



Society of Actuaries in Ireland

Data Science forum

Ger Bradley (he/him), Chair DS Committee

13th June 2024

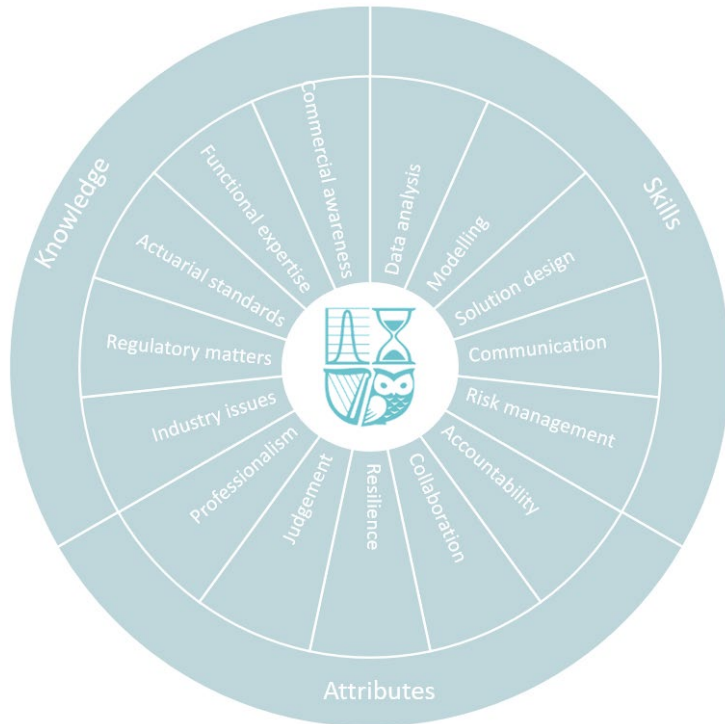


Disclaimer

The views expressed in this presentation and all subsequent presentations today, are those of the presenter(s) and not necessarily those of their employer(s) (if any) or the Society of Actuaries in Ireland.



Competency Wheel



Skills

- Data analysis
- Modelling
- Solution design
- Communication
- Risk management

Attributes

- Accountability
- Collaboration
- Resilience
- Judgement
- Professionalism

Knowledge

- Industry issues
- Regulatory matter
- Actuarial standards
- Functional expertise
- Commercial awareness



SAI Strategy 2024 to 2026 – Areas of Increased Focus





QUOTE OF THE DAY, NEW YORK TIMES, AUGUST 5, 2009

- "I keep saying that the sexy job in the next 10 years will be Data Scientist."
- HAL VARIAN, chief economist at Google.
- Was he right?
- Nearly!



The Actuary (The Calculated Risk #1) by K.T. Bowes | Goodreads

Visit >



2024:Introduction to the current Data Science Committee

1. Ger Bradley (Chair)
2. Bence Zaupper (Deputy Chair)
3. Alan McDonagh
4. Aaron Mcglone
5. Anita Subramani
6. Brian Cunningham
7. Clare Reidy
8. Conor Cronin
9. Dara Roberts
10. Donal McGinley

1. Eilish Bouse
2. Grainne Mcguire
3. Hani Ghulam Abbas
4. Jack Harrington
5. James Bredin
6. Jean Rea
7. Jennifer Loftus
8. Kate Barry
9. Kate Bell
10. Laura Higgins
11. Laura Rossi

1. Luke Gaughan
2. Marian Keane
3. Noman Zafar
4. Octavio Palomo Sanchez
5. Pedro Ecija Serrano
6. Priya Mantri
7. Ramona Dolan
8. Robert Murphy
9. Sinead Heavey
10. Stephen Brennan



Data Science Sub-Committees

1. Regulation and professional Standards (Marian Keane)
2. Communication (Robert Murphy)
3. CPD (Laura Rossi)
4. Study Groups (Bence Zaupper)
5. Newsletter/Blogs (Kate Barry)
6. Consumer Protection and Public Interest (Kate Bell)



First SAI Data Science Newsletter



Society of Actuaries in Ireland *Data Science Committee Newsletter*

May 2024

Introduction

Dear all,

The Data Science sub-committee (as it was originally) was founded with the primary goal of enabling our

A series of sub-groups have been created to achieve this and to ensure that actuaries are recognised for their technical skills and not just business acumen. It is

Moreover, we actively support initiatives aimed at fostering inclusivity and diversity within the data science community. Most notably, committee members have



WIDS: Datathon 2024 Challenge: Equity in Healthcare

Datathon
Impact...

4,000

Competitors

100

Countries

75%

Women

90%

First-Timers

- Sponsor Gilead Sciences
- Rich data on metastatic breast cancer treatment
- Providers, facilities, and patients.
- Objective: to identify possible inequities in patient care
- [The Women in Data Science Dublin Regional Conference](#) (Eventbrite)
- Friday 21st June in UCD.
- Speakers include three members of the SAI community
 - Mary Coghlan (EY); Michelle Aw (Réitigh Software); and Jennifer Loftus Acorn.
- Tickets only €10
- ALL GENDERS ARE WELCOME!!!

Women in
Data Science
Worldwide | Dublin

Conference

📍 UCD, DUBLIN

📅 21 JUNE, 2024

🕒 9:00AM

[REGISTER NOW](#)

#WiDSDublin2024



Agenda

Title	Company	Speakers
Intro	DS Comm Chair	Ger Bradley
(Introduction to) The EU AI Act – New opportunities for actuaries in the second-line?	Forvis Mazars	Gary Stakem, David O’Sullivan
A Day in the life of an Actuary with AI co-pilots	KPMG	Jean Rea, Stephen Brennan, Tomasz Gagola, Iliana Simova
Insurance Claims Fraud Detection using Machine Learning and Deep Learning AI models	Deloitte	Graham Crowley, Dr.Pranav Sai S R
Transforming L&H Underwriting & Claims with Gen AI – where do we stand?	SCOR	Vicky Gardner, Antoine Ly, Pierre Gilloury
		Coffee
A game of two halves: similarities and differences between ‘old’ AI and GenerativeAI”	WTW	Arlen Galicia Carreon, Vatsal Gomber
Looking back to look forward: Data Science and AI’s role in the Health sector”	EY	Mary Coughlan, Luke Gaughan
Results of survey and comparison to South Africa	DS Comm	Kate Bell
Panel Discussion	President Elect TUD KPMG Deloitte Freelance	Roz Briggs Prof Sarah Jane Delany Jean Rea Brendan Guckian Pedro Ecija Serano



Society of Actuaries in Ireland

The AI Act – Opportunities for Actuaries in the Second-Line

Gary Stakem (he/him) – Forvis Mazars

David O'Sullivan (he/him) – Forvis Mazars

13 June 2024



“Actuaries should be really excited about becoming compliance officers”





Who will champion innovation?



Risk

Compliance

Internal
Audit

External
Audit

Boards

Regulators



The compliance function will need diverse skills

Compliance &
legal skills

Consumer
protection
knowledge

Coding &
machine
learning

Cyber security

Actuarial
science

Commercial
nous

Business &
economic
environment

Holistic
insurance
management

Project
management
& influence



Actuaries can enable well governed AI

Risk

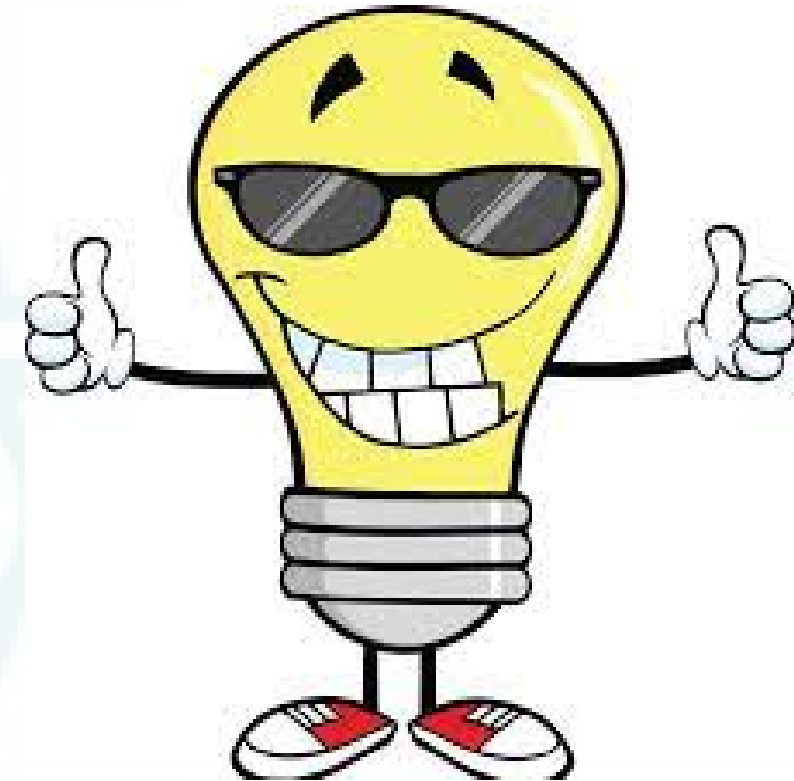
Compliance

Internal
Audit

External
Audit

Boards

Regulators





AI Act – Risk Management Systems

Prohibited

High Risk

Limited Risk

Minimal Risk

Chapter III Section II: Requirements for High-Risk AI Systems (Articles 8 to 15)

- Art 9 – Risk Management Systems
- Art 10 – Data and Data Governance
- Art 14 – Human Oversight
- Art 15 – Accuracy & Robustness



The Compliance Actuary requires a broad skillset

Know related regulation

GDPR | Solvency II | Insurance
Distribution Directive | DORA |
Digital Services Act | Consumer
Protection Code | Differential Pricing

Learn Coding & ML Fundamentals

Python, R, SQL | ML models &
architecture | XAI techniques

Influence & Communication

Understand risk & compliance frameworks

Compliance management | Data
protection principles | Cybersecurity
fundamentals

Develop broad stakeholder relationships

Sales | Underwriting | IT | Risk |
Legal | Compliance | Claims



Actuaries can enable well governed AI

Risk

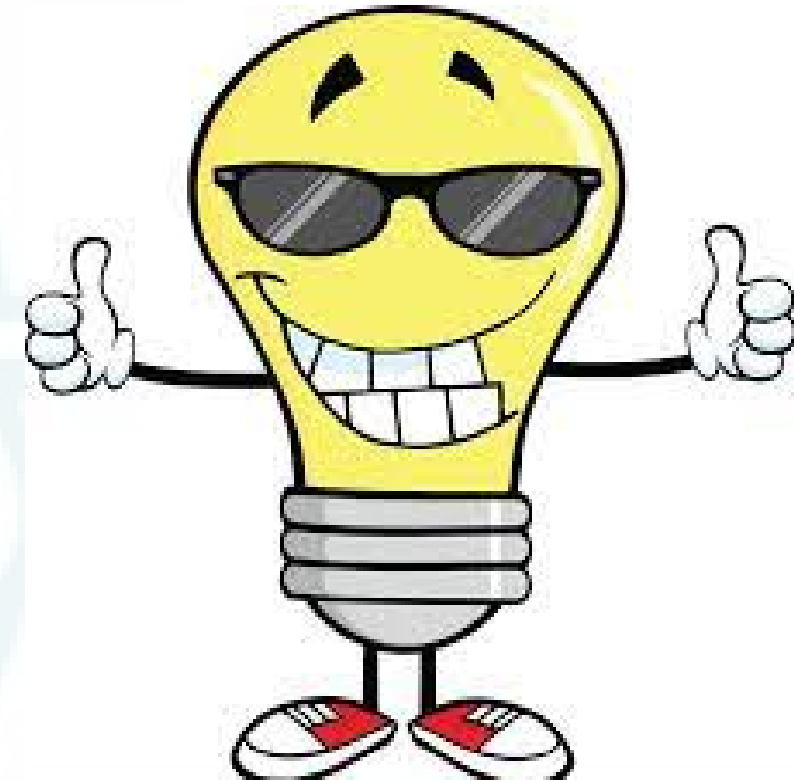
Compliance

Internal
Audit

External
Audit

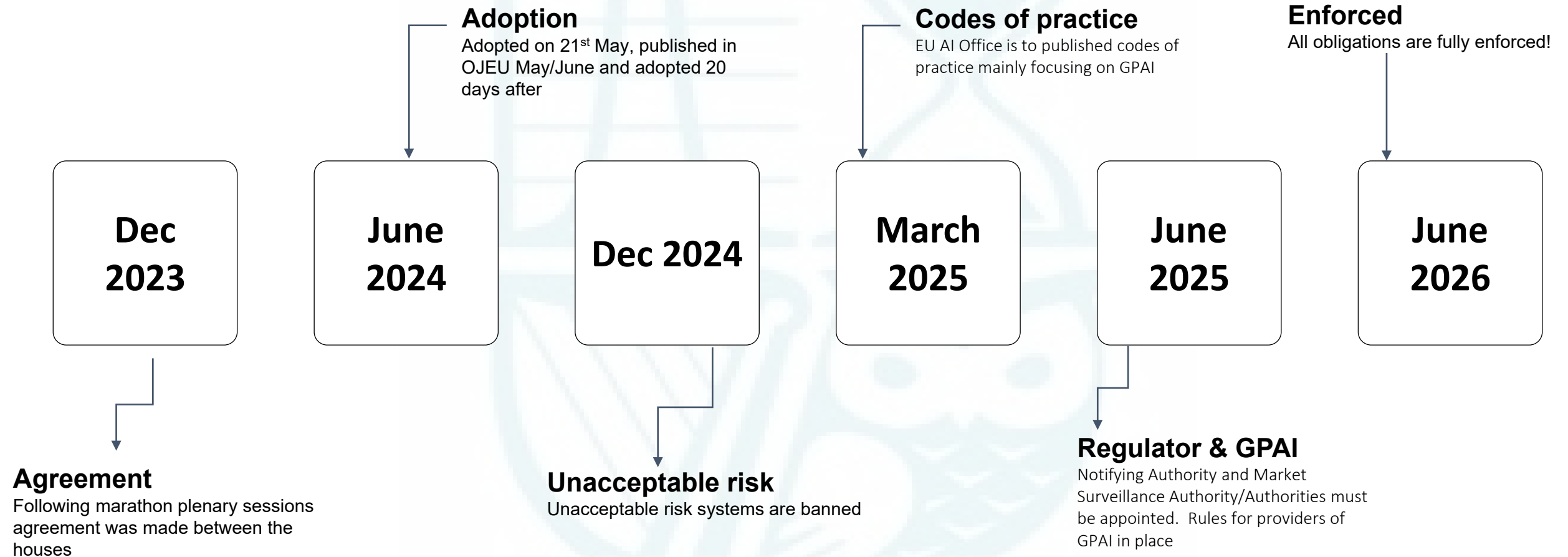
Boards

Regulators



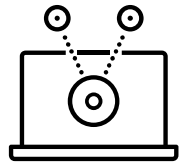


The AI Act

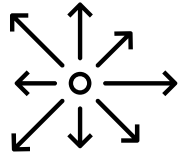




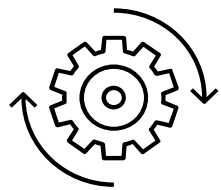
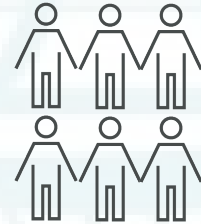
Roles under the Act



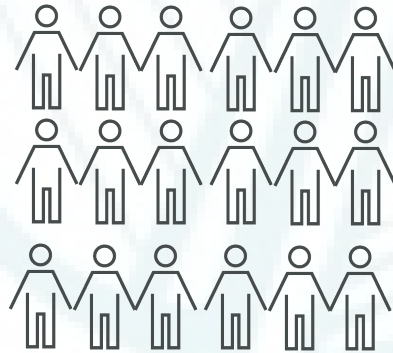
Providers



Distributors



Operators





AI risk levels

Unacceptable risk

- Banned AI systems
- Includes systems that deploy subliminal techniques beyond a persons consciousness to distort behaviour or make decisions.
- Exploit vulnerabilities, infer emotions

High risk

- Listed in Annex III of the Act.
- Large amount of obligations
- Conformity test needed
- Includes credit assessments, **insurance pricing**, HR practices etc.

Limited risk

- Includes generative AI systems such as ChatGPT
- Also includes general purpose AI, or systems that may have a systemic risk on society
- Transparency and management requirements

Minimal risk

- Every other AI system
- No real obligations
- Monitor the system to ensure it does not adapt and fall into another category



High risk AI systems

High risk

- Listed in Annex III of the Act.
- Large amount of obligations
- Conformity test needed
- Includes credit assessments, **insurance pricing**, HR practices etc.



Biometrics



Employment



Judicial system



Critical infrastructure



Public & private services



Migration



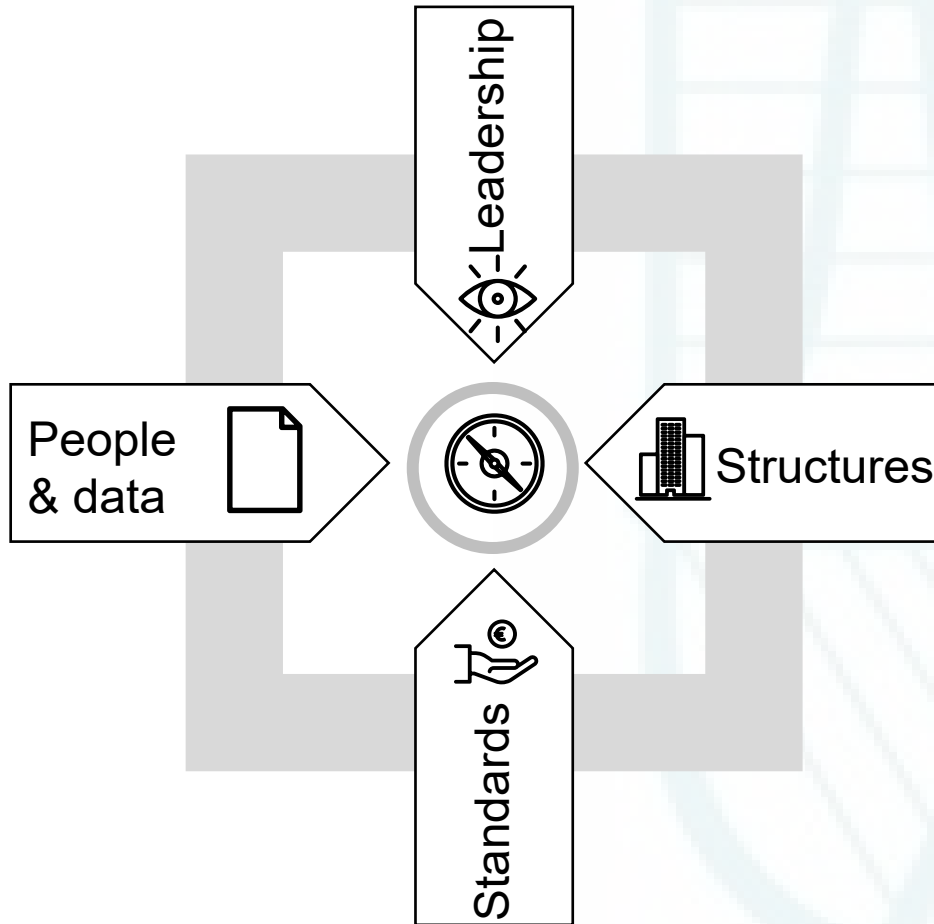
Education



Law enforcement

risk assessment and pricing in relation to natural persons in the case of life and health insurance

Next steps



Act Fast

Move Slowly



Q&A

Please raise your hand to ask a question,
and wait for a mike to get to you



Society of Actuaries in Ireland

A day in the life of an actuary with AI copilots

Jean Rea (she/her), Iliana Simova (she/her)

& Stephen Brennan (he/him)

13/06/2024



With you today



Jean Rea

Partner, Consulting

jean.rea@kpmg.ie



Jean Rea
Partner at KPMG Ireland



Iliana Simova

Manager, Data Science

iliana.simova@kpmg.ie



Iliana Simova
Data Scientist | Natural Language
Processing



Stephen Brennan

Manager, Actuarial

stephen.a.brennan@kpmg.ie



Stephen Brennan
Non-Life Actuary



A day in the life of an Actuary with AI copilots

- Integration of AI into our daily work
- In-house AI tools
- Q&A

Integration of AI into our daily work













Demonstration - Context

- Request to develop an expert judgement log template.
- Template must meet the Central Bank's expectations

Urgent: Completion of Internal Task and Project Overview: Client X Summarize

 Khodake, Saurabh
To  Brennan, Stephen

24/05/2024

Dear Team,

I hope this message finds you well. Before we delve into the details of our new project, I would like to remind everyone to complete the pending internal task related to our quarterly review. This task is of utmost importance and requires immediate attention.

Now, let's move on to our new endeavor involving a potential client, referred to as Client X for confidentiality purposes. Client X, a financial institution of considerable repute, operates within a complex regulatory environment.

We have been entrusted with several significant tasks, each of which is crucial to the success of our project:

1. **Expert Judgement Log**: Develop a template for the Expert Judgement Log that aligns with the guidelines issued by the regulatory authority. This document is a critical part of actuarial documentation and must be user-friendly, easy to comprehend, and designed in such a way that it can be easily updated and maintained by Client X's team.
2. **Risk Assessment**: Conduct a comprehensive risk assessment of Client X's current operations. This will involve identifying potential risks, assessing their impact, and developing strategies to mitigate them.
3. **Regulatory Compliance Review**: Carry out a thorough review of Client X's compliance with existing regulations. This will involve examining their current policies and procedures, identifying any areas of non-compliance, and recommending necessary changes.



Step 1 – Identify and summarise the task

Activity

Chat

Teams

Calendar

Calls

OneDrive

Copilot

...

Apps

Search

New chat

Copilot

For Microsoft 365

- What's new?**
What's the latest from person , organised by emails, chats and files?
- Track your tasks**
What should be on my radar from emails last week?
- Don't miss out**
Summarise Teams messages where I was @mentioned this week.
- Get calendar info**
When's my next meeting with person ?
- Understand quickly**
Provide a comprehensive summary of my emails about [the FY24 Sales Report]
- Decode acronyms**
What does [LLM] stand for?

View prompts

Use / to insert people, files and more



Step 2 – Understand the expectations

Copilot

Your everyday AI companion

Can you summarise the Central Bank of Ireland's expectations with regards to expert judgement logs?

Commercial data protection applies to this chat.



