considerations
- Types of Testing: Functional, integration, bias, etc.
- Continuous Testing and Monitoring

3

AI GOVERNANCE IN ACTION

IAA EDUCATION PAPER ON TESTING OF AI MODELS: KEY SECTIONS

AI MODEL TESTING

TESTING THE CORE PRINCIPLES OF ETHICAL AI MODELS

- Rigorous testing to ensure **the fairness, transparency, accountability, and robustness** of AI and ML models
- Various **methodologies and metrics** to assess principles
- Actuaries may need to adopt **different testing approaches** for AI models, which may vary from conventional actuarial models

FAIRNESS AND ETHICAL CONSIDERATIONS

- Potential biases that can arise from **data selection** and **algorithm design**, and ways to mitigate such risks
- The need for responsible **disclosure of model vulnerabilities** and the establishment of **governance frameworks**
- Actuaries can play a pivotal role in fostering **trust and social responsibility** in AI applications in their organizations

TYPES OF TESTING

- Testing methods applicable to AI models, each designed to evaluate **different aspects of performance and reliability**
- Importance of **ongoing testing** throughout the **model lifecycle** to identify and mitigate potential issues early
- Comprehensive testing is essential for ensuring that AI models function **as intended** and meet **established standards**

PREPARING DATA FOR TESTING

- Steps involved in **curating and organizing data** to ensure effective testing of AI models
- Data quality – **accuracy, completeness, and relevance** – is fundamental to reliable testing outcomes
- **Data preprocessing**, e.g. normalization and anonymization, improves model performance while maintaining ethical standards

IAA EDUCATION PAPER ON TESTING OF AI MODELS : OVERVIEW (1 OF 2)

	Testing the core principles	Fairness and ethical considerations
What are the key takeaways?	• Key requirements for trustworthy AI include **fairness, transparency, accountability, and robustness** • Essential **testing metrics** include accuracy, fairness, robustness and explainability to provide insights and evidence of model functionality • **Ongoing model** validation is necessary to ensure continued compliance with evolving standards and practices	• Fairness in AI requires identifying and mitigating biases in **data and algorithms**. Various fairness metrics e.g. demographic parity, equal opportunity differences • Ethical guidelines should be established to govern **the design, implementation, and evaluation** of AI systems • Establishing protocols for responsible disclosure of **model vulnerabilities** and setting up **governance frameworks** are essential
Why is this important?	• Rigorous testing ensures AI models are **reliable, fair and explainable**, reducing the risk of errors in critical decision-making processes • The use of standardized metrics allows for **continuous monitoring and improvement**, facilitating **regulatory compliance and transparency** in model deployment and operation • Ongoing validation is essential to adapt to **changing environments** and **emerging ethical standards**, safeguarding the integrity of AI systems	• Establishing ethical guidelines fosters **accountability and transparency**, helping organizations align their AI practices with societal values and expectations • Involving **diverse stakeholders** leads to a more comprehensive understanding of ethical implications, fostering broader community trust and acceptance of AI • Regular **fairness audits** and the establishment of **clear evaluation criteria** enable ongoing assessment and improvement of AI models, ensuring they remain fair, reliable, and trustworthy over time
What is the actuarial relevance?	• Actuaries must consider **regulatory compliance related to AI applications**, being prepared to demonstrate how they ensure the trustworthiness of models used in their work • Actuaries can **contribute to risk management strategies** that incorporate AI, enhancing the overall reliability of actuarial predictions and analyses • Actuaries need to **collaborate with technical experts** when required, especially when dealing with data preparation, setting up testing environments, or interpreting complex AI algorithms	• Understanding **fairness metrics** enables actuaries to evaluate the models used in their analyses and advocate for improvements where necessary • Actuaries must recognize how biases in AI models can impact risk assessments and pricing strategies, potentially leading to **unfair treatment of specific groups** • Actuaries can play a key role in **establishing ethical guidelines** within their organizations, ensuring that AI applications align with professional standards

IAA EDUCATION PAPER ON TESTING OF AI MODELS : OVERVIEW (2 OF 2)