Step 3 – Draft the Expert Judgement Log

AutoSave Off Document1 - Word Search Brennan, Stephen BS

File Home Insert Draw Design Layout References Mailings Review View KIDS Help Acrobat

Clipboard Font Paragraph Styles Editing Voice Add-ins Editor Copilot KIDS Styles

Page 1 of 1 0 words English (Ireland) Text Predictions: On Accessibility: Good to go Display Settings Focus 110%



Result

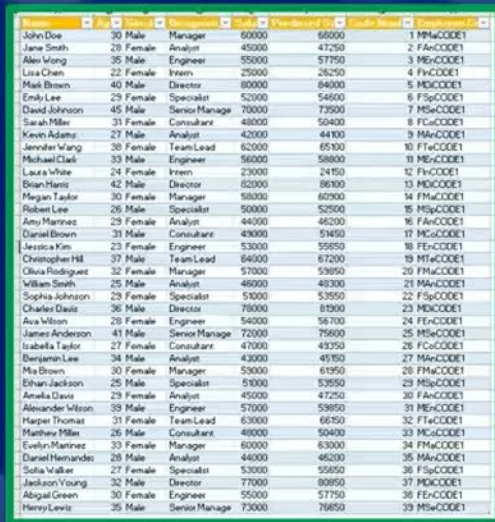
Client X – Expert Judgement Log

ID	Description	Owner/ Approver	Rationale	Validation	Materiality/ Sensitivity	Subjectivity/ Uncertainty
EJ-001	Selection of mortality assumptions for annuity business	John Smith	Based on industry experience and best practice	Compared with external benchmarks and peer companies	High materiality and low sensitivity	Low subjectivity and low uncertainty
EJ-002	Adjustment of lapse rates for unit-linked business	Jane Doe	Based on historical data and expected trends	Back-tested with actual experience and scenario analysis	Medium materiality and medium sensitivity	Medium subjectivity and medium uncertainty
EJ-003	Estimation of expense inflation for long-term business	John Smith	Based on economic forecasts and company budget	Reviewed by senior management and external auditor	Low materiality and high sensitivity	High subjectivity and high uncertainty

In-house AI tools

Excel Analysis Demo Overview

Excel
Spreadsheet



Employee	Age	Gender	Role	Salary	Target	Code
John Doe	30	Male	Manager	60000	60000	1 MNA0001
Jane Smith	28	Female	Analyst	45000	47250	2 FA00001
Alex Wong	35	Male	Engineer	55000	57750	3 ME00001
Lisa Chen	22	Female	Intern	25000	26250	4 FV00001
Mark Brown	40	Male	Director	80000	84000	5 MD00001
Emily Lee	29	Female	Specialist	52000	54600	6 FSp0001
David Johnson	45	Male	Senior Manage	70000	73500	7 MS00001
Sarah Miller	31	Female	Consultant	48000	50400	8 FC00001
Kevin Adams	27	Male	Analyst	42000	44100	9 MA00001
Jennifer Wang	38	Female	Team Lead	62000	65100	10 FT00001
Michael Clark	33	Male	Engineer	56000	58800	11 ME00001
Laura White	24	Female	Intern	23000	24150	12 FV00001
Brian Harris	42	Male	Director	82000	86100	13 MD00001
Megan Taylor	30	Female	Manager	58000	60900	14 FM00001
Robert Lee	26	Male	Specialist	50000	52500	15 MSp0001
Amy Martinez	29	Female	Analyst	44000	46200	16 FA00001
Daniel Brown	31	Male	Consultant	49000	51450	17 MC00001
Dorissa Kim	23	Female	Engineer	53000	55650	18 FE00001
Christopher Hill	37	Male	Team Lead	64000	67200	19 MTA0001
Olivia Rodriguez	32	Female	Manager	57000	59850	20 FM00001
William Smith	25	Male	Analyst	46000	48300	21 MA00001
Sophia Johnson	29	Female	Specialist	51000	53550	22 FSp0001
Charles Davis	36	Male	Director	78000	81900	23 MD00001
Ava Wilson	28	Female	Engineer	54000	56700	24 FE00001
James Anderson	41	Male	Senior Manage	72000	75600	25 MS00001
Isabella Taylor	27	Female	Consultant	47000	49350	26 FC00001
Benjamin Lee	34	Male	Analyst	49000	49500	27 MA00001
Mia Brown	30	Female	Manager	59000	61950	28 FM00001
Ethan Jackson	25	Male	Specialist	51000	53550	29 MSp0001
Ariella Davis	29	Female	Analyst	45000	47250	30 FA00001
Alexander Wilson	39	Male	Engineer	57000	59850	31 ME00001
Harper Thomas	31	Female	Team Lead	63000	66750	32 FT00001
Matthew Miller	26	Male	Consultant	48000	50400	33 MC00001
Evelyn Martinez	33	Female	Manager	60000	63000	34 FM00001
Daniel Hernandez	28	Male	Analyst	44000	46200	35 MA00001
Sofia Walker	27	Female	Specialist	52000	54600	36 FSp0001
Jackson Young	32	Male	Director	77000	80850	37 MD00001
Abigail Green	30	Female	Engineer	55000	57750	38 FE00001
Henry Lewis	35	Male	Senior Manage	73000	76650	39 MS00001



Python code



Visualisations



Flowcharts



Analysis



Description



Excel to Python conversion with Generative AI



Inputs

- ✓ Excel workbook containing model across multiple sheets
- ✓ Configuration file specifying expected input and output variable sheet locations and names manually compiled by user
- ✓ Unique name for the model (default model name taken from excel file path)

Outputs

- ✓ Python script that executes original excel model with named input and output variables for understanding
- ✓ Configuration file of input variables in JSON format with default variable values taken from original excel model
- ✓ Static reference tables used in model calculations saved separately to a csv file
- ✓ Automatic unit testing of generated python script to check its performance using original excel model parameters

Q&A

Please raise your hand to ask a question, and wait for a mike to get to you



Society of Actuaries in Ireland

Data Driven Claims Fraud Detection
using Machine Learning and Deep Learning
Speakers - Graham Crowley, Pranav Sai S R

13th June 2024



About the Speakers

Graham Crowley – FSAI, CERA



Email: gcrowley@deloitte.ie

Contact: +353 1 417 2381

- Qualified Actuary with over 19 years' experience in the Irish non-life insurance industry.
- Prior to joining Deloitte in June 2022, Graham held senior actuarial and executive roles in Allianz Ireland.
- Specialises in Audit, Assurance and Advisory related work, focusing on Reserving, Capital Management, Reinsurance, Data Analytics, Claims Transformation and Solvency II.



About the Speakers

Dr S.R.Pranav Sai – PhD Actuarial Science



Email: psai@deloitte.ie

Contact: +353 1 417 3254

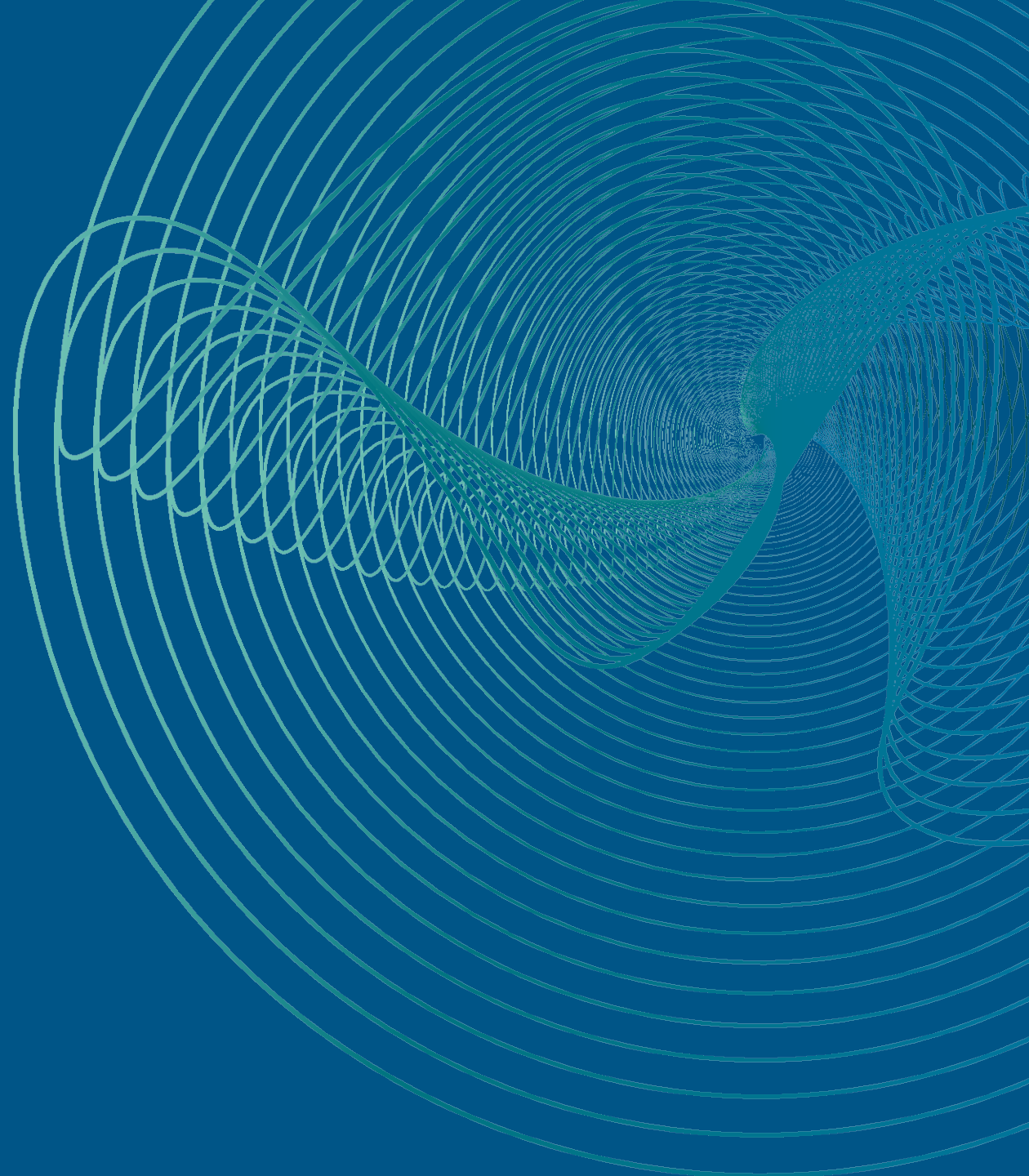
- Part qualified actuary with over 4 years of actuarial experience. Joined Deloitte Actuarial Modelling Centre (AMC) in July 2022.
- Specialises in:
 - Programming Languages – Python, R, VBA, C, SAS
 - Tools & Platforms – Power BI, Power Automate, AWS
 - Methodologies – Machine Learning, Deep Learning
- Have 7 research papers, 3 international conference presentations and 1 book chapter to my credit.



Agenda

- Background to Insurance Fraud
- Challenges in Insurance Fraud Detection
- Fraud Detection Architecture
- Fraud Model POC

Background to Insurance Fraud





Loss due to Insurance Fraud

Irish Market

Loss of €200 Million annually in Ireland

Every Motor insurance customer pays €50 extra to pay for fraud claims.

Sources: The Irish Times (24th Oct 2023)

US Market

Detected Fraud

US\$ 34 Billion

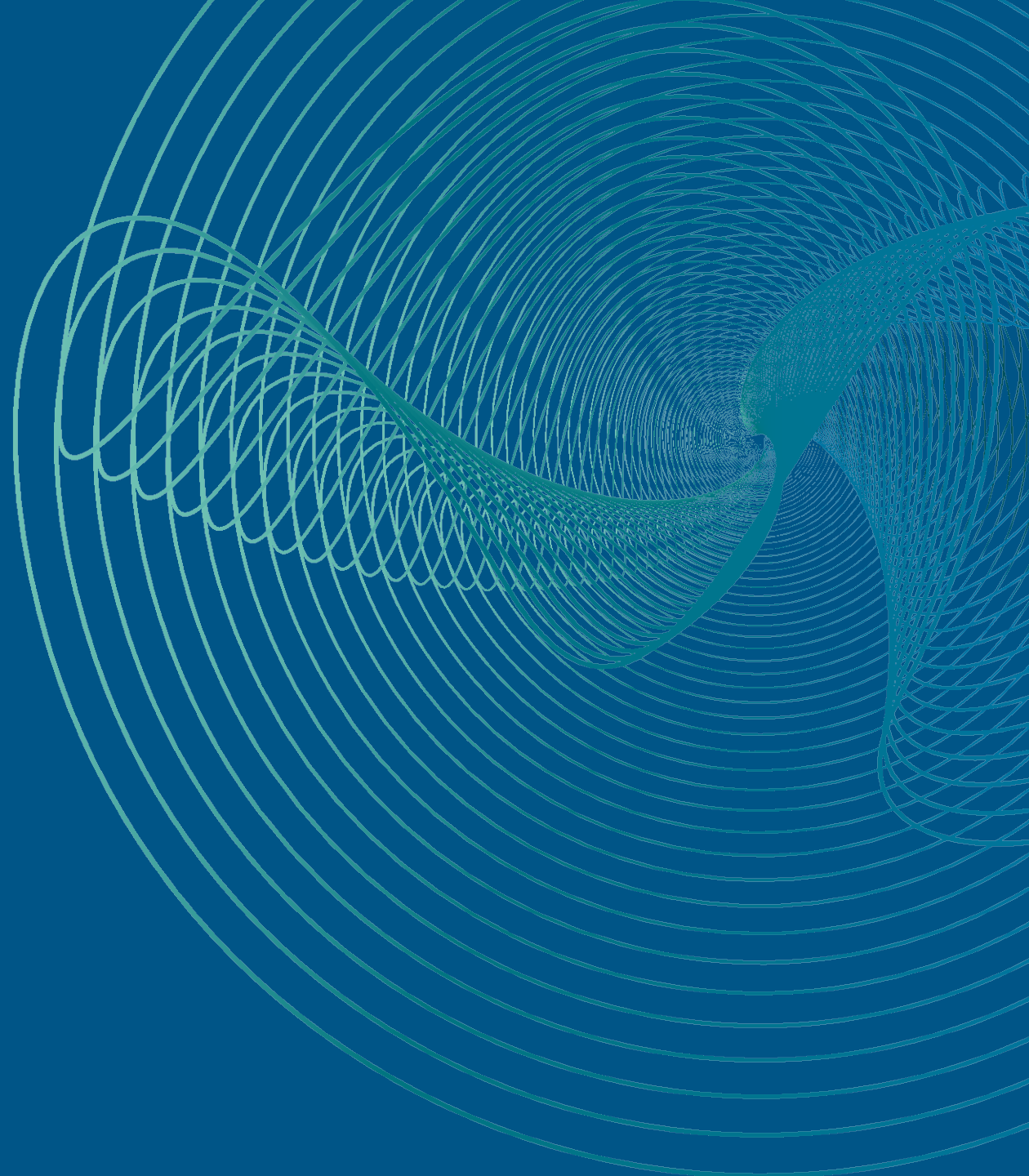
Investigated Claims

Total Claims US\$ 340 Billion

Undetected Fraud

Sources: 2022 Fraud USA Statistics from Coalition Against Insurance Fraud

Challenges in Insurance Fraud Detection





Major challenges in data-driven approach

1. Availability of the data
2. Data imbalance
3. Identifying appropriate classification model
4. Business interpretation



Availability of the data

Not easy to get access to the insurance data at an industry level

Public data not suitable for fraud detections

Confidentiality of user information

Angoss Software Knowledge Seeker (Australia)

- Automobile insurance – Claims data
- 15,420 records
- 6% fraudulent claims
- 32 features

Automobile Insurance Data (French)

- Claims data
- 27 features
- 150,000 records
- 2% fraudulent claims



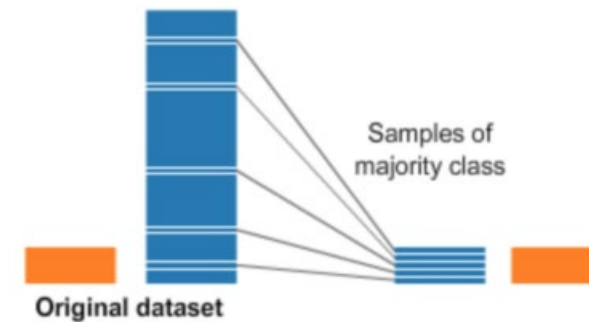
Data Imbalance

Less number of fraudulent claims compared to non-fraudulent claims

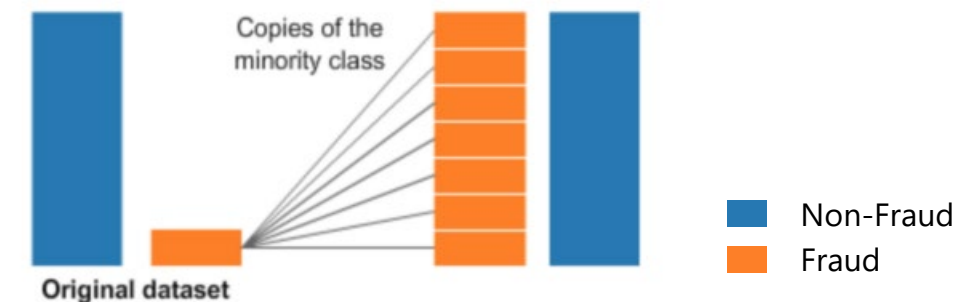
Skewed nature of the dataset results in the bias during training

High accuracy could be deceptive

Undersampling



Oversampling



- Ali, A., Shamsuddin, S. M., & Ralescu, A. L. (2013). Classification with class imbalance problem. *Int. J. Advance Soft Compu. Appl*, 5(3).
- Mellor, A., Boukir, S., Haywood, A., & Jones, S. (2015). Exploring issues of training data imbalance and mislabelling on random forest performance for large area land cover classification using the ensemble margin. *ISPRS Journal of Photogrammetry and Remote Sensing*, 105, 155-168.



Identifying appropriate classification model

Efficacy of the classification model could differ with the datasets used and the line of business

Choose classification models which brings explainability



Business interpretation



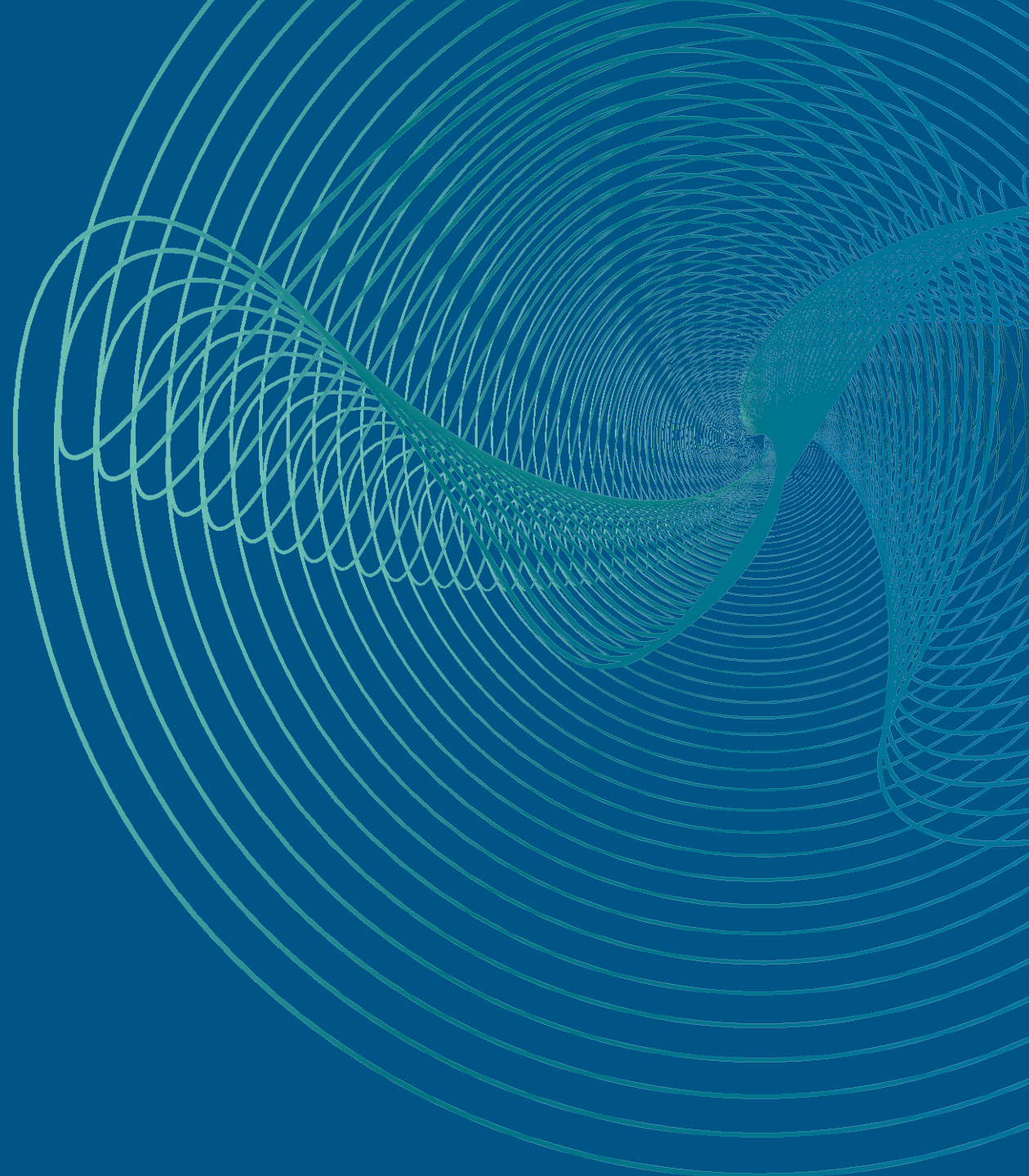
Certain questions that needs to be addressed

- How can I trust your model?
- How does the model make its decisions?

Model Interpretability Vs Model Performance trade-off

Source: Johansson U, Sönströd C, Norinder U, Boström H. Trade-off between accuracy and interpretability for predictive in silico modeling. *Future Med Chem.* 2011 Apr;3(6):647-63. doi: 10.4155/fmc.11.23. PMID: 21554073.

Fraud Detection Architecture





Approach to developing a Data-Driven fraud model

Objectives

Define a Framework for fraud prevention and detection

Identify best-suited model for a given LoB

Build a product for insurance fraud classification

Define a Framework for fraud prevention and detection in insurance business using actuarial and data science techniques

A comprehensive study of the performance of various fraud detection models on different lines of insurance business, and indicating the best-suited model for a given line of insurance business

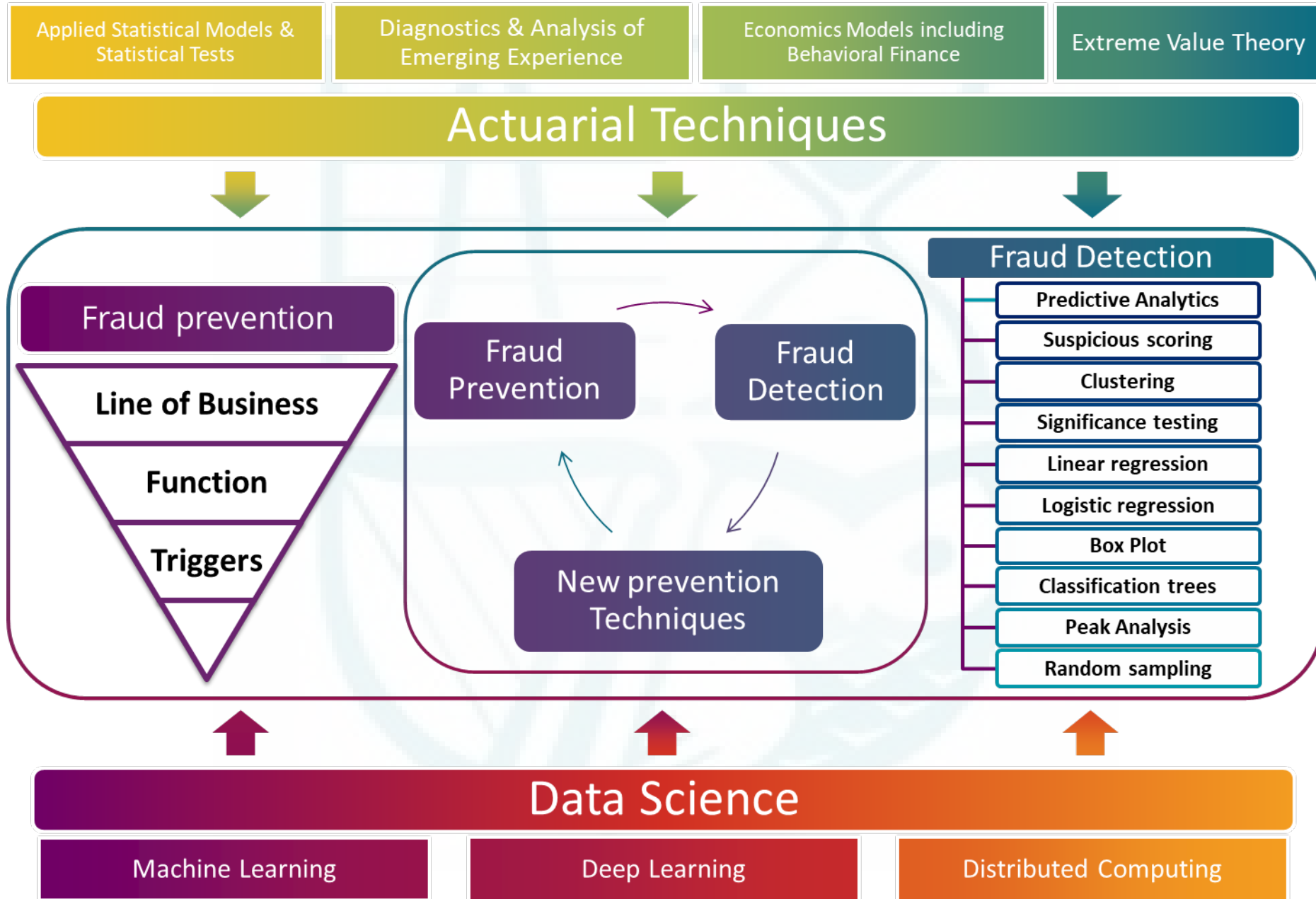
Build an Insurance Fraud Classifier using open-source languages (Python/R)

Scope of Work

Non-Life

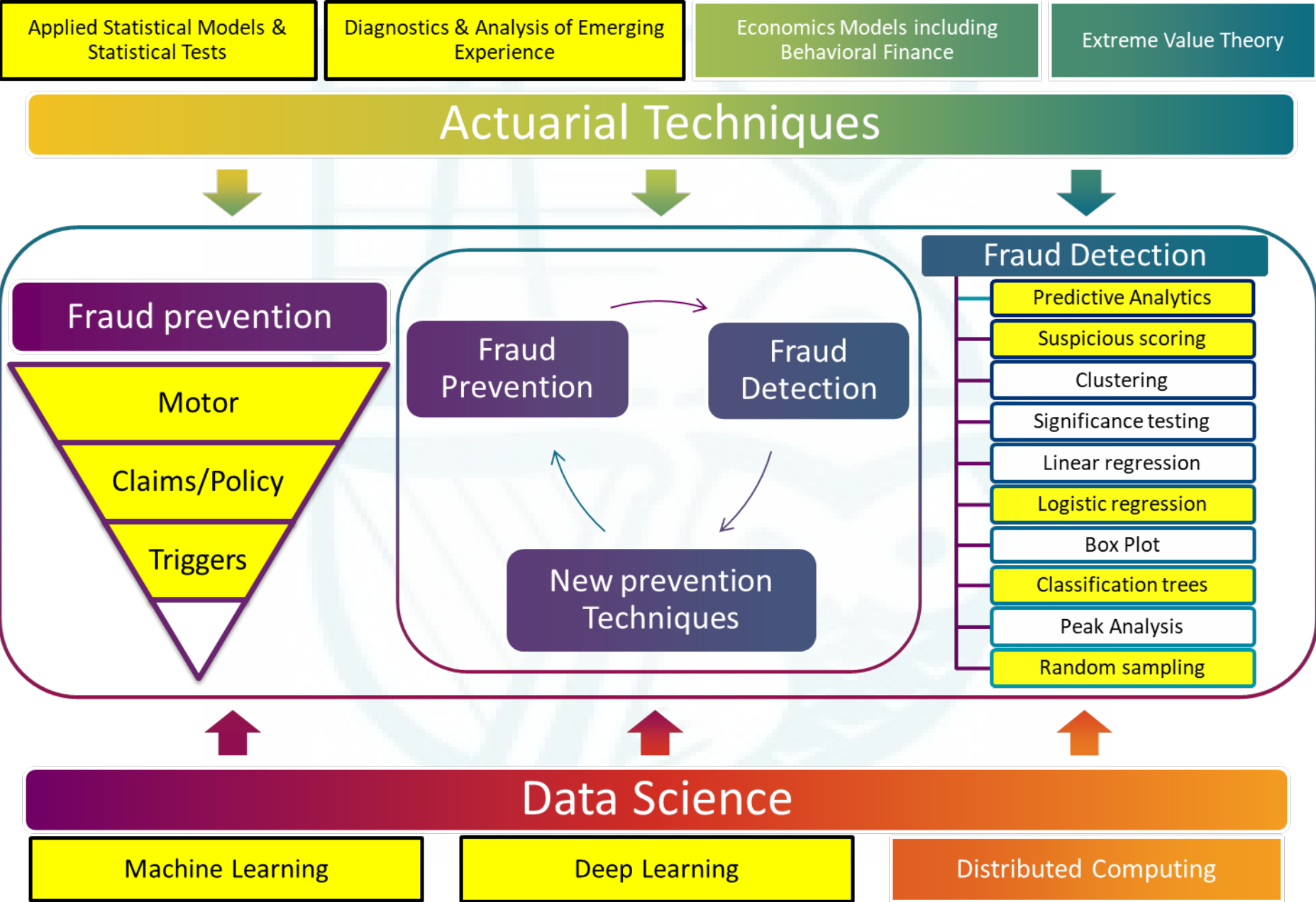


Customer/Provider Fraud Prevention and Detection Framework

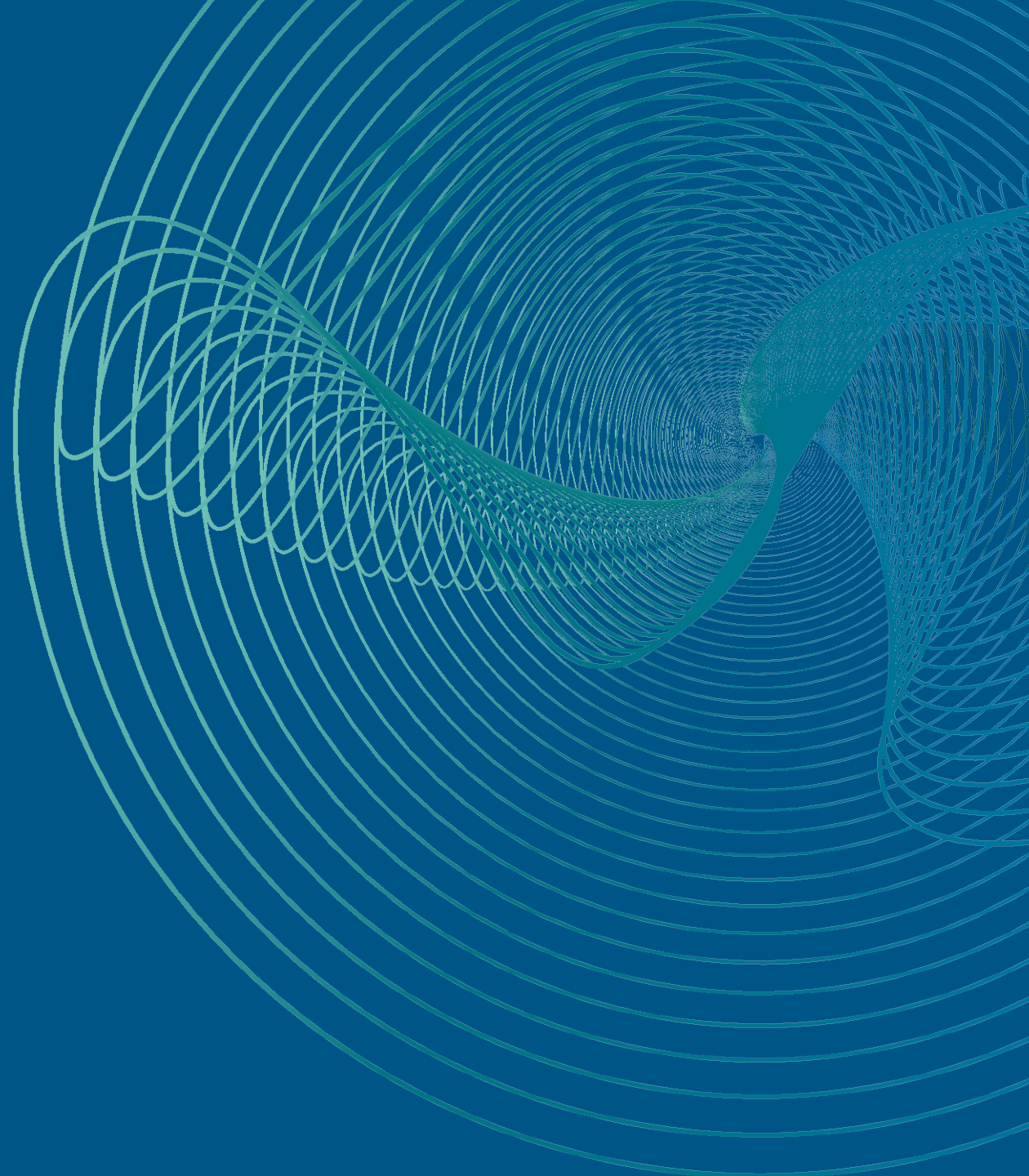




Customer/Provider Fraud Prevention and Detection Framework

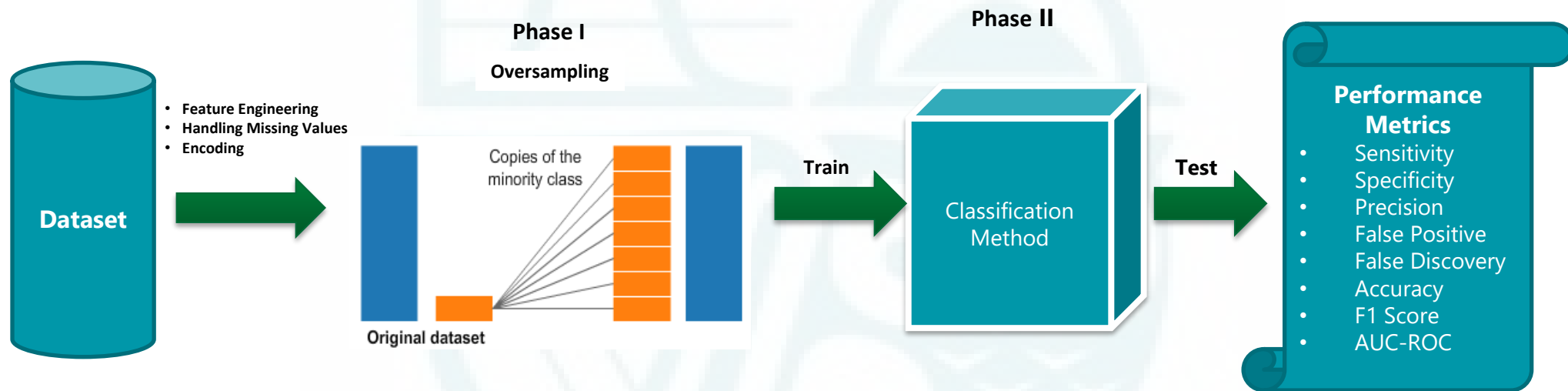
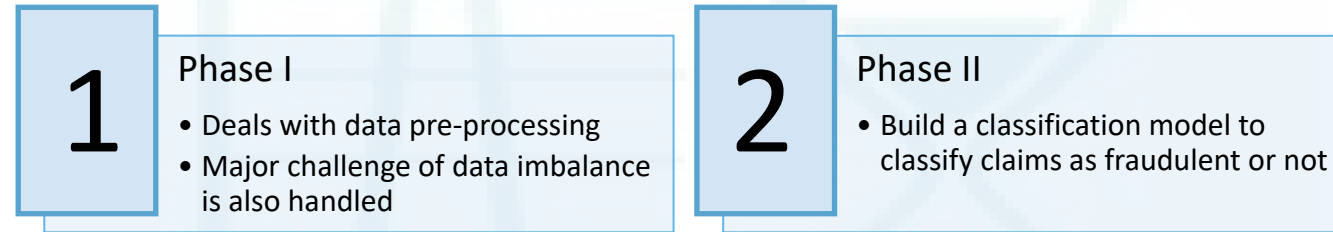


Fraud Model POC





The Two-phased method



The goal is to find a golden combination of a technique in Phase I and a specific model in Phase II for assured best performance of a Fraud Detection Model



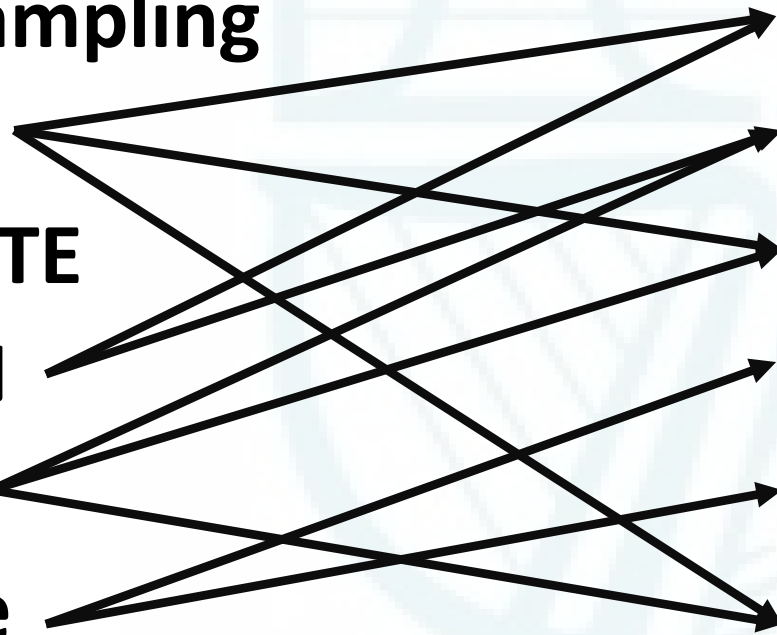
Flexibility of the Two-phased method

Phase I

- **Undersampling**
- **SMOTE**
- **MWMOTE**
- **ADASYN**
- **TGANs**
- **Baseline**

Phase II

- **Gradient Boosting**
- **Decision trees**
- **Random forests**
- **XGBoost**
- **LightGBM**
- **Neural Networks**





Results

	Models	AUC-ROC	Sensitivity	Specificity	Precision	Accuracy	F1 Score
Decision Tree	Baseline	0.9566	0.9248	0.9885	0.9174	0.9808	0.9211
	SMOTE	0.9534	0.9208	0.9860	0.9006	0.9781	0.9106
	ADASYN	0.9508	0.9155	0.9862	0.9016	0.9776	0.9085
	TGANs	0.9548	0.9214	0.9883	0.9155	0.9801	0.9185
Random Forest	Baseline	0.9462	0.8947	0.9977	0.9818	0.9852	0.9362
	SMOTE	0.9493	0.9027	0.9959	0.9682	0.9846	0.9343
	ADASYN	0.9500	0.9057	0.9942	0.9556	0.9834	0.9300
	TGANs	0.9460	0.8942	0.9977	0.9820	0.9852	0.9361
XGBoost	Baseline	0.9307	0.8615	0.9999	0.9989	0.9831	0.9252
	SMOTE	0.9458	0.8970	0.9945	0.9572	0.9826	0.9262
	ADASYN	0.9270	0.9835	0.8705	0.5119	0.8842	0.6733
	TGANs	0.9111	0.8223	1.0000	1.0000	0.9784	0.9025
LightGBM	Baseline	0.9486	0.8977	0.9994	0.9952	0.9871	0.9440
	SMOTE	0.9499	0.9014	0.9988	0.9905	0.9869	0.9438
	ADASYN	0.9523	0.9105	0.9940	0.9547	0.9839	0.9320
	TGANs	0.9482	0.8970	0.9994	0.9950	0.9870	0.9435
GBM	Baseline	0.9425	0.8852	0.9997	0.9975	0.9858	0.9380
	SMOTE	0.9451	0.8958	0.9945	0.9576	0.9825	0.9257
	ADASYN	0.9288	0.9779	0.8796	0.5288	0.8916	0.6864
	TGANs	0.9282	0.8566	0.9992	0.9992	0.9224	0.9224
Neural Networks	Baseline	0.9406	0.8826	0.9986	0.9885	0.9845	0.9325
	Weighted	0.9557	0.9418	0.9644	0.7852	0.9617	0.8564
	Undersampled	0.9525	0.9374	0.9676	0.9663	0.9526	0.9516
	SMOTE	0.9496	0.9533	0.9459	0.7087	0.9468	0.8130
	ADASYN	0.9389	0.9822	0.8955	0.5650	0.9061	0.7173
	TGANs	0.9392	0.8795	0.9989	0.9908	0.9844	0.9318



Fraud detection model validation

↑ \square *Sensitivity* = $\frac{\text{Fraud claims identified as fraud}}{\text{Total fraud claims (actual)}} = \frac{TP}{P} = \frac{TP}{TP+FN}$

↑ \square *Specificity* = $\frac{\text{Non-fraud claims identified as nonfraud}}{\text{Total non-fraud claims (actual)}} = \frac{TN}{N} = \frac{TN}{TN+FP}$

↑ \square *Precision* = $\frac{\text{Fraud claims identified as fraud}}{\text{Total claims identified as fraud by the model}} = \frac{TP}{TP+FP}$

↓ \square *False Positive Rate* = $\frac{\text{Non-fraud claims identified as fraud}}{\text{Total non-fraud claims (actual)}} = \frac{FP}{N} = \frac{FP}{FP+TN}$

↓ \square *False Discovery Rate* = $\frac{\text{Non-fraud claims identified as fraud}}{\text{Total claims identified as fraud by the model}} = \frac{FP}{FP+TP}$

↑ \square *Accuracy* = $\frac{\text{Total correct predictions both fraud and nonfraud}}{\text{Total claims}} = \frac{TP+TN}{P+N}$

↑ \square *F1 Score* = $\frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2TP}{2TP+FP+FN}$



Fraud Detection Tool





Questions

Please raise your hand
to ask a question, and
wait for a mike to get to
you



Thank You



Society of Actuaries in Ireland

Transforming Life & Health underwriting & claims with generative AI

Antoine Ly, Chief Data Science Officer, SCOR

Vicky Gardner, Head of Life & Health Data Analytics Solutions, SCOR

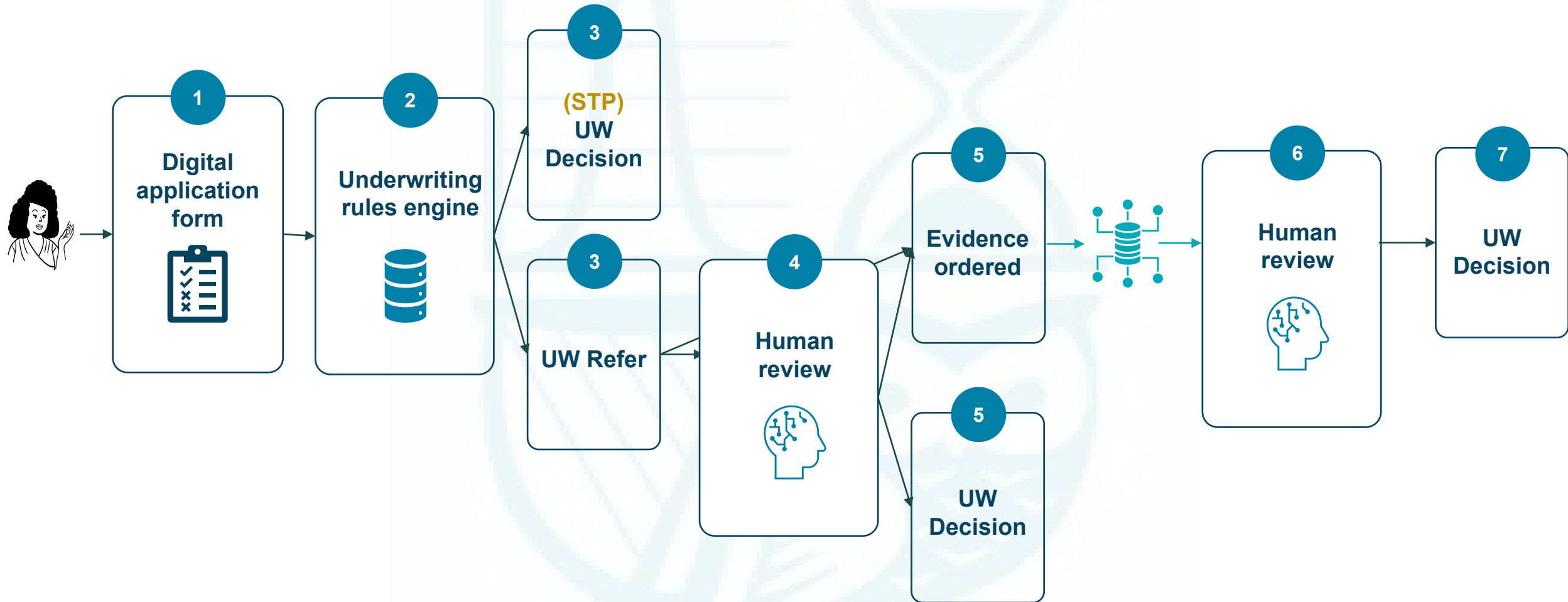
13 June 2024

Current underwriting process



Underwriting journey

Majority of applicants are straight-through processed but ~30% need human review

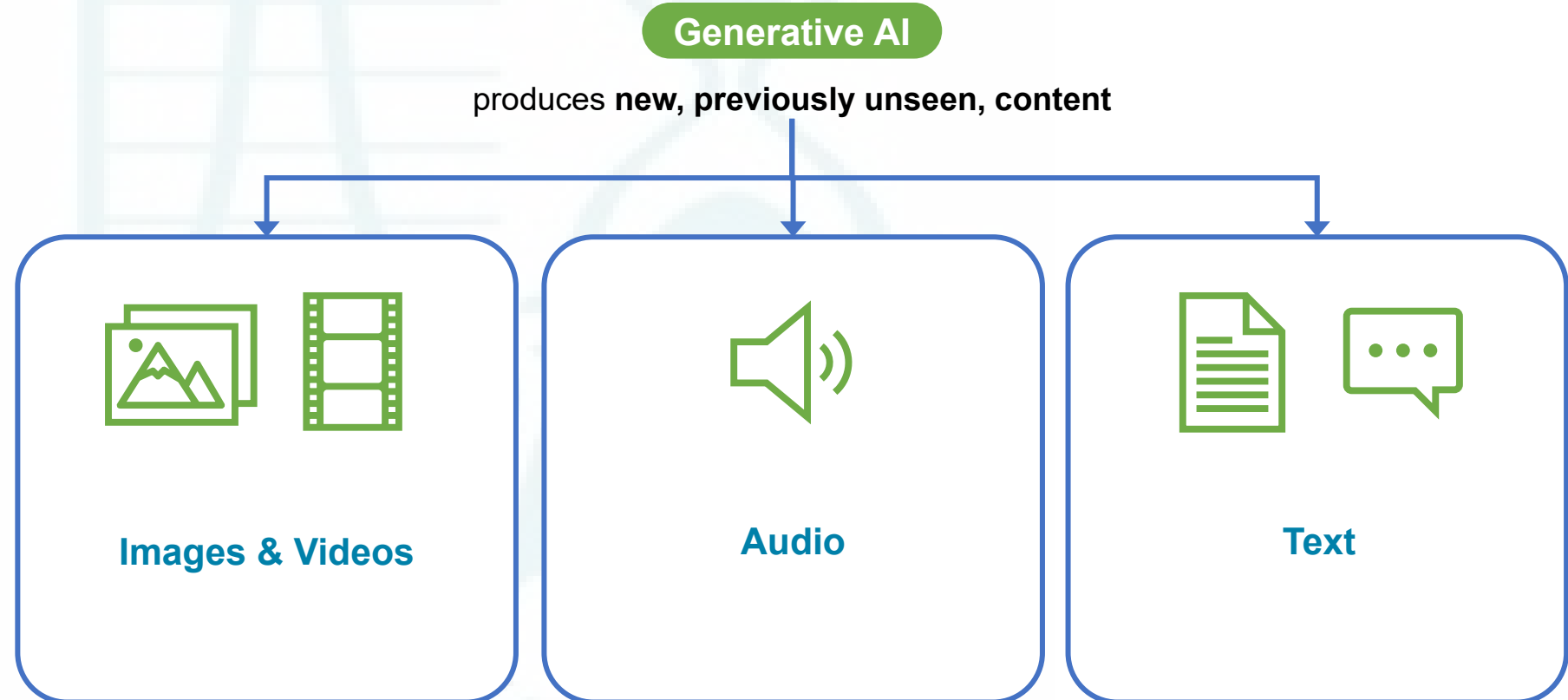
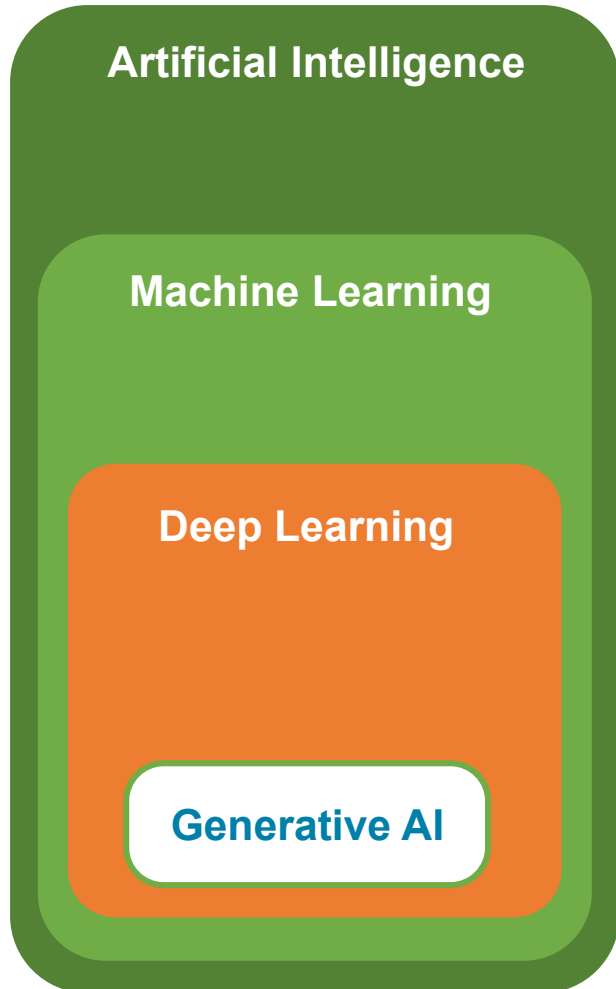


What is Generative AI (Gen AI)?