	Types of testing	Preparing data for testing
What are the key takeaways?	• **Functional Testing**: Ensures that the AI system performs its intended functions correctly by verifying predictions against expected outcomes • **Output Appropriateness Testing**: Validates the clarity, interpretability, and actionability of the model's outputs • **Bias and Fairness Testing**: Analyzes system outputs across demographic groups to identify and mitigate biases, ensuring fairness in outcomes • **Explainability Testing**: Ensures model decisions can be understood and trusted by analyzing internal mechanics and providing clear, interpretable outputs	• **Data Augmentation Techniques**: Enhance the variety and size of testing datasets by generating synthetic data, over-sampling minority classes, under-sampling majority classes, and injecting noise into data • **Data Labeling and Annotation**: Establish clear guidelines and processes to ensure consistent and accurate data labeling, minimizing labeling biases • **Data Privacy and Security Considerations**: Adhere to data minimization principles, employ anonymization and pseudonymization techniques, and implement strict access controls
Why is this important?	• **Each type of testing** is crucial for identifying and resolving issues early in the development process, reducing the risk of significant failures later on • Bias and fairness testing helps in identifying and **correcting any biased behaviors** in models, promoting **ethical standards** and ensuring **equitable treatment across different demographic or socio-economic groups** • Explainability testing ensures models **do not operate as black boxes**, thus maintaining **transparency**, building user **trust**, and facilitating **compliance**	• **Data Augmentation Techniques**: Help create more robust and varied datasets, which can improve the generalization and performance of AI models, preventing the models from overfitting to limited training data • **Data Labeling and Annotation**: Reduces bias and improves the credibility of model outputs, directly impacting model performance and trustworthiness • **Data Privacy and Security Considerations**: Important for compliance with legal standards, protecting sensitive information, and maintaining public trust in the AI models
What is the actuarial relevance?	• By being **knowledgeable about testing methodologies**, actuaries can better **communicate** with data scientists and technical teams, ensuring comprehensive testing practices are implemented • Consulting with AI/ML experts during explainability testing can help actuaries **design effective guidelines and interpret results** • Actuaries can advocate for **rigorous testing protocols** that align with regulatory requirements, thereby enhancing the **credibility and reliability** of AI-driven decisions.	• Actuaries can advocate for **best practices in data management** within their organizations, promoting high standards for **data collection, processing, and use** in AI models. • Actuaries should implement **quality control measures** such as "human-in-the-loop" systems to verify and enhance data labeling accuracy. Domain experts' involvement is essential, especially for **complex datasets or models**

EVIDENCE OF INSURABILITY (EOI) MODEL VALIDATION: CASE STUDY

The Evidence of Insurability (EOI) Model seeks to streamline the Group Voluntary Life insurance approval process by **identifying low-risk applicants** through a **predictive ML model**, bypassing the traditional EOI underwriting process for accelerated coverage.

	IMPROVE CUSTOMER EXPERIENCE	IDENTIFY "GOOD" RISKS	ACCELERATED UNDERWRITING
☹	The traditional EOI underwriting usually includes **long questionnaires and manual reviews,** causing many applicants to lose interest and abandon their applications	Many low-risk applicants are subjected to the same rigorous EOI underwriting process as higher-risk individuals, which may be **unnecessary and frustrating**.	Manual and paper-based underwriting processes can be **slow** and prone to **human error**.
☺	EOI Model aims to streamline this process, making it **quicker and more user-friendly**, thereby encouraging more applicants to complete their submissions and **enhance overall customer satisfaction**.	The model seeks to **identify low-risk applicants through predictive analytics**, allowing them to obtain coverage without undergoing the EOI process, thus accelerating their access to insurance.	With machine learning, the EOI Model aims to **accelerate underwriting decisions and reduce costs**, allowing underwriters to focus on more complex cases.

EVIDENCE OF INSURABILITY (EOI) MODEL VALIDATION: MODEL AT-A-GLANCE

Feature	Description
Model objective	A **claim incident classification model** to predict the claim probability (target variable)
Model type	Model is an **Extreme Gradient Boost (XGB)** machine learning model
Data description	**Data source**: Internal data from 2016 to 2021 **Features**: Demographics, insurance plan features, historical claims
Data preparation	Data split into **in-sample, out-of-sample, out-of-time datasets** for training and testing
Prediction processing	**Ranking**: Predicted probabilities of incidents are ranked from low to high **Bucketing**: Sorted predictions are assigned to 10 equal-sized buckets
Risk triage	**Fast approval**: Risk Bins 1 to 4 **Standard EOI**: Risk Bins 5 to 10
Implementation	Programming language: **Python**