Context

The launch of Open AI's Chat GPT in November 2022 has highlighted the huge potential of Gen AI across a wide range of tasks



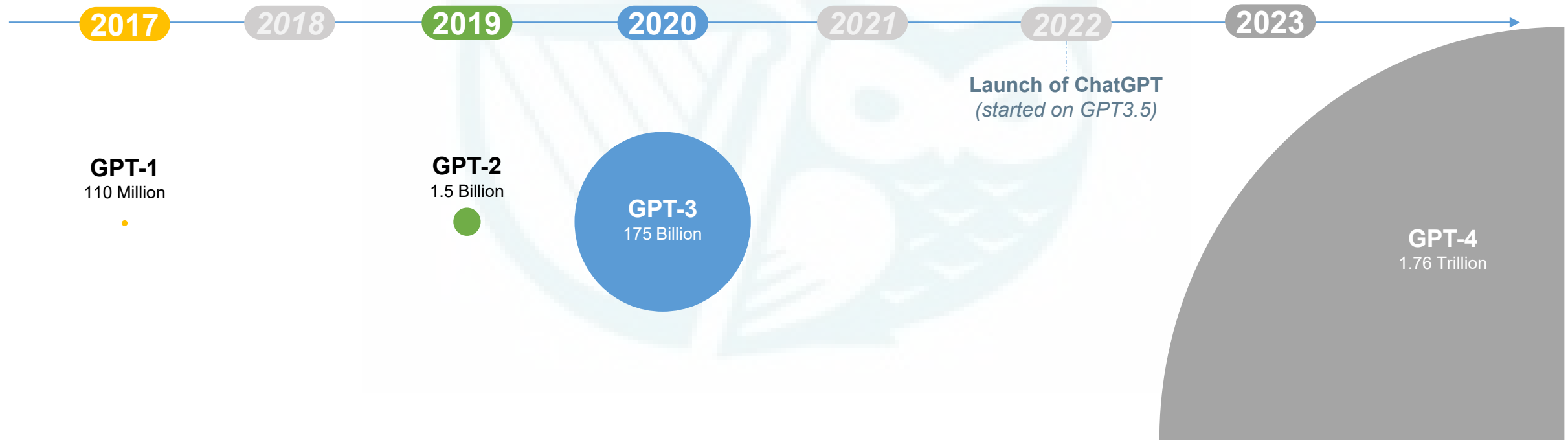


Context

Text is one of the main use cases today, propelled by ever-growing computing power and large language models (LLMs)

The models are not new – but the tech is now mature enough to turn them into truly powerful solutions, based on a wide range of parameters

Number of parameters of Open AI's GPT models





Context

Gen AI has the potential to power several use cases in the life & health (re)insurance industry, across the whole customer journey

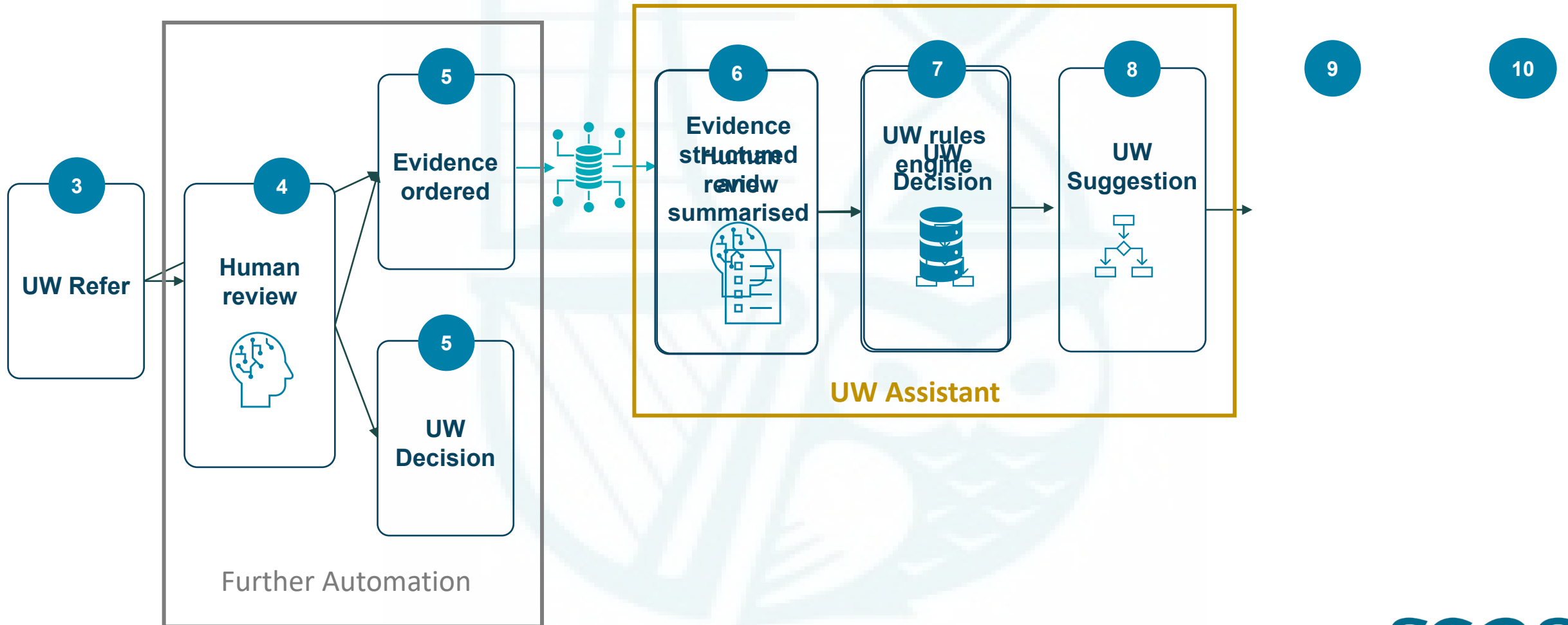


How can generative AI help
underwriting and claims
processes?



New Underwriting journey

The review of structured and unstructured evidence can be considerably quicker and *recommended* UW decisions returned for human review





Summary

Details

Search summary...

Gender/occupation/citizenship

Gender Female

Occupation Accountant

Citizenship Information not specified in provided documents

Travel No foreign travel vaccination discussion noted

Vitals

Height 175 cm

Weight 93 kg

BMI 30.4

Blood pressure readings

Reading 1 145 / 90 06/01/2023

Tobacco use history/status

Tobacco use Current smoker, 20 cigarettes per day

Personal medical history

Heart and blood pressure issues Hypertensive disease 06/01/2020

Cancer Family history of breast cancer in sister 12/01/2020

Respiratory disorders Asthma 06/01/2020

Musculoskeletal Issues ACL, discussed surgery but proceeded only with physio 23/02/2020

Surgery/Medical Procedures ACL, discussed surgery but proceeded only with physio 06/01/2020

Recent prescribed Medication Amlodipine 5mg Tab 1 tab per day, Micardis 80mg - 25mg 1 tab per day 12/01/2020

Application_Richie.PDF

Page 1 of 57

Application_Richie.P...

PATIENT:
DATE OF BIRTH: 11/14/1962
DATE: 08/18/2023
VISIT TYPE: Office Visit
PROVIDER:

This 60 year old female presents for hypertension, anxiety and insomnia. Established patient

Table with 3 columns: #, Detail Type, Description. Contains 9 rows of medical assessment and plan orders.

Provider Plan Diagnosis code placed for administrative purposes.

History of Present Illness

1. hypertension
It is currently stable. Risk factors include African American race, age over age 60, depression, high salt intake, inactive lifestyle, male gender and obesity. Pertinent negatives include chest pain, dyspnea and headache.



Summary

Details

Pages of classifications

Cover sheet	1-3
Exams, Labs	5-10
ECG	16
GP reports	17-20
Misc. (handwritten etc.)	21-50

Personal information

[Edit values](#)

Name	Richie Williams
Date of birth	11/14/1962
Marital status	Married
Policy number	Information not specified in provided documents

Impairments

[Edit values](#)

Heart and blood pressure issues	Hypertensive disease
Mental health issues	Information not specified in provided documents
Cancer	Family history of breast cancer in sister
Endocrine disorders	Information not specified in provided documents
Respiratory disorders	Asthma
Gastrointestinal disorders	Information not specified in provided documents
Marfan Syndrome disorders	Not implemented yet, please review Open chat
Brain or Nervous System Disorders	Information not specified in provided documents
ENT issues	Information not specified in provided documents
ENT issues	Information not specified in provided documents

Application_Richie.PDF

Page 1 of 57

Application_Richie.P... ▼

PATIENT:
 DATE OF BIRTH: 11/14/1962
 DATE: 08/18/2023
 VISIT TYPE: Office Visit
 PROVIDER:

This 60 year old female presents for hypertension, anxiety and insomnia. Established patient

#	Detail Type	Description
1.	Assessment Impression	Essential (primary) hypertension (I10). stable on meds.
	Patient Plan	Advised to maintain a low-fat, low-cholesterol diet. Counseled on reducing risk factors to reduce chance of heart attack/stroke. Reviewed lab results in detail. Counseled regarding importance of weight loss. Maintain a low-sodium diet (less than 2 grams per day).
	Plan Orders	CMP to be performed. counseling included. -Routine.
2.	Assessment Impression	Mixed hyperlipidemia check labs..
3.	Assessment Impression	Anxiety disorder, unspecified continue meds..
4.	Assessment Impression	Insomnia, unspecified stable on meds..
5.	Assessment Impression	Hyperlipidemia LDL as above..
6.	Assessment Plan Orders	Radicular pain in left Physical Therapy in ddd. .
7.	Assessment	Encounter for screening
8.	Assessment Plan Orders	Hyperglycemia (R73 HEMOGLOBIN A1C t
9.	Assessment	Body mass index (BM

History of Present Illness
1. hypertension
 It is currently stable. Risk factors include high salt intake, inactive lifestyle, male, pain, dyspnea and headache.

Chat with **Assistant**

Hello, I am an Artificial Intelligence based assistant. How can I help you?

Could you please search for any Marfan syndrome Disorders?

Sure, I haven't been fine tuned to accurately find this. However, based on the reading of the document, I did find some Marfan syndrome information you might want to check in page [16,17](#) and [50](#).

Ask a question





Benefits

Used in underwriting, claims or as a post-issue tool



Reduces human error and improves consistency

Enables quicker manual underwriting or claims processing

Underwriters and claims assessors able to focus more on high-value tasks



Benefits

The business case centres around the savings in operational costs without impacting the risk profile

Example (medium-sized insurer with high STP rate)	Without UW assistant tool	With UW assistant tool - Scenario 1	With UW assistant tool - Scenario 2
Applications with additional medical evidence (per year)	10,000		
Human underwriter – cost per hour	€50		
Human underwriter – time per case	45 mins	30 mins	10 mins
Total human underwriting cost (per year)	€375k	€250k	€83k
Potential annual savings		€125k	€292k

What are the challenges in building a
Gen AI tool for underwriting and
claims?

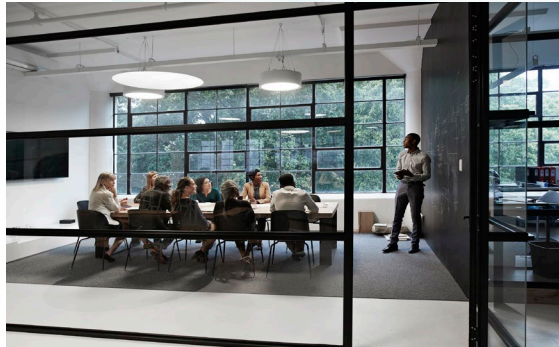


Challenges

The promise of Generative AI is high, but it is moving quickly and needs considered adoption into business processes



Fast-moving environment



Management buy-in



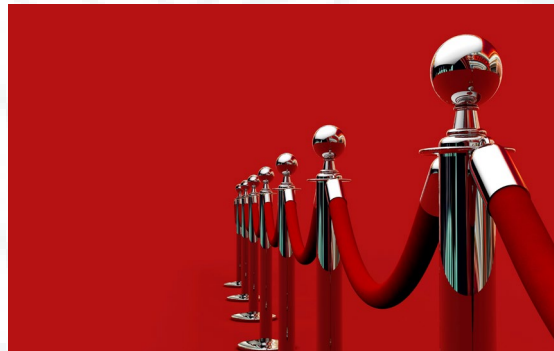
Insurance specificities



Benefits > Costs?



Security



Guardrails



Testing

Why do we need underwriting and claims expertise to help build a solution?



A tool needs to be more than an LLM

Underwriting and claims expertise is important in prompt engineering and post-processing

Date	Height	Weight	BMI
1 Jan 2022	1.70 cm	90.2 kg	31.2
30 May 2022	1.69 cm	88.3 kg	30.9
18 Nov 2022	1.70 cm	86.2 kg	29.8
1 May 2023	1.69 cm	80.1 kg	28.0

Date	Height	Weight	BMI
1 Jan 2022	1.70 cm	90.2 kg	31.2
30 May 2022	1.69 cm	58.3 kg	20.4
18 Nov 2022	1.70 cm	86.2 kg	29.8
1 May 2023	1.69 cm	80.1 kg	28.0

What BMI will the underwriter want to see?

How will we spot data errors?

Electronic Health Record	
Date	BMI
1 Jan 2022	31.2

Blood Test Report	
Date	BMI
12 June 2022	33.0

Impairment	UW Decision
'Mild' Asthma + no smoking	Standard rates
'Mild' Asthma + smoking	+50%
...	
'Severe' Asthma + no smoking	+250%

Which data source do we trust when they tell us different things?

Application Form	
Date	BMI
1 June 2022	30.9

How do we ensure we extract sufficient and relevant information for each impairment?



Summarisation is good but full integration is the gold standard

The real value comes when underwriting summaries can be structured to feed underwriting rules engines...but still with human review

Underwriting
summary for human
underwriters to
review

+ Integration into
underwriting
workbenches and
admin systems

+ Link to
underwriting manual
to return suggested
underwriting
decision

When will it fully replace human
underwriters?

Never ?



Risks and mitigations

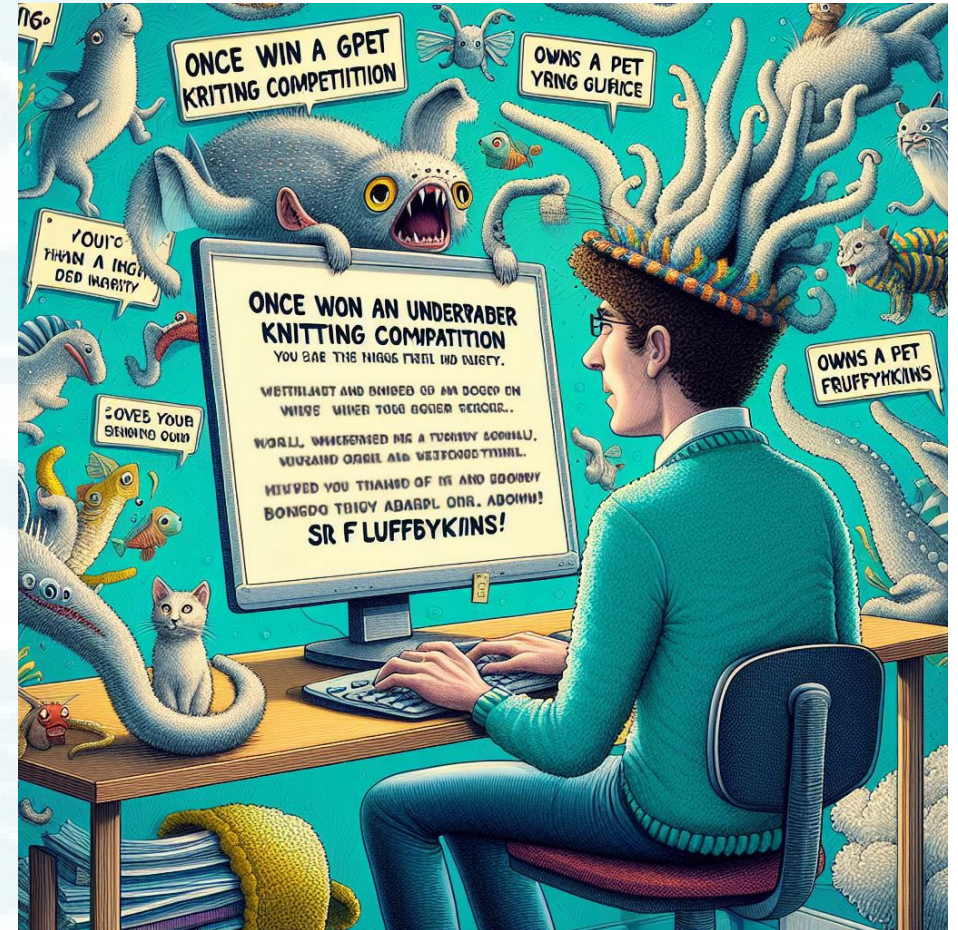
All AI carries risk, but generative AI has additional risk

Risks

- Hallucinations – incorrect conclusions
 - Decisions too harsh
 - Decisions too lenient
- Inability to act on misrepresentation at claim stage
- Legal – the right to request human decisions
- Legal – use of impermissible data
- Data/systems may evolve

Mitigations

- Human review of every case used in UW/claims
- Regular testing





Thank You!

Please raise your hand to ask a question, and wait for a mike to get to you



Society of Actuaries in Ireland

Coffee – come back in 15 minutes

13 June 2024



Society of Actuaries in Ireland

A game of two halves: Similarities and differences between 'old' AI and GenerativeAI

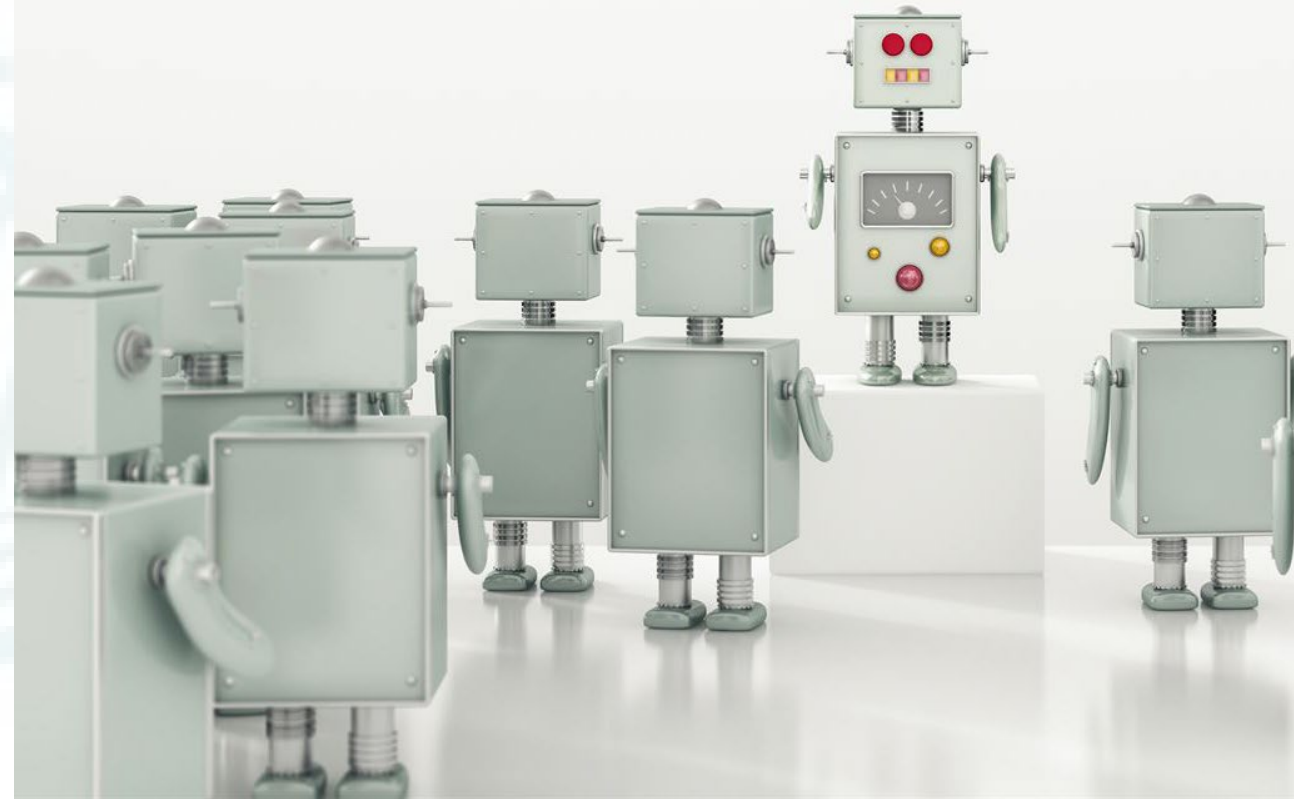
Arlen Galicia Carreon (she/her)

Vatsal Gomber (he/him)

13 June 2024

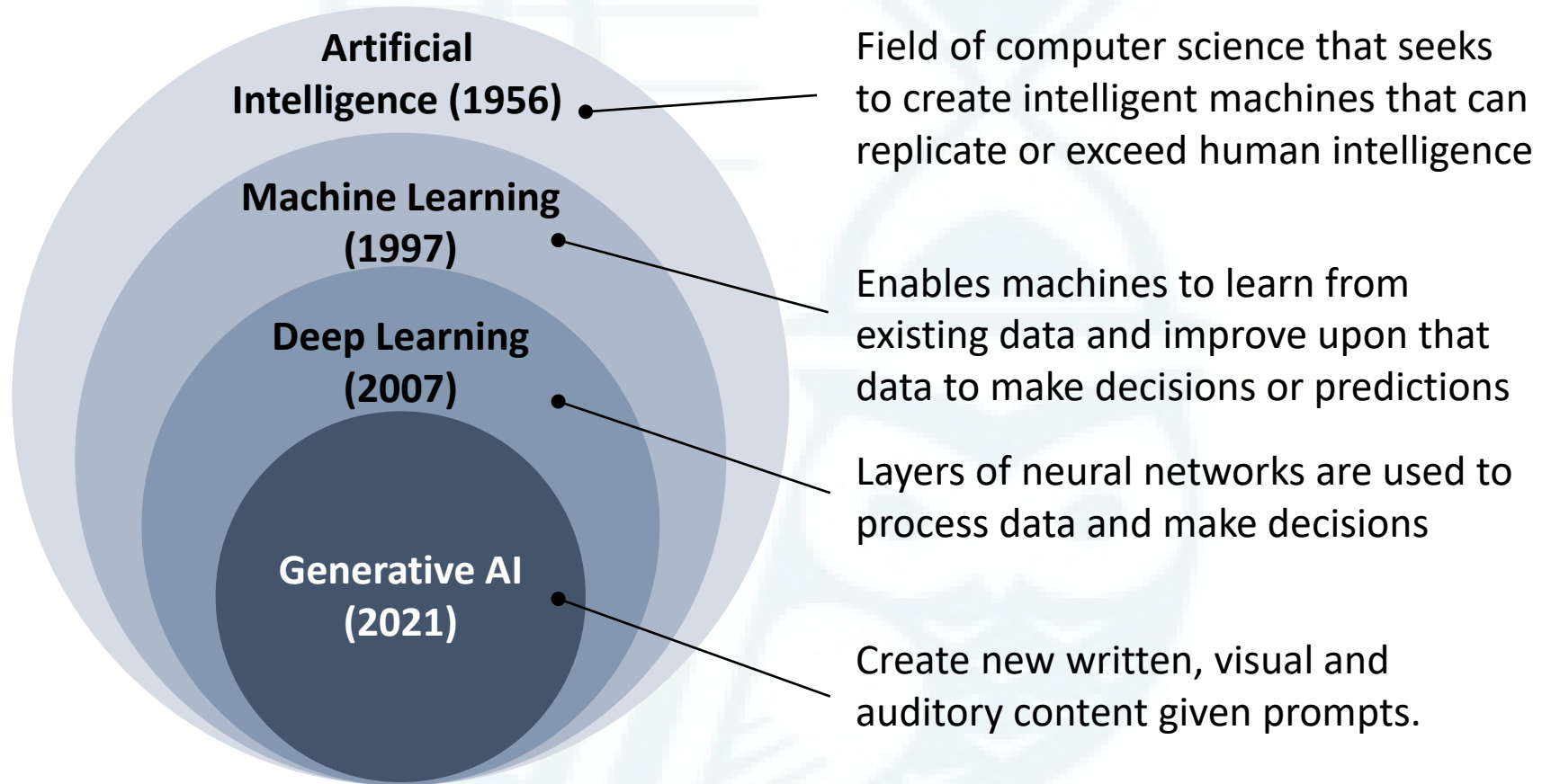


- Distinguish between traditional AI used in analytics and the new wave of Generative AI. We'll explore their distinct applications and discuss their strengths, weaknesses, opportunities, and threats that are unique to these technologies.
- Presenters:
 - Arlen Galicia Carreon – Associate Director at WTW (she/her)
 - Vatsal Gomber – Senior Consultant at WTW (he/him)





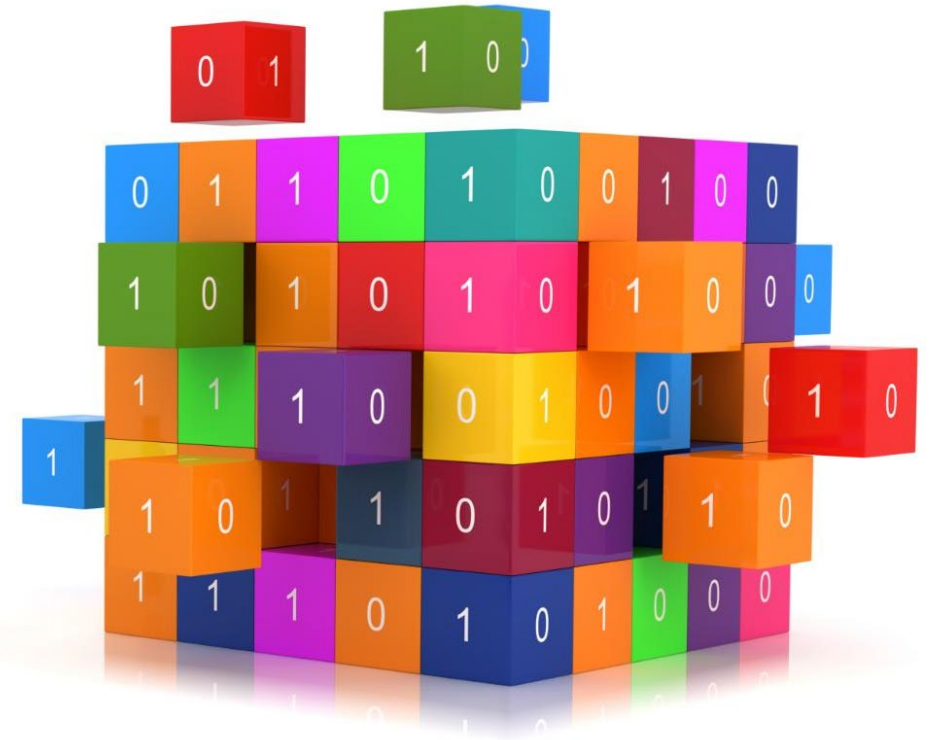
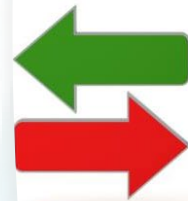
Relationship between Traditional AI and Generative AI





Narrow Artificial Intelligence

- Aims to create machines capable of intelligent behaviour
- Includes methods like machine learning, natural language processing, robotics, and more
- Limited to specific tasks
- Does not have the ability to create anything new





Examples of Narrow AI

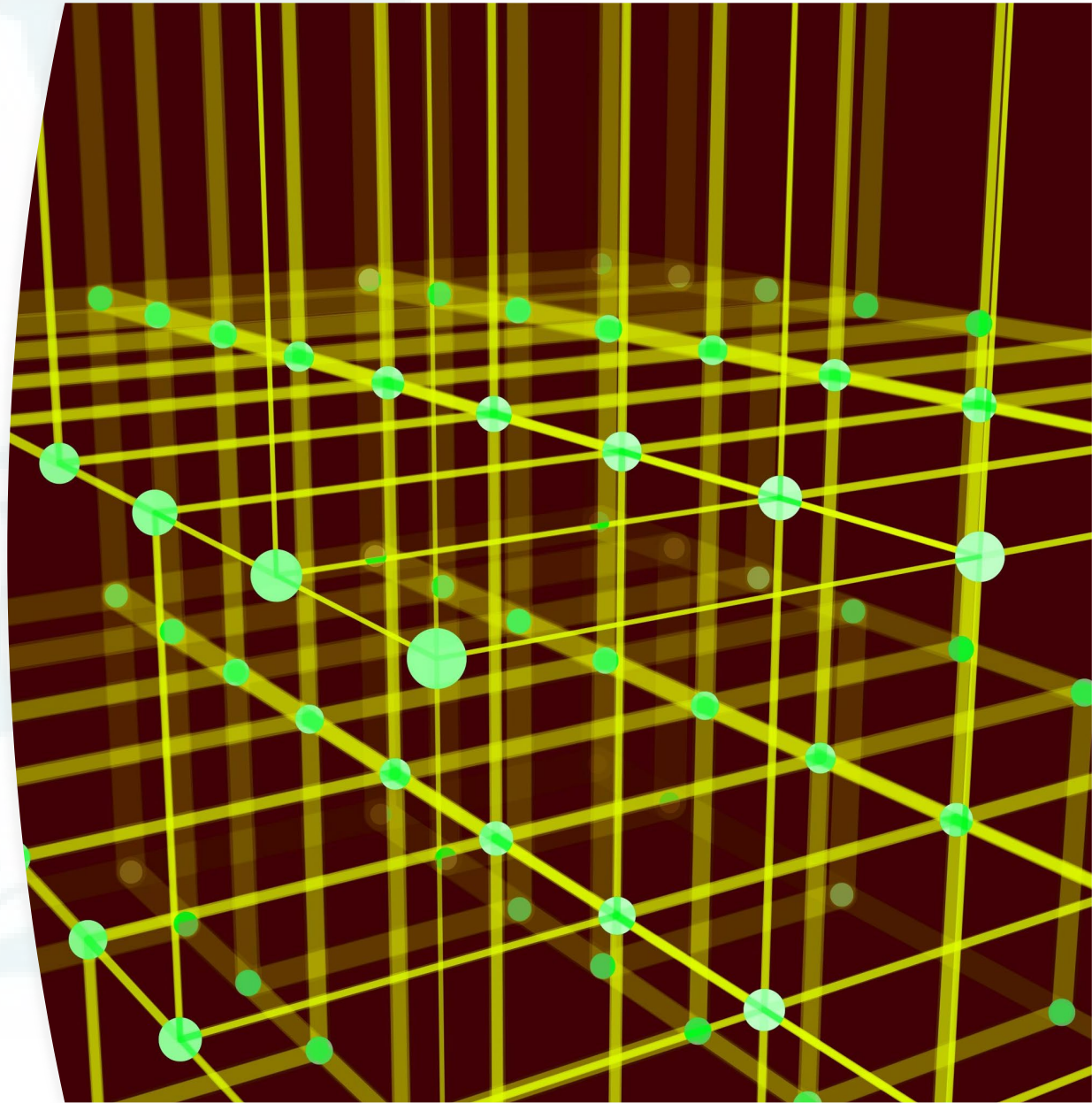
- AI-powered fraud detection systems in banks which analyse transaction patterns in real-time to flag potentially fraudulent activity
- Some actuarial examples
 - Improved risk assessment and customer understanding in Underwriting
 - GLMs for Pricing or understanding the relationships between key variables
 - Automated Claims Processing





Generative AI

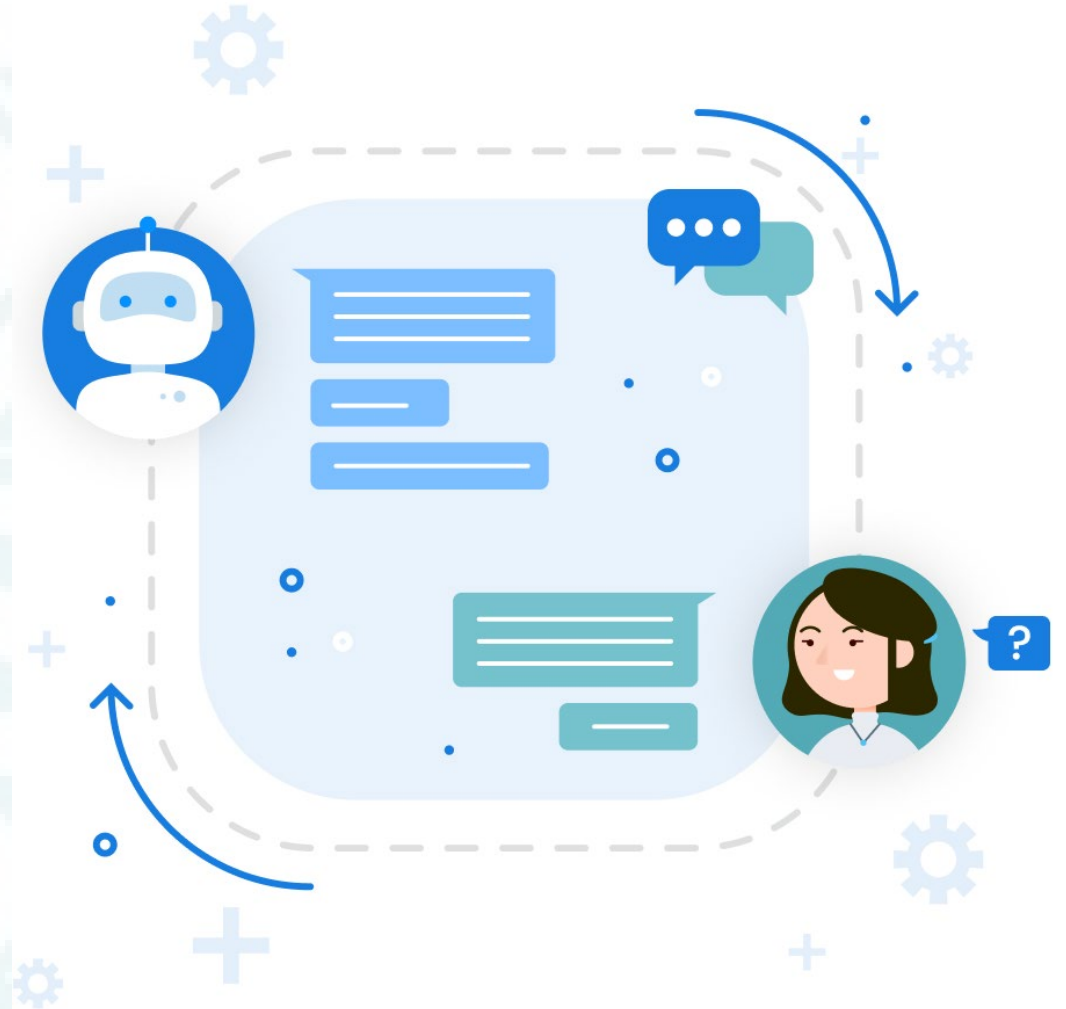
- Refers to artificial intelligence that can generate **new content**
- Ranging from text and images to music and code





Examples of Generative AI

- ChatGPT – allows multimodal conversation
- DallE – allows to create images
- The most recent one Sora – text to video model
- Some actuarial examples
 - Coding assistants for modellers
 - Code writing
 - Debugging
 - Code clean-up and efficiency
 - Legacy code documentation & reformatting
 - Automated production of customised and tailored customer communication
 - Automated data cleansing





Examples of Generative AI

Prompt: Photorealistic closeup video of two pirate ships battling each other as they sail inside a cup of coffee.





Examples Narrow AI vs GenAI

- **Data Analysis**
 - Narrow AI – understanding, summarizing and generating insights from structured data, predictions
 - GenAI – Structuring unstructured data, augmenting limited datasets, generating model points, simulating synthetic training/testing data
- **Dynamic Assumption Modelling**
 - Narrow AI – understanding the important explanatory variables, their impacts and correlations
 - GenAI – Understanding the core reasons for the assumption trends, focusing on the root causes and potentially solving wider issues



SWOT Analysis – Narrow AI





SWOT Analysis – Generative AI





Key differences

What does it do?

- Narrow AI: Prediction Classification
- Generative AI: Creation, Innovation

How is it applied?

- Narrow AI: Automation, Decision Support
- Generative AI: Content generation

Who can use it?

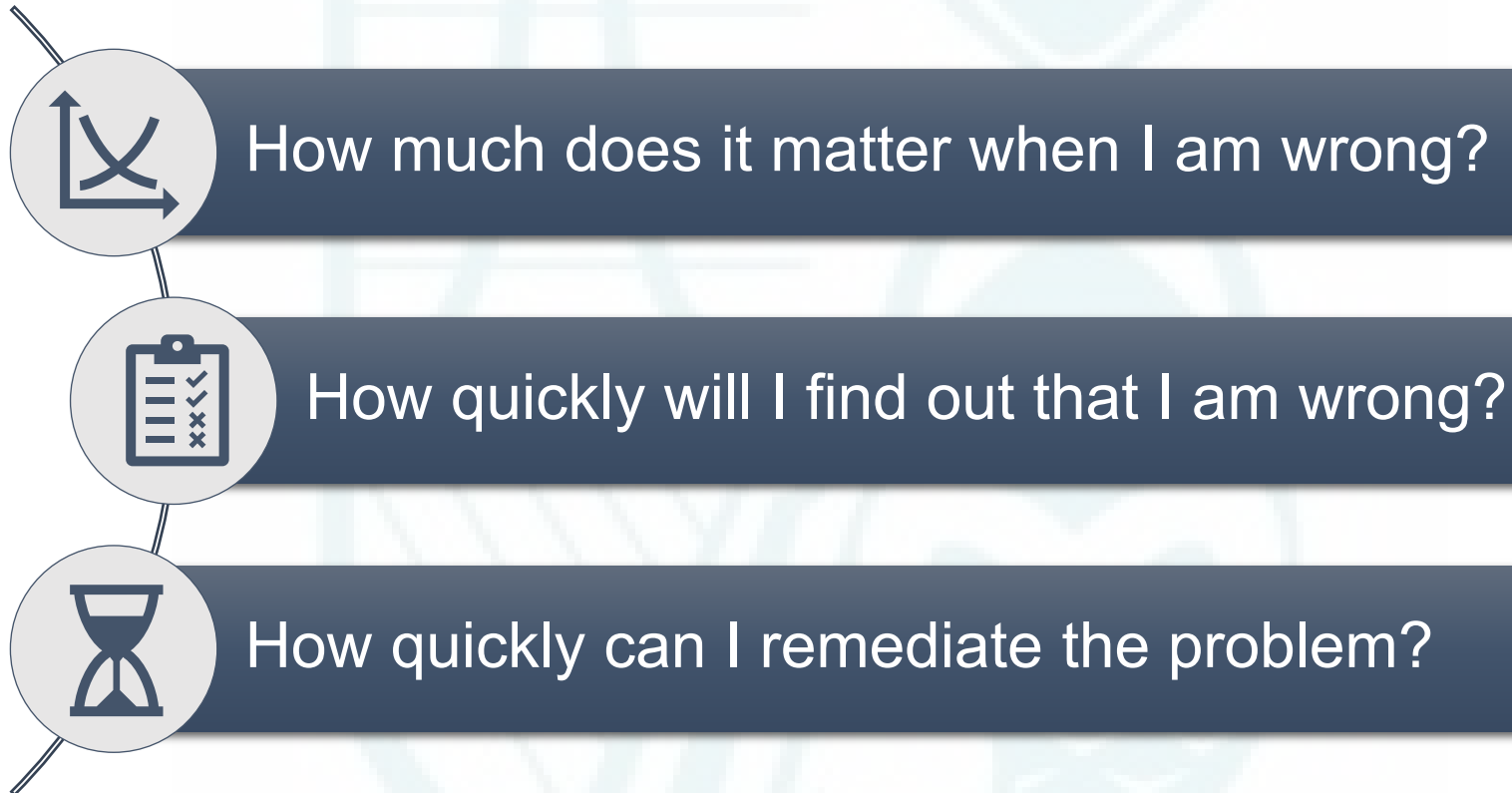
- Narrow AI: Requires knowledge and specialized skills
- Generative AI: Anyone – Prompt Engineering

How can it help actuaries?

- Narrow AI: Risk Assessment, Pricing
- Generative AI: Code Generation, Code translation, Automate testing



What happens when things do go wrong?





Questions?

Please raise your hand to ask a question, and wait for a mike to get to you

Arlen.GaliciaCarreon@wtwco.com

Vatsal.Gomber@wtwco.com



Society of Actuaries in Ireland

Looking back to look forward - Data Science and AI's
role in the Health sector

Dr Mary Coghlan, Luke Gaughan

13 June 2024



Dr Mary Coghlan,
Partner,
Head of Health Data Analytics & AI



Luke Gaughan,
Senior Consultant,
Non-Life Actuarial

Agenda

1. The Health Care Sector
2. An EY Case Study
3. The Health Insurance Industry

The Health Care Sector





The Current Landscape

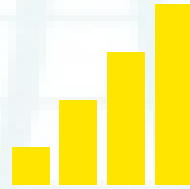
Trends and challenges in the Health Sector

Patient Care Trends

Increase in patient volume and complexities



Rising prevalence of chronic diseases



Growing demand for personalised medicine

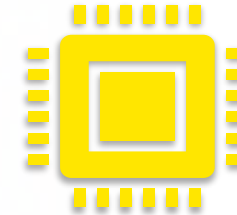


Data/Technology Trends

Large inflow of patient health-related data



Technological advancements and innovations



Operational Trends

Growing need to reduce health care costs using technology



Shrinking operational workforce in health care facilities



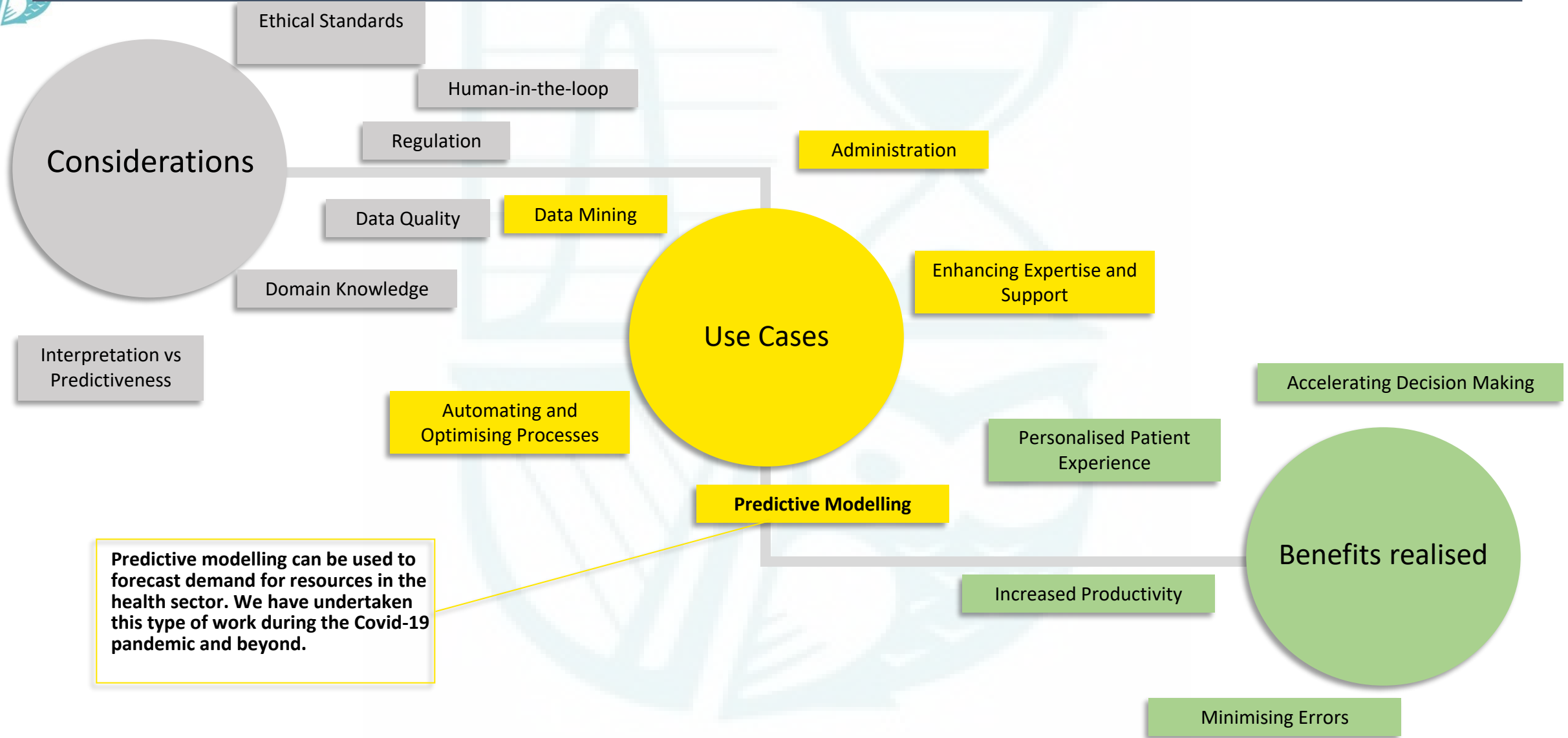
Increasing use of artificial intelligence





Use Cases for Data Science

Benefits realised to date and key considerations

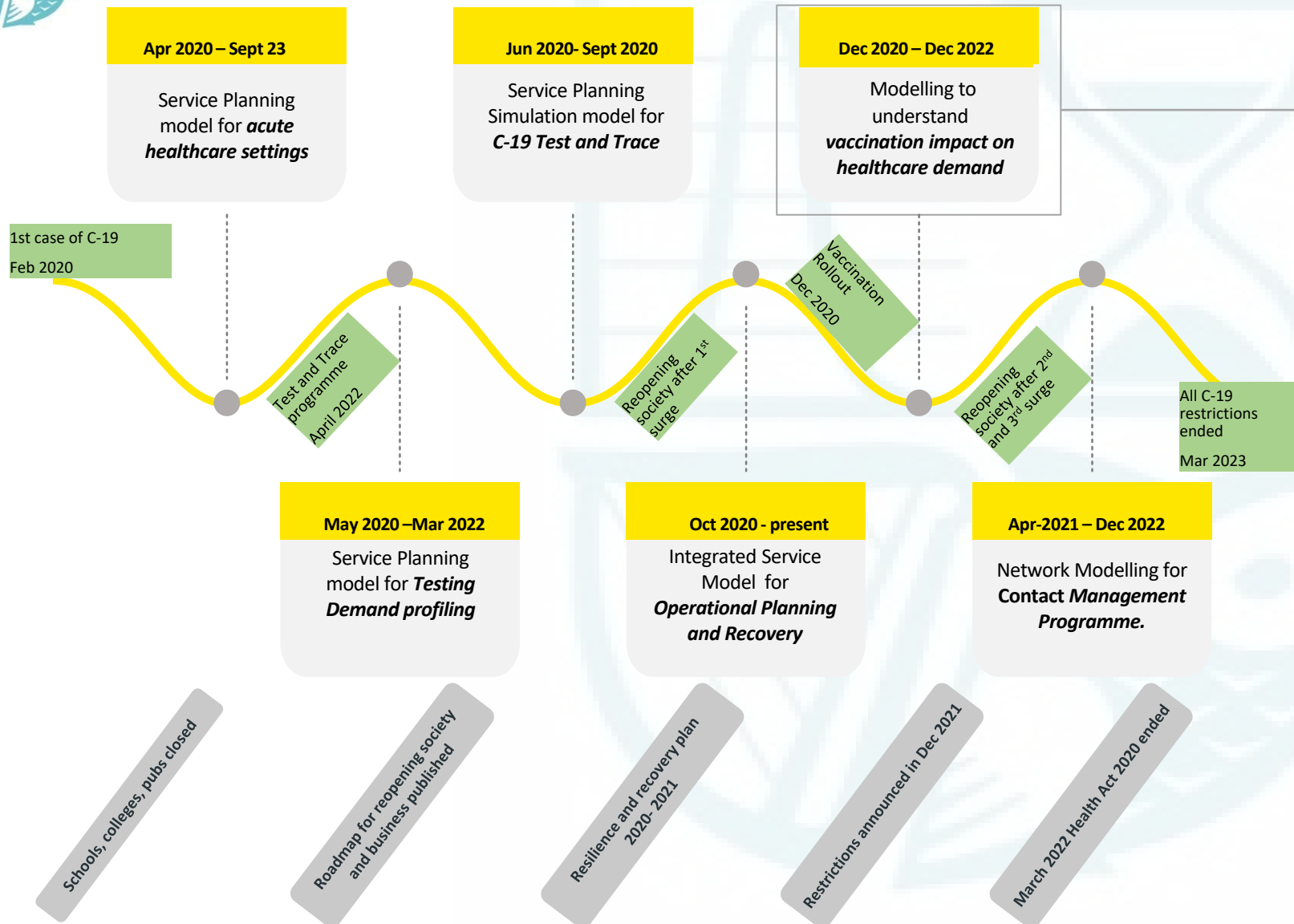


An EY Case Study on Predictive Modelling in the Health Sector





EY's support during COVID-19 to Health Services



Vaccination Modelling:

Irish vaccine rollout commenced in late December 2021 with high-risk cohorts including health care workers and residents of long-term facilities.

EY developed model to **forecast the impact of the vaccination programme on the levels of hospitalisation resulting from COVID-19** and the subsequent demand this creates for acute hospital beds.

This model was closely **linked to the COVID-19 hospitalisation model** and was deployed to make longer term **predictions based on available clinical trial data and experience globally.**

Model Inputs: The model accounted for the various types of vaccine used, their performance, volumes ordered and administered as well as approval dates of any new vaccines. The model also accounted for the order in which the public was to be vaccinated – with at risk groups prioritised.

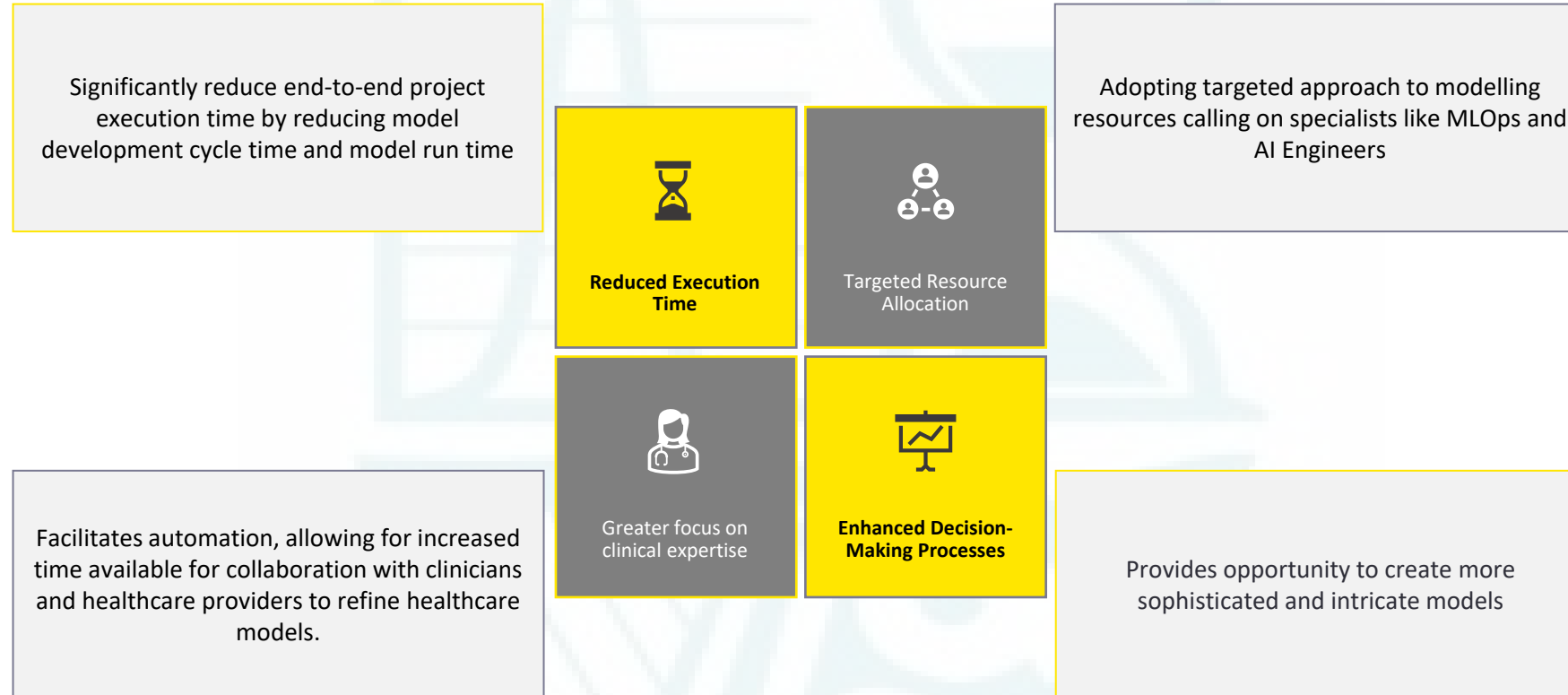
Model Parameters: The model was iterative and adaptable, keeping pace with the everchanging dynamics of COVID-19 in Ireland . Baseline demand analysis was further enriched by the addition of **scenario modelling** to provide opportunities for greater flexibility and deeper discussions.