EVIDENCE OF INSURABILITY (EOI) MODEL VALIDATION: INPUT VALIDATION

	Selected Test Cases	Selected Findings	Recommendations
Input configuration	• The model processes raw data for training • The model processes the treated data frames for feature engineering appropriately • Dataset for generating the is appropriately partitioned into IS/OOS/OOT datasets to ensure that the model generalizes well to new, unseen data • Raw data fields selected for feature engineering are reasonable from an actuarial perspective	1. The model converts "male" to "M" and "female" to "F". However, the current form of checking is risky because the string could be in a different case (e.g. MALE, Male), resulting in an incorrect conversion	1. Before checking for male / female, the code should explicitly force a case on the input
Input controls	• Input data used to train and build the model is validated for accuracy and reliability as part of a review process • The model cleans data to resolve data quality issues such as redundant characters and incorrect data types • There exists exception handling in modelling features • Unit tests are written to ensure coding behaves as expected	1. Column names are defined in *[one function]* and then are renamed again in first line of *[another function]*. Duplicate renaming is not ideal and could lead to data quality control issues 2. The model includes limited unit tests	1. Perform all renaming at once in *[function]* 2. Consider writing unit tests for each method of the *[class function]*. This will help ensure that each part of the code behaves as expected and makes it easier to catch regressions later on
Input dataflow	• Required data fields are created for training from raw data • The model processes data and creates treated data frames in readiness for feature engineering • The treated data frame after feature engineering is output into a file and ready to be passed to the XGBoost model	1. The source tables for target generation appear to be correct, however, no evidence is observed on whether or not the aforementioned tables are ingested in the coding because table names are not observed in the code	1. Provide a clearer audit trail, or a sample of the data files, to demonstrate that the three tables are ingested by the training algorithm

EVIDENCE OF INSURABILITY (EOI) MODEL VALIDATION: CALCULATION VALIDATION

	Selected Test Cases	Selected Findings	Recommendations
Model training and tuning	Evaluate the appropriateness of XGBoost model for the business purpose of this use case in terms of • Rationale for the selection • Alignment with AI guiding principles set by the company • Alignment with Model Risk Management Policy Review the feature selection process: • Transformers (e.g., sklearn for one-hot encoding) are correctly applied across training, OOS, and OOT datasets. • Model features are checked for feature quality, i.e. predictive power and stability across datasets Review the model training process / hyperparameter tuning: • The process and justification for selecting 21 out of 24 model features post-training and tuning, such as using metrics to measure model feature importance • Utilize automated unit tests to ensure model robustness	1. Only 1 year's worth of data is used for testing 2. Error-handling could be enhanced. For example, if the model has not been successfully trained or if the predictions yield probabilities of 0 or 1, this may lead to issues when cutting the range in pd.cut 3. The predicted variable (incident rates) is imbalanced by nature	1. Review the model again in a year with more data. Also, consider using "out-of-person" data with a different risk profile to further test the model on unseen data 2. Consider adding error-handling mechanisms to manage edge cases can prevent runtime errors, e.g. try except blocks 3. While techniques such as applying class weights would help to address the issue of imbalanced data, there are alternative approaches. For example, consider using the outcome of actual / historical underwriting results instead, which is less imbalanced but still a binary outcome

EVIDENCE OF INSURABILITY (EOI) MODEL VALIDATION: OUTPUT VALIDATION

	Selected Test Cases	Selected Findings	Recommendations
Output configuration	• The model is applicable to and underwrites Group Voluntary Life applicants for different Group Term Life insurance products appropriately. • The model reproduces consistent output for the same input across multiple runs and how this is influenced by the tuning process, such as the use of random_state. • Test the model's output with boundary input values or extreme inputs or invalid input values to ensure that the output remains reliable and consistent.	1. There is no evidence of testing the output with boundary or extreme or invalid inputs.	1. As part of testing and monitoring model performance, test cases should be designed to involve boundary or extreme or invalid input values. 2. Furthermore, these test cases should ideally assess how well the model interpolates between unseen data. These test cases could be informed by actual underwriting results in the past that were of similar nature.
Output reasonableness	• The predicted incident rates are broadly aligned with the actual incident rates across the 10 risk bins. • Model outputs are compliant with regulatory standards for underwriting, especially fairness. • Model outputs can be easily interpreted by underwriters, i.e. explainability of model results	1. It can be observed that the predicted rates are broadly aligned with actual incident rates as shown in the Decile Bin Plot for OOS Sample and OOT Sample. However: • Bin 6 in OOS sample shows a relatively large gap between the predicted • Bins 6 - 10 in OOT sample show widening gap between predicted incident rate and actual incident rate. 2. Cross-validation was not performed.	1. The OOS and OOT datasets are re-sampled to repeat the analysis to further assess whether discrepancies are observed for Risk Bins 1 - 4, or widening discrepancies persist for subsequent Risk Bins. 2. Consider performing cross-validation e.g. K-fold cross-validation

THANK YOU