Model Outputs: The various inputs were combined to model a **day-on-day measure of vaccine protection in the community** and a subsequent risk profile for hospitalisation. This calculated **risk profile** was then fed into the **COVID-19 hospitalisation model** to project hospital demand into the future.

The methods and tools provided a new ways of thinking about service planning



How our work would have benefited from emerging technologies



Example: During the modelling phase, HSE requested various scenarios. Although our model was equipped to generate these scenarios, running new simulations would take additional modelling time. Nevertheless, with the implementation of Gen AI, we can now create an interface that allows healthcare organisations to input scenarios, thereby facilitating rapid responses and aiding in more informed decision-making

The Health Insurance Industry





Developing Data Science Methods

How prescriptive analytics is gaining traction



Descriptive
Analytics

Insights into the past:

“What has happened?”



Predictive
Analytics

Understanding the future:

“What could happen?”



Prescriptive
Analytics

Advise on possible outcomes:

“What should we do?”

Applications for
Prescriptive Analytics in
Health Insurance

Performance optimisation

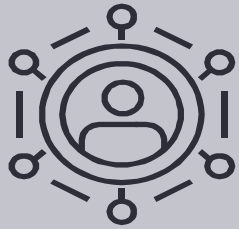
Marketing strategies

Claims management

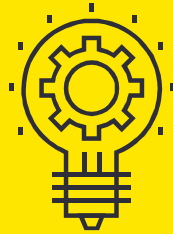


Exploring Generative AI

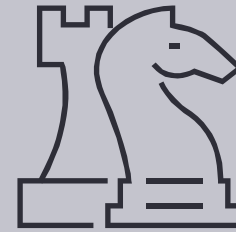
A future solution – with challenges



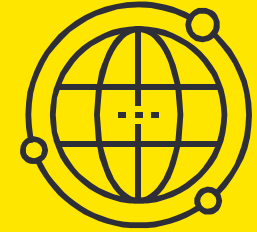
**Hyper-personalise
engagement**



**Drive efficiency via
automation**



**Augment/
“Co-pilot” decision
making**

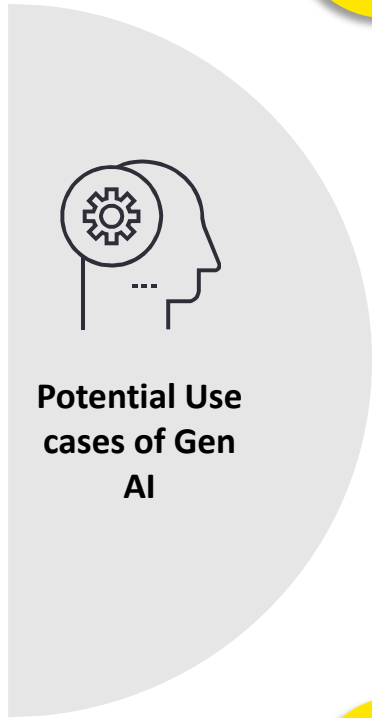


**Reinvent industry
models and value
propositions**



Transformation areas

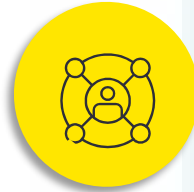
A sample of use cases for Generative AI in insurance



Potential Use cases of Gen AI



Healthcare Management



Member Services



Corporate Functions



Claims Management



Marketing and Sales

Q&A

Please raise your hand to ask a question, and wait for a mike to get to you



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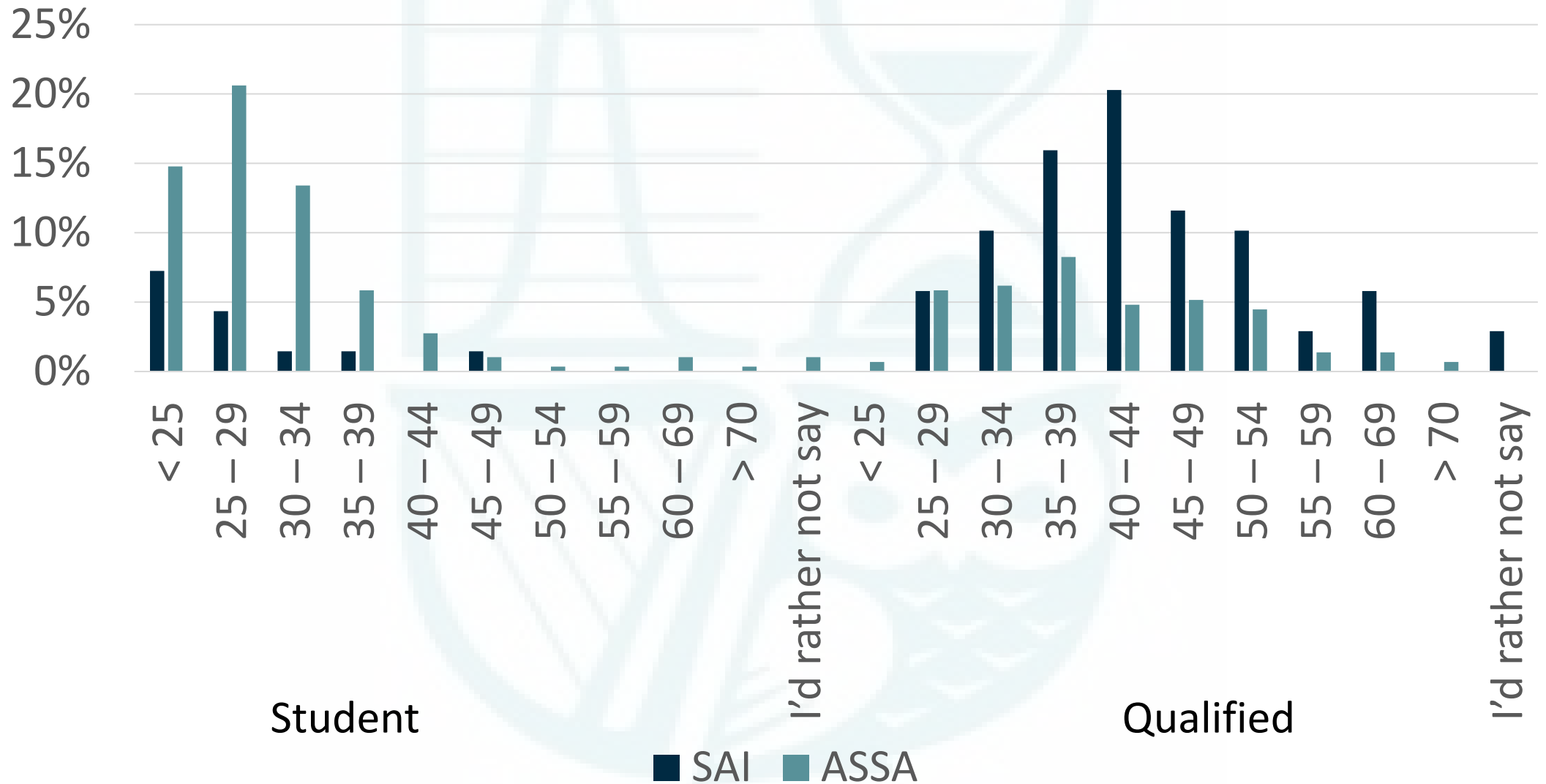
Society of Actuaries in Ireland

Data Science Survey
Kate Bell (she/her)

13/06/2024

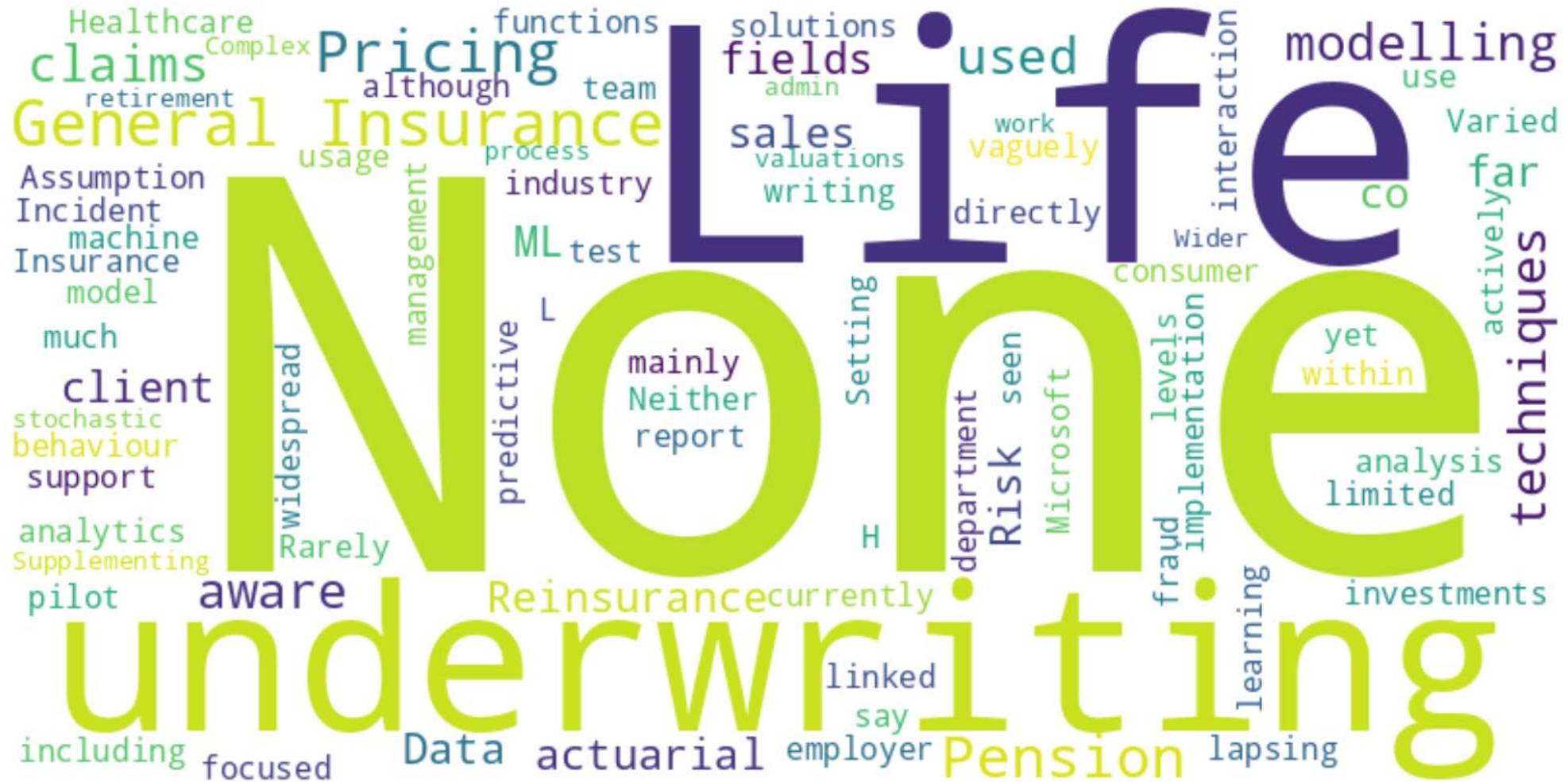


Age group and qualification status



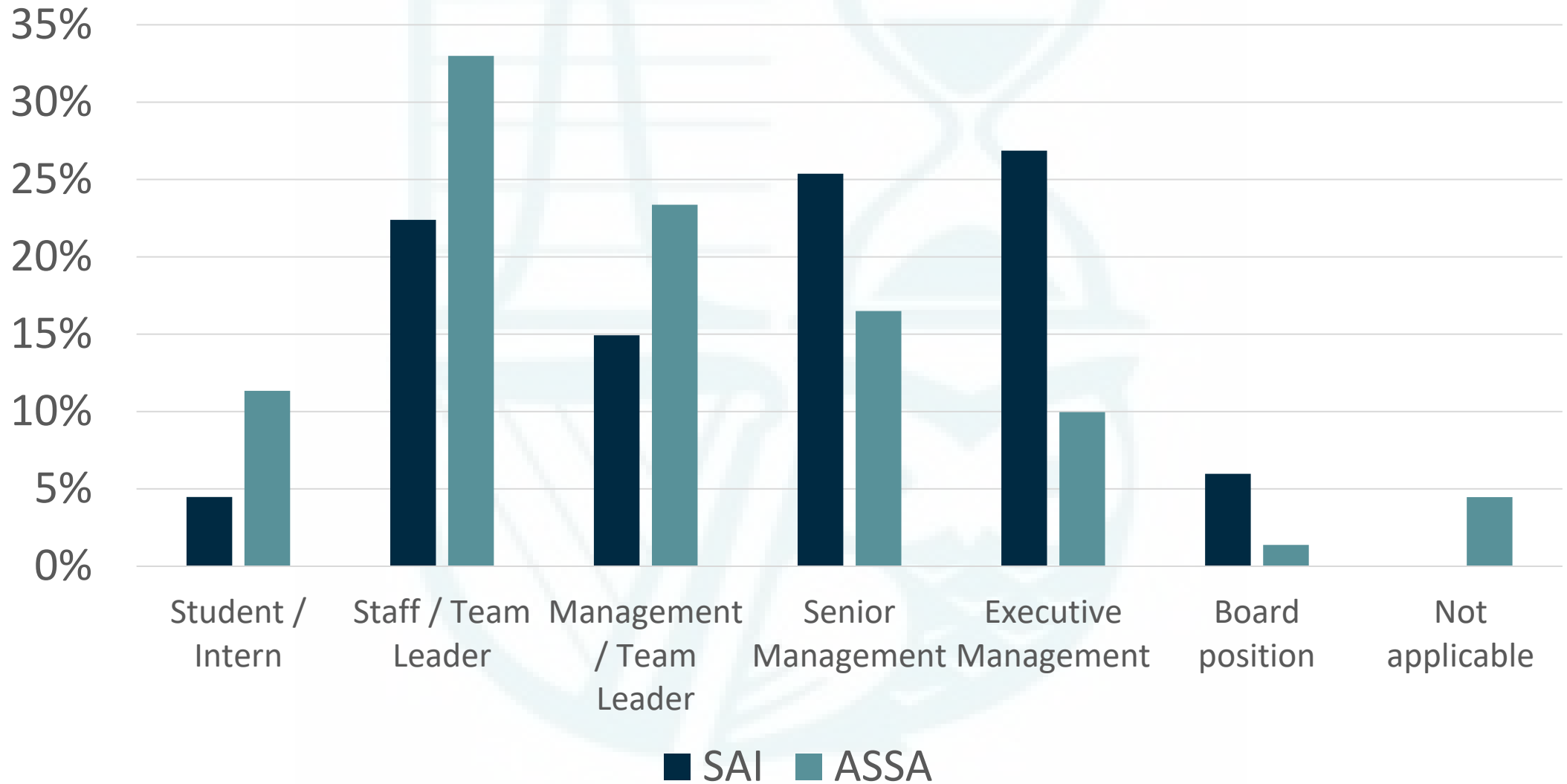


In which of the fields listed above are machine learning techniques most often utilized?



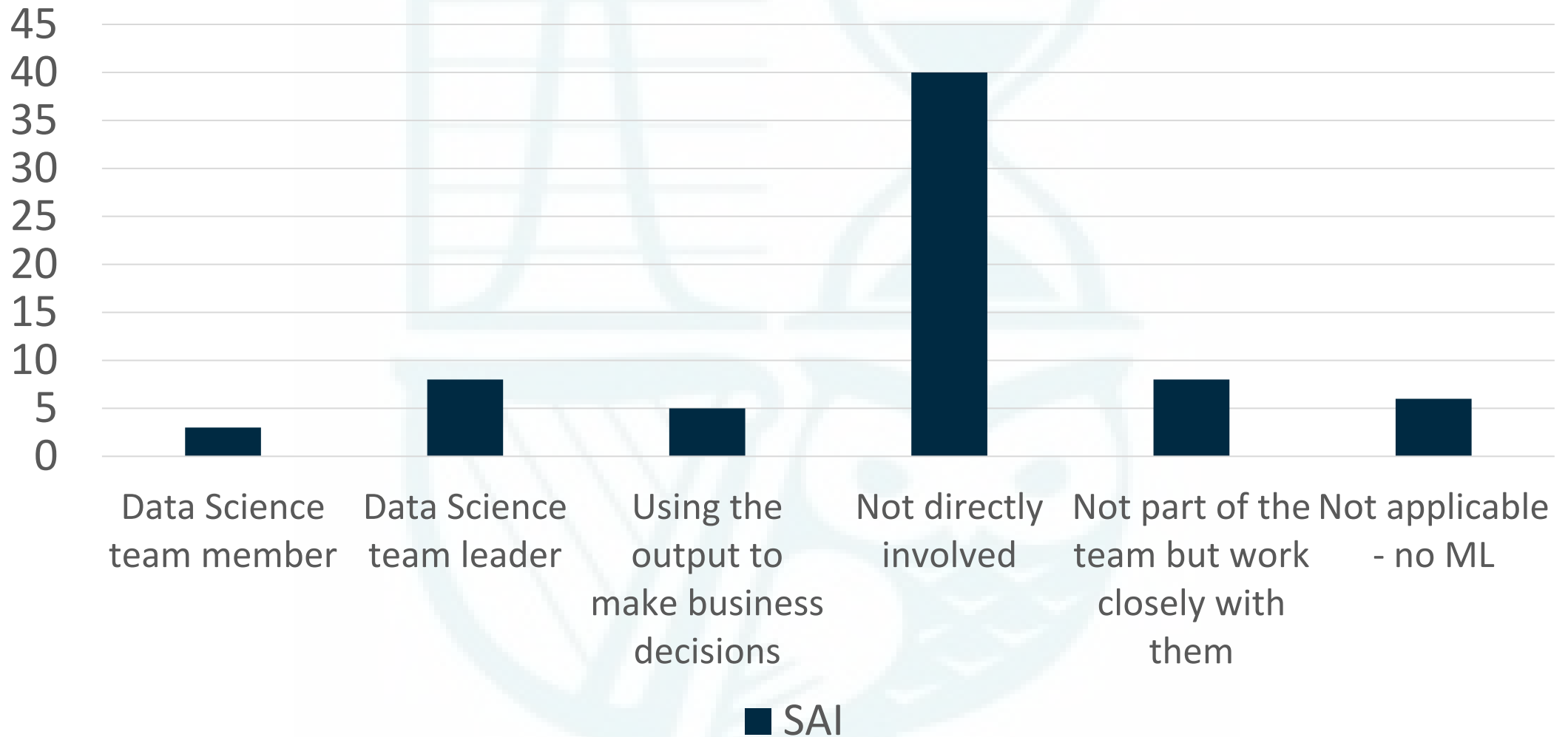


Which of the following options most accurately describes the seniority of your current role in your organisation?



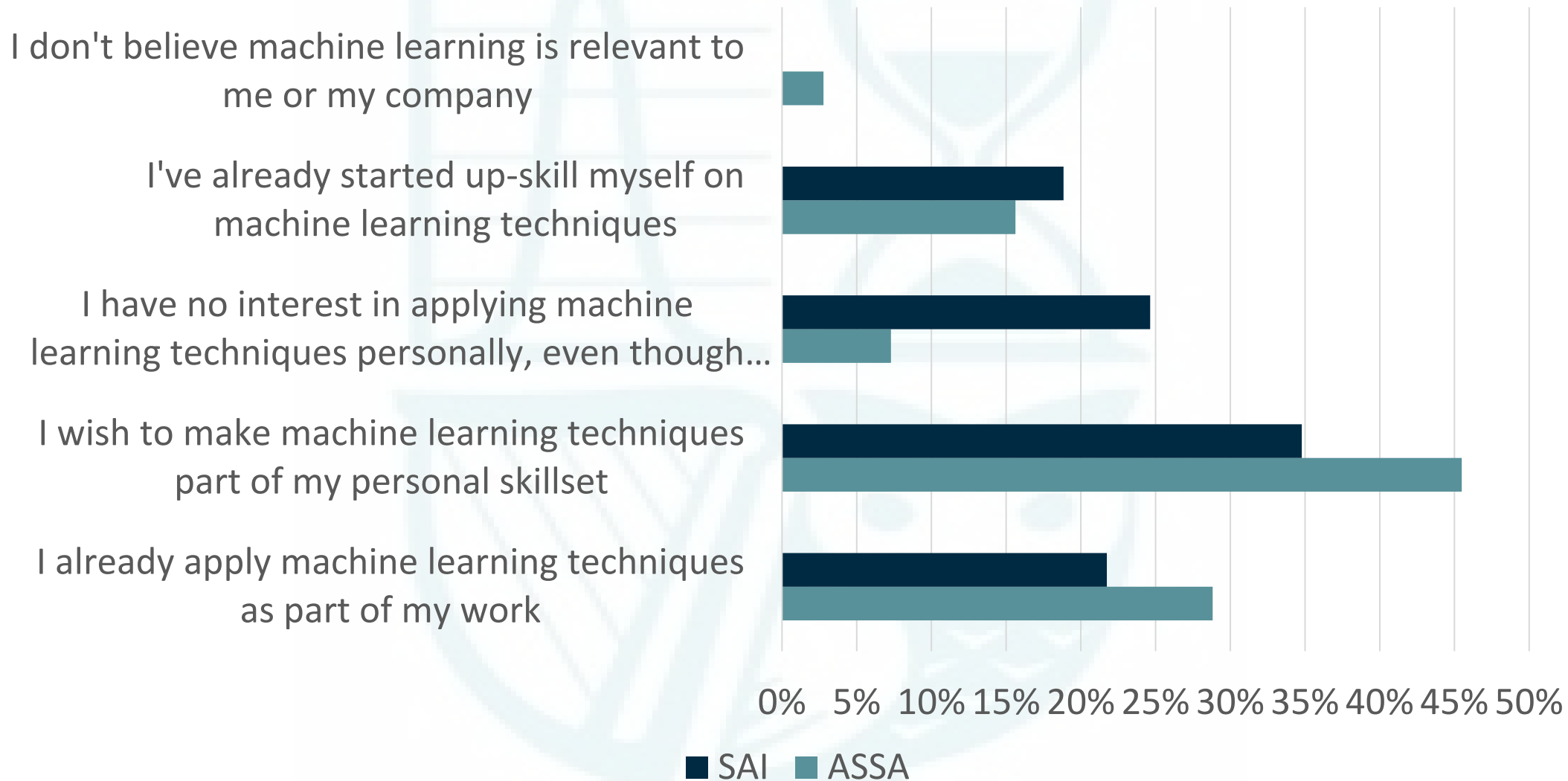


What is your relationship / association with the people (team) using machine learning techniques in your company?



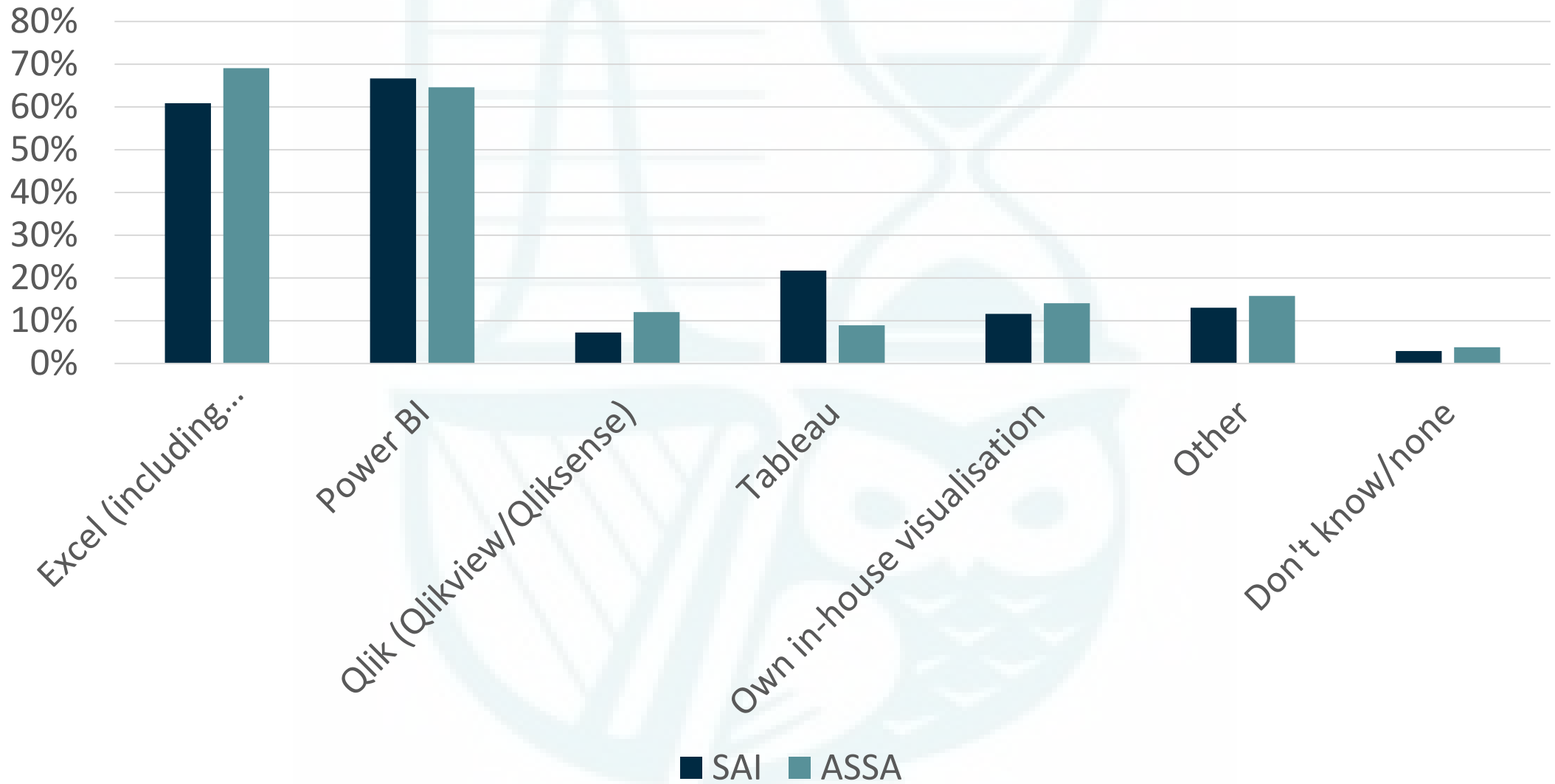


Select the statement which is most descriptive of your current thinking around data science and machine learning.



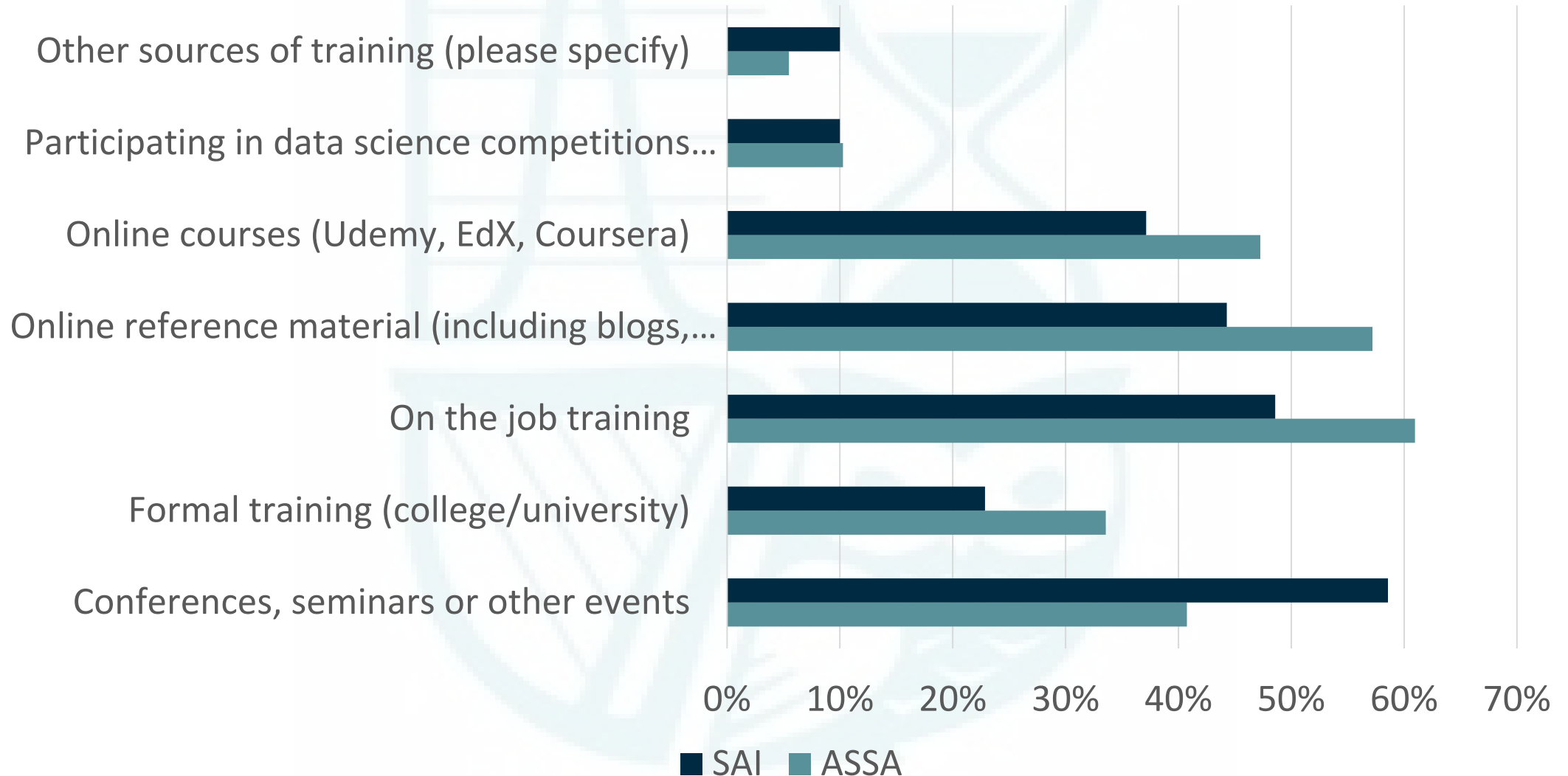


Which third-party visualisation / business intelligence are you or your organisation using?





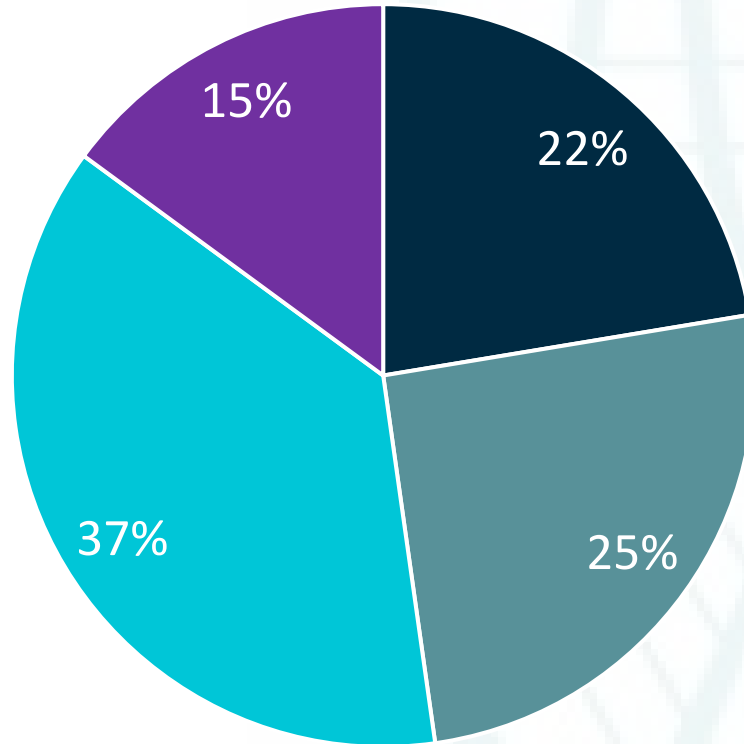
Which of the following methods you have found useful to find out more about data science, machine learning or big data?





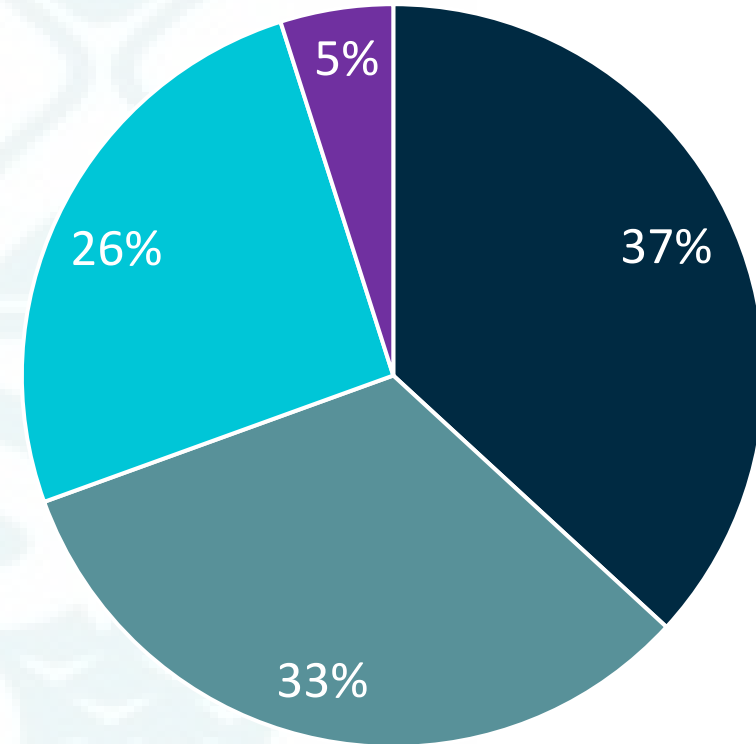
How often are important decisions made in your company informed and supported by data analytics? (or clients if you are a consultant).

SAI



■ All the time ■ Mostly
■ Some of the time ■ Not at all

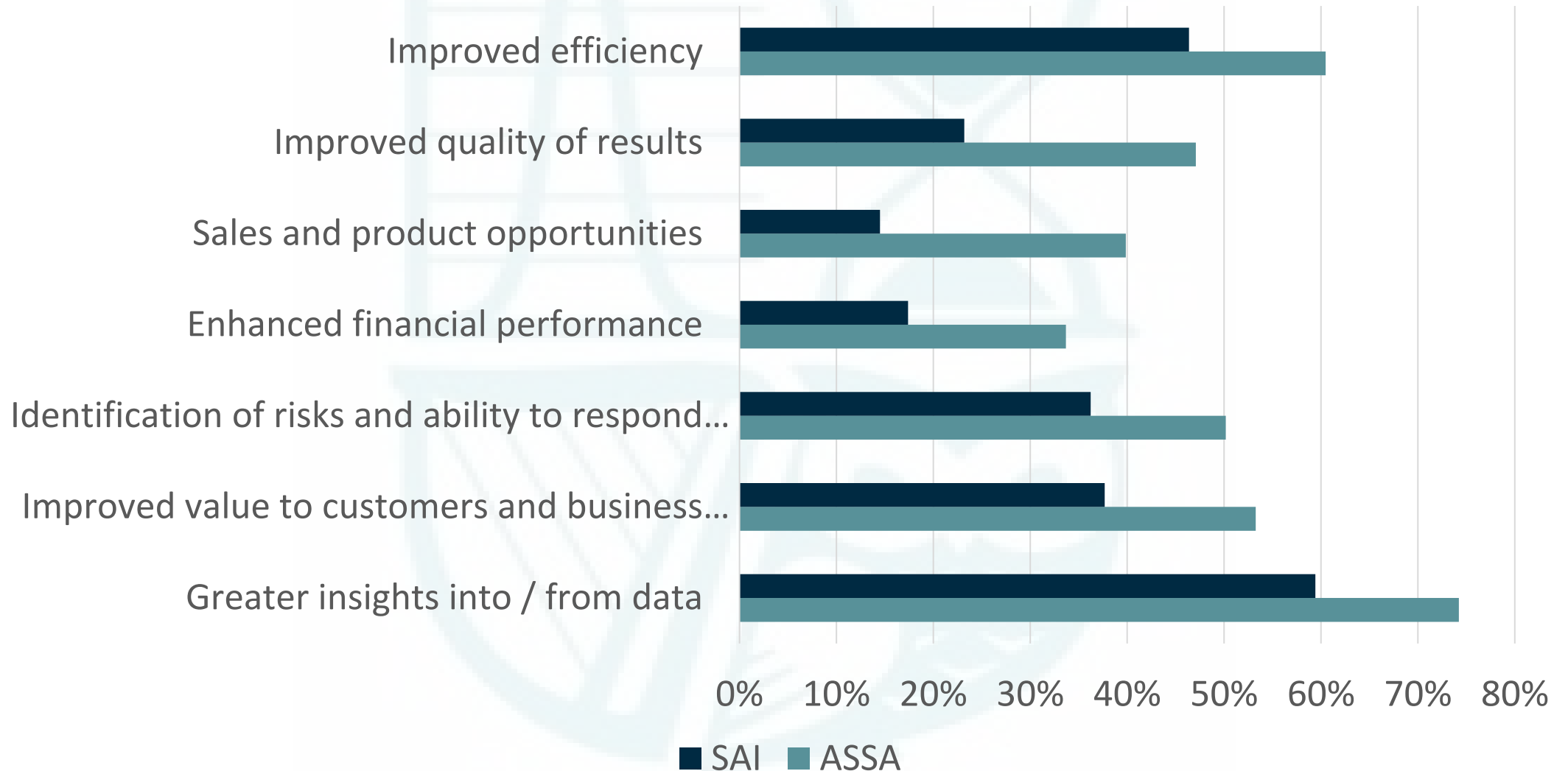
ASSA



■ All the time ■ Mostly
■ Some of the time ■ Not at all

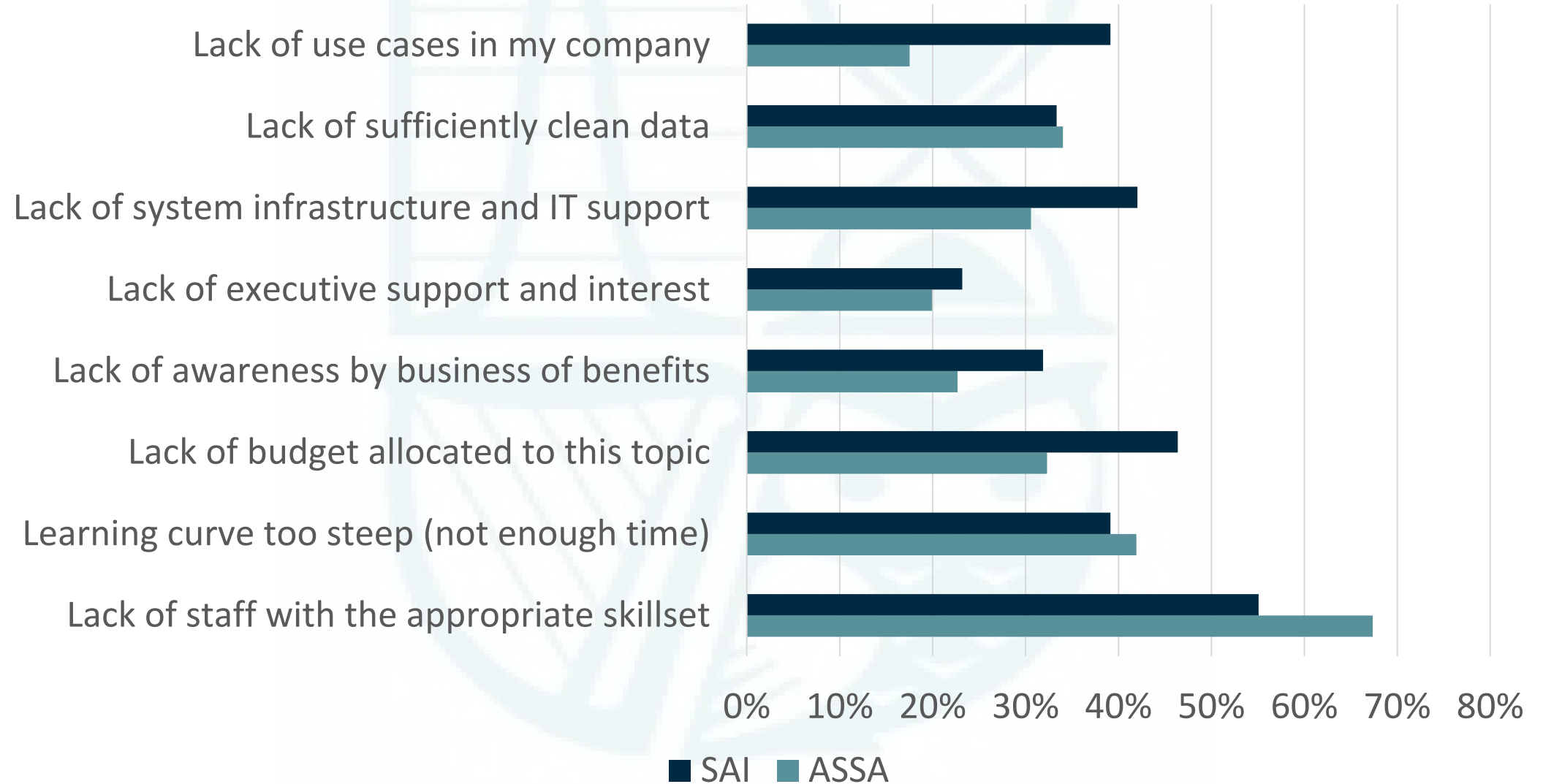


Rate to what extent (if any) you think data science and machine learning have benefited your company.



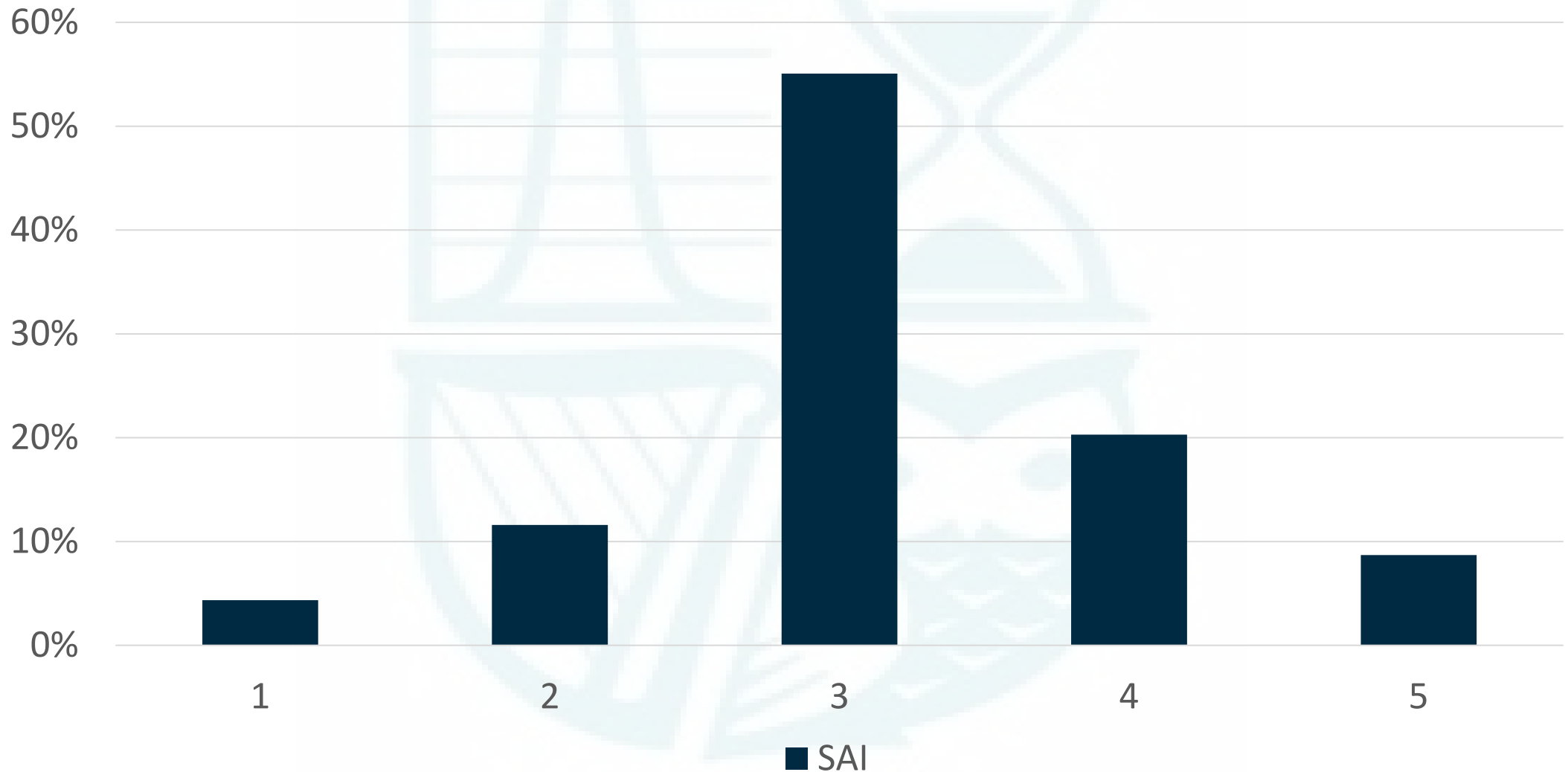


Rate to what extent the following is hampering the adoption of data science and machine learning techniques within your organization?



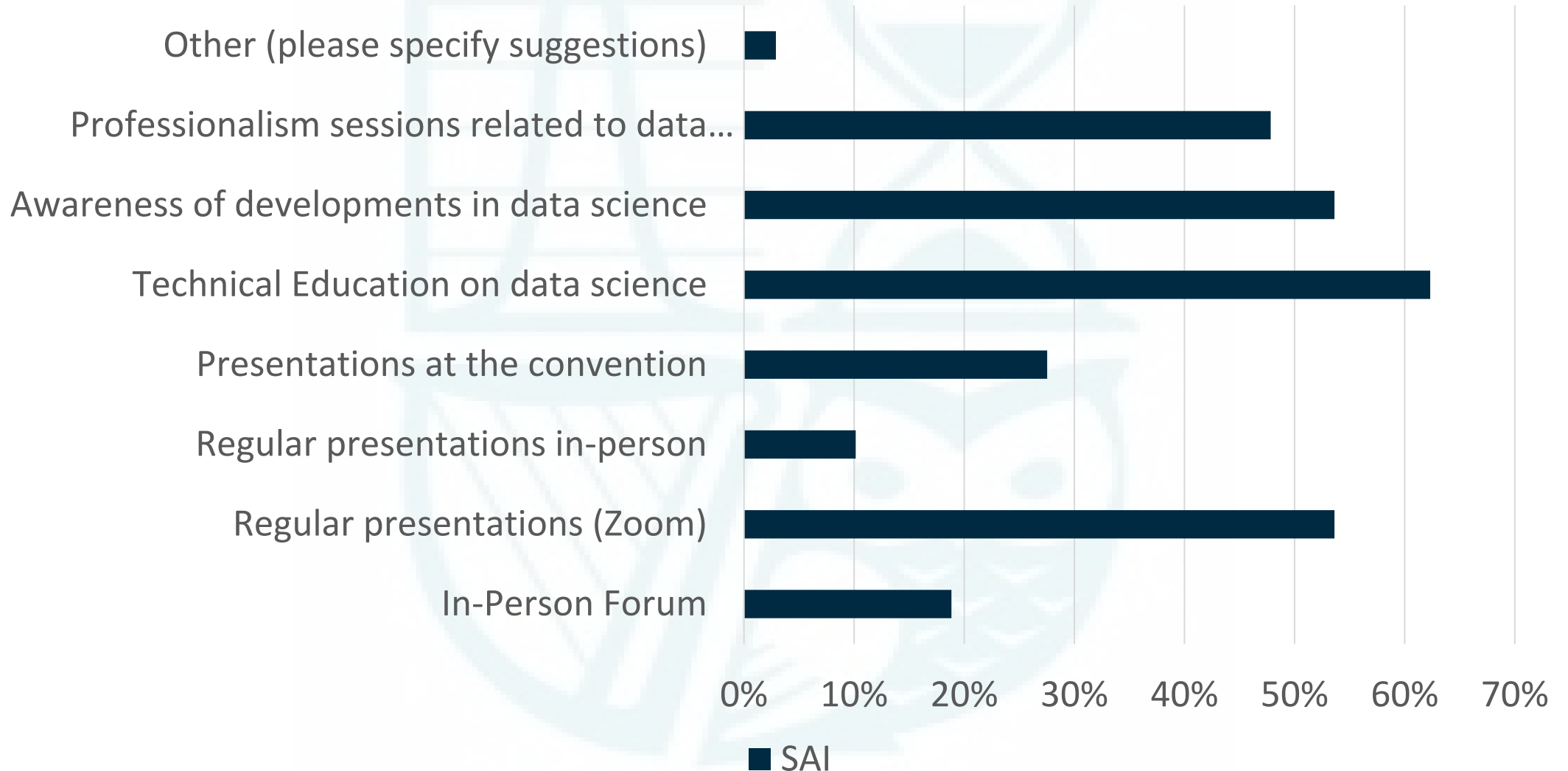


How satisfied are you with the support and resources SAI provide for data science (where 1 is very dissatisfied, and 5 is very satisfied)?



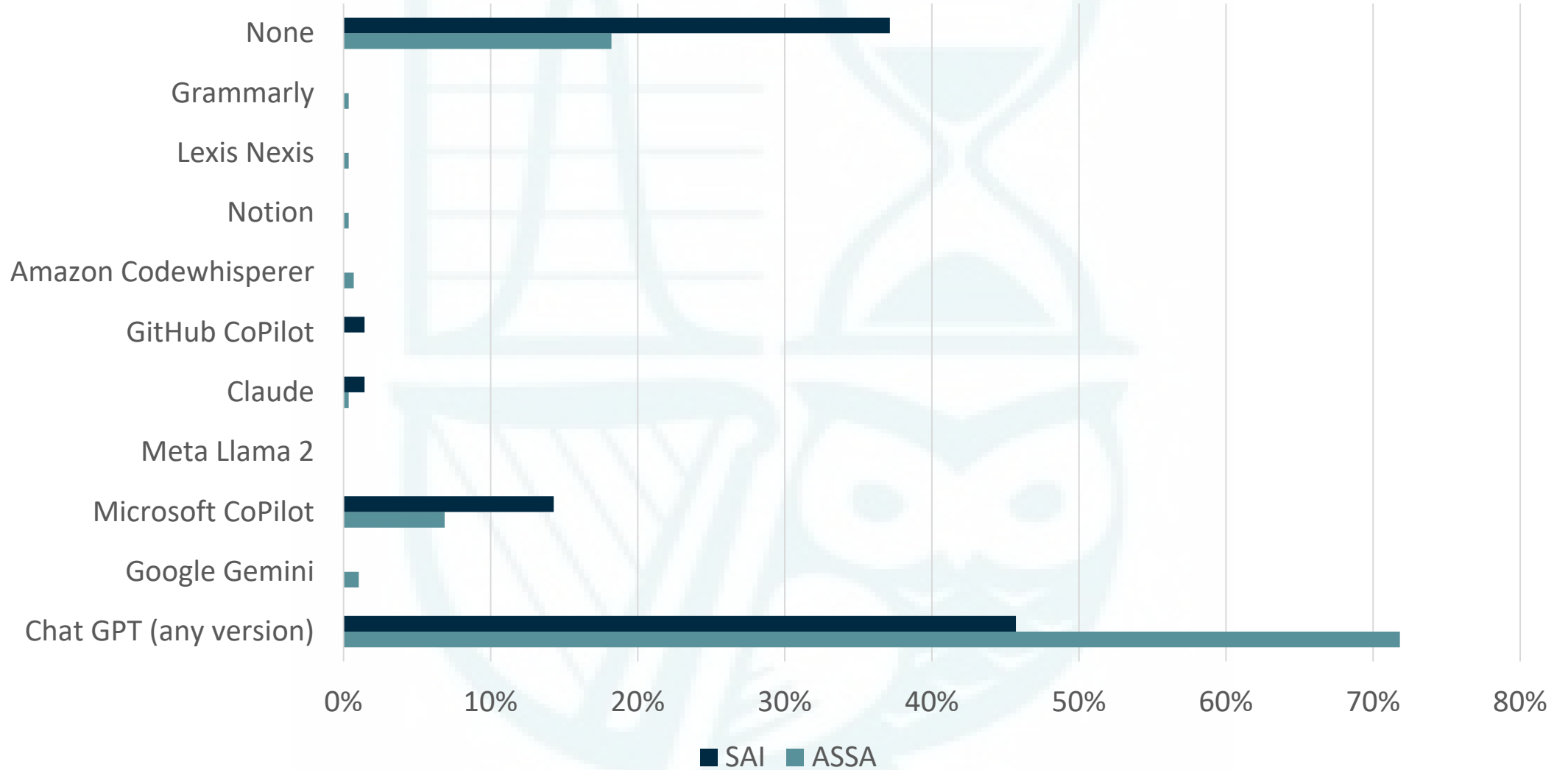


What could the Society do more of in terms of Data Science awareness & support?



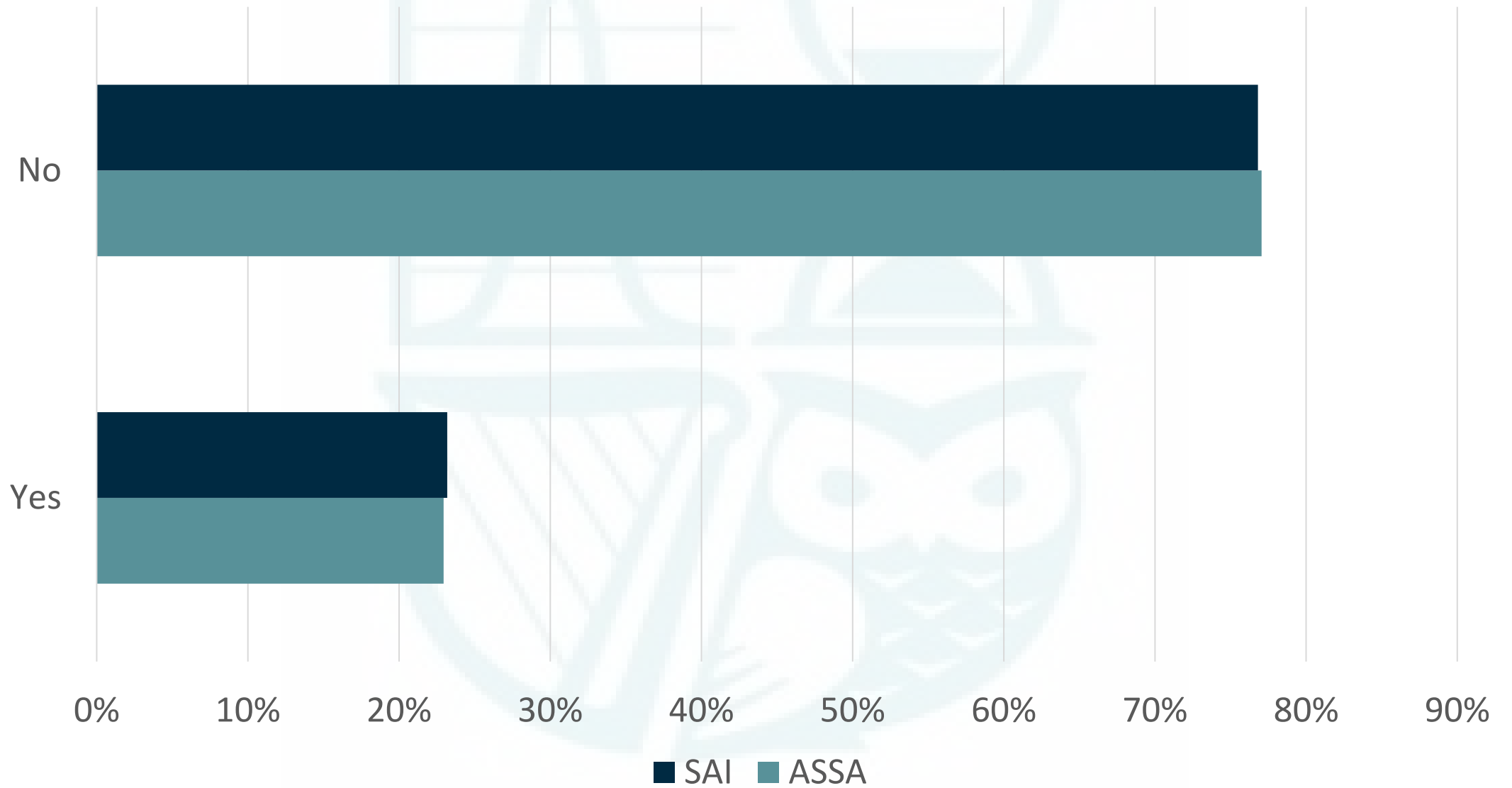


What LLM are you using on a regular basis?



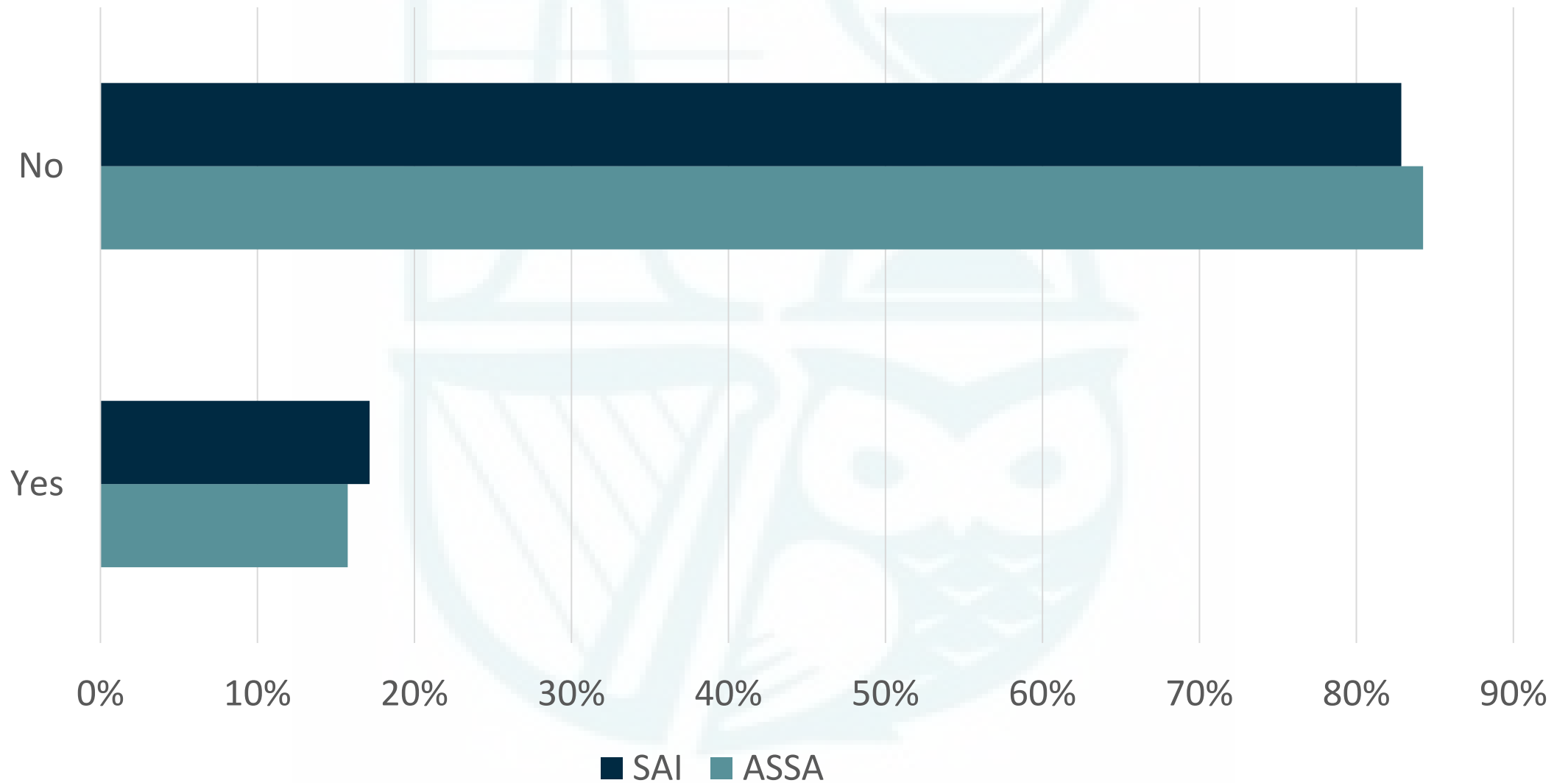


Are you currently making use of any paid LLM offerings?



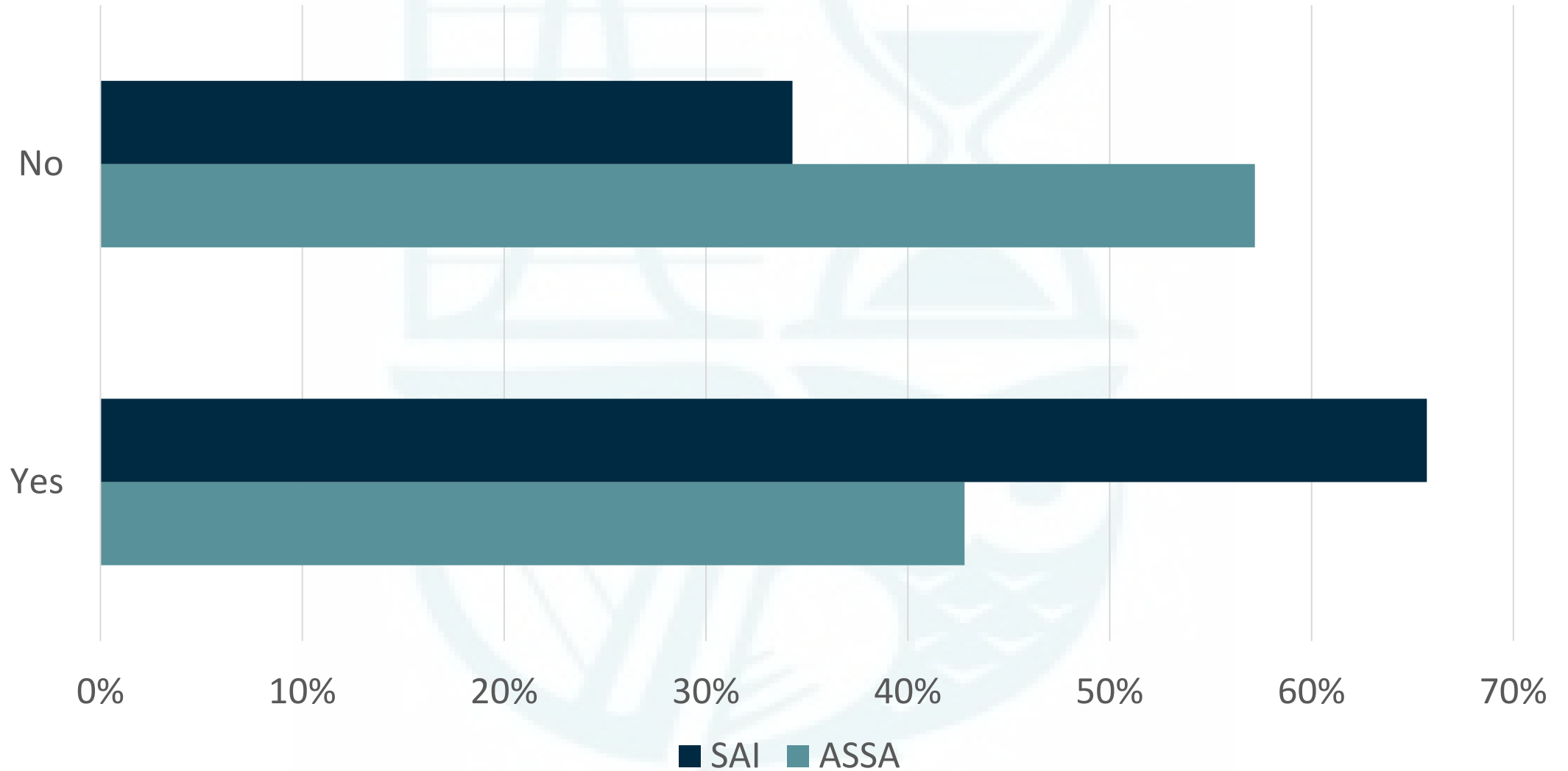


If you answered yes in the previous question, is your organisation paying for these services on your behalf?



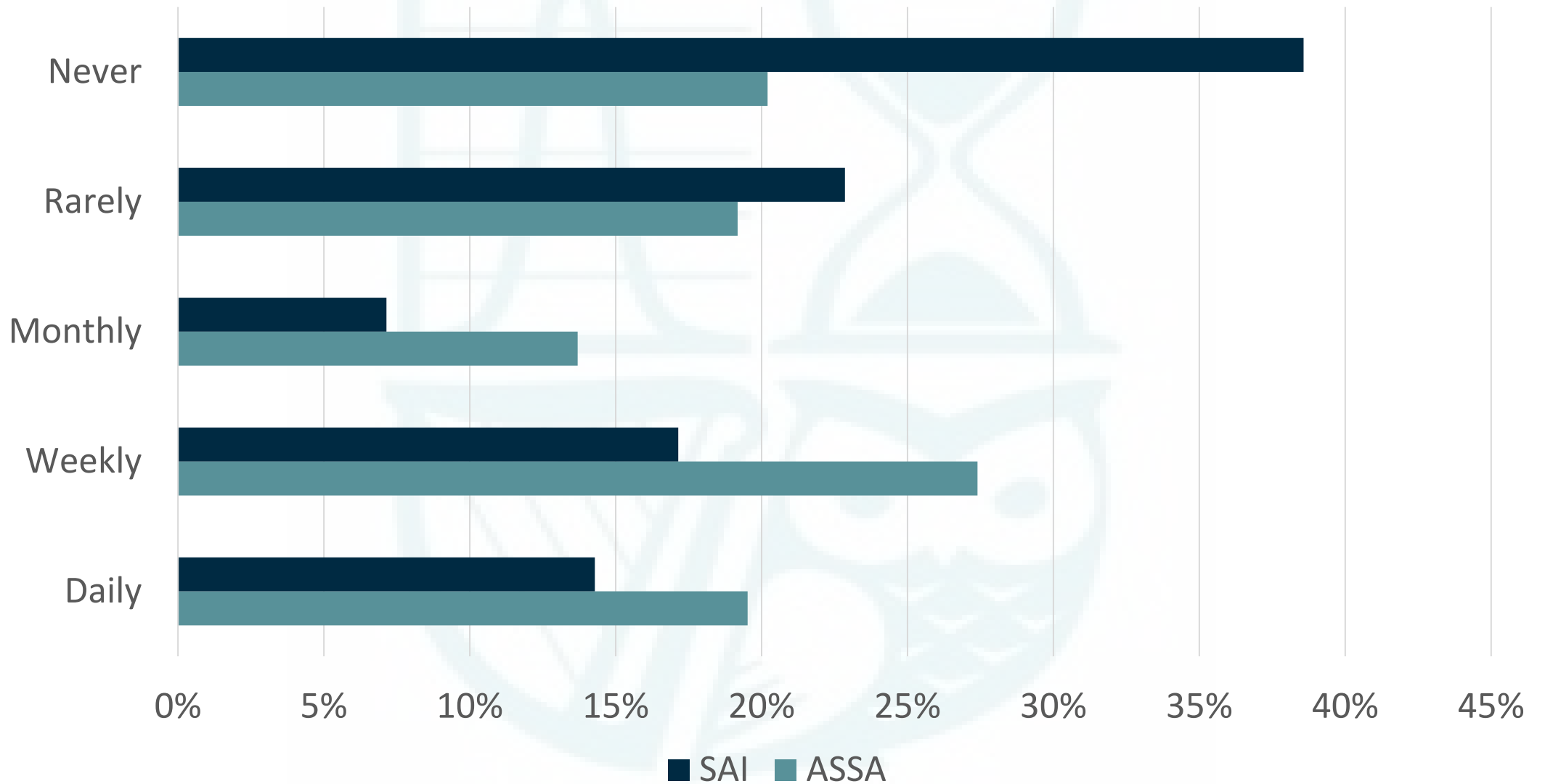


Does your organisation have an official policy on the usage of LLMs?



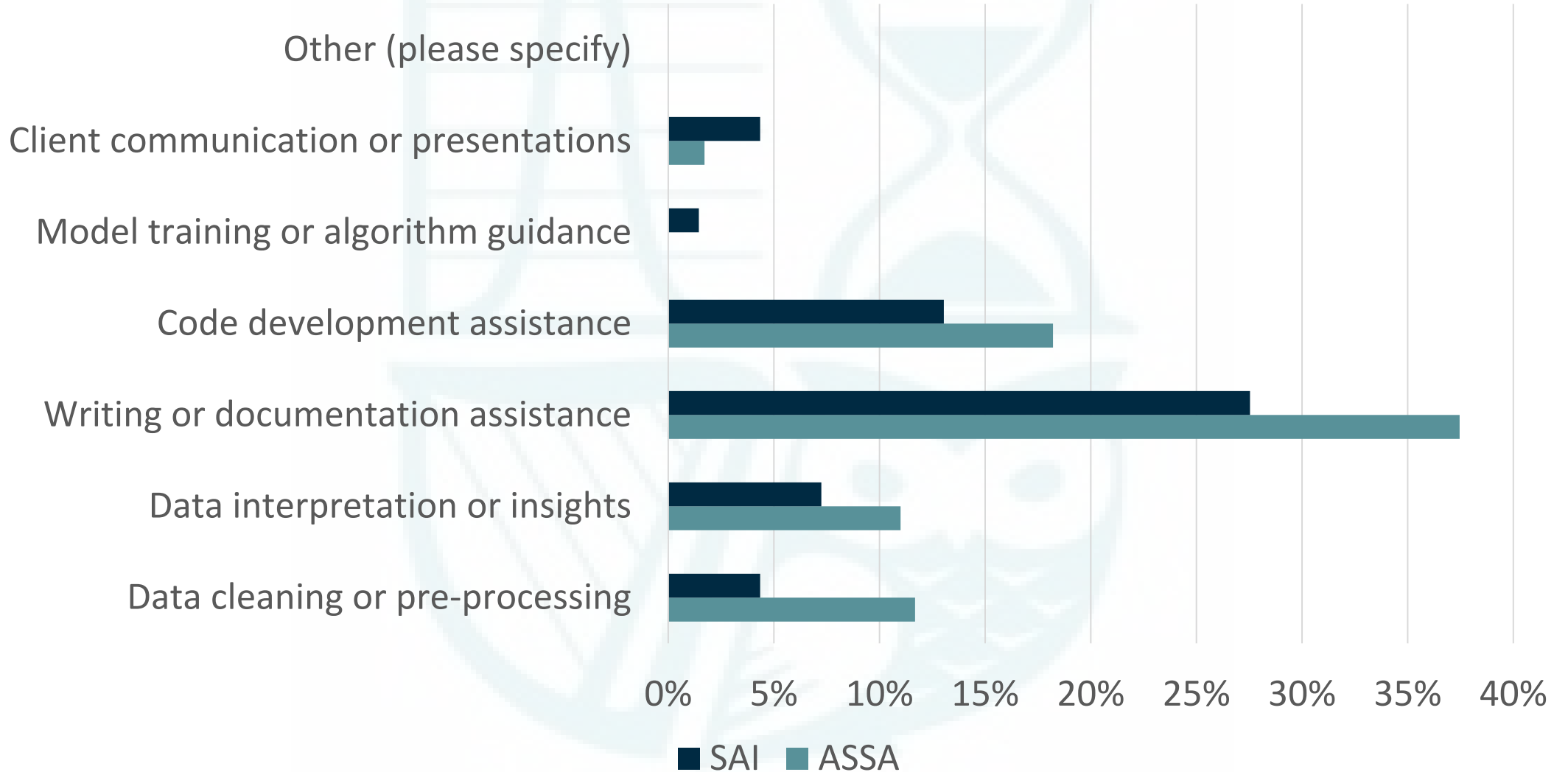


How often do you use LLMs (like ChatGPT) in a work context?



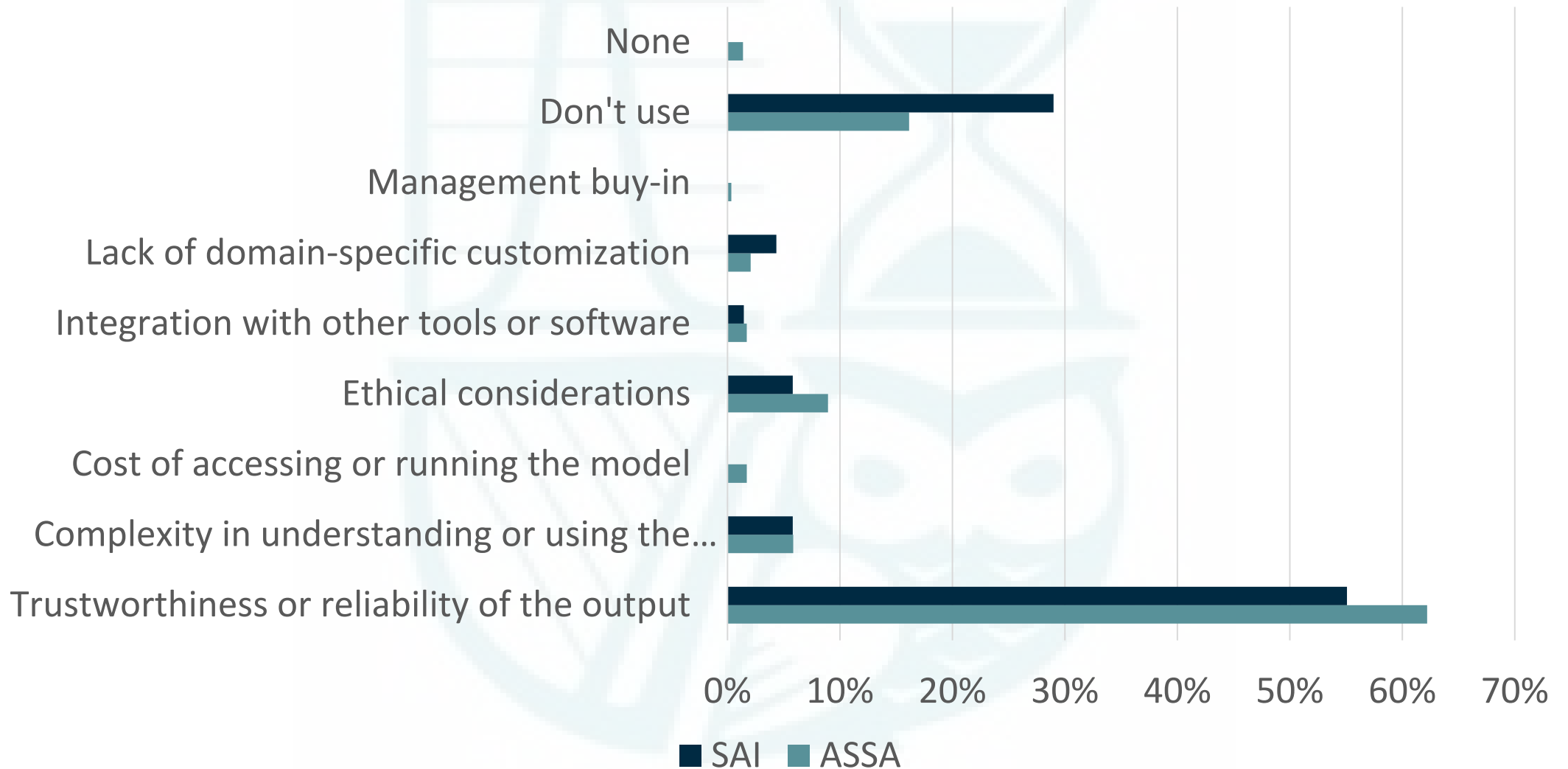


For what purposes do you primarily use LLMs in your actuarial work?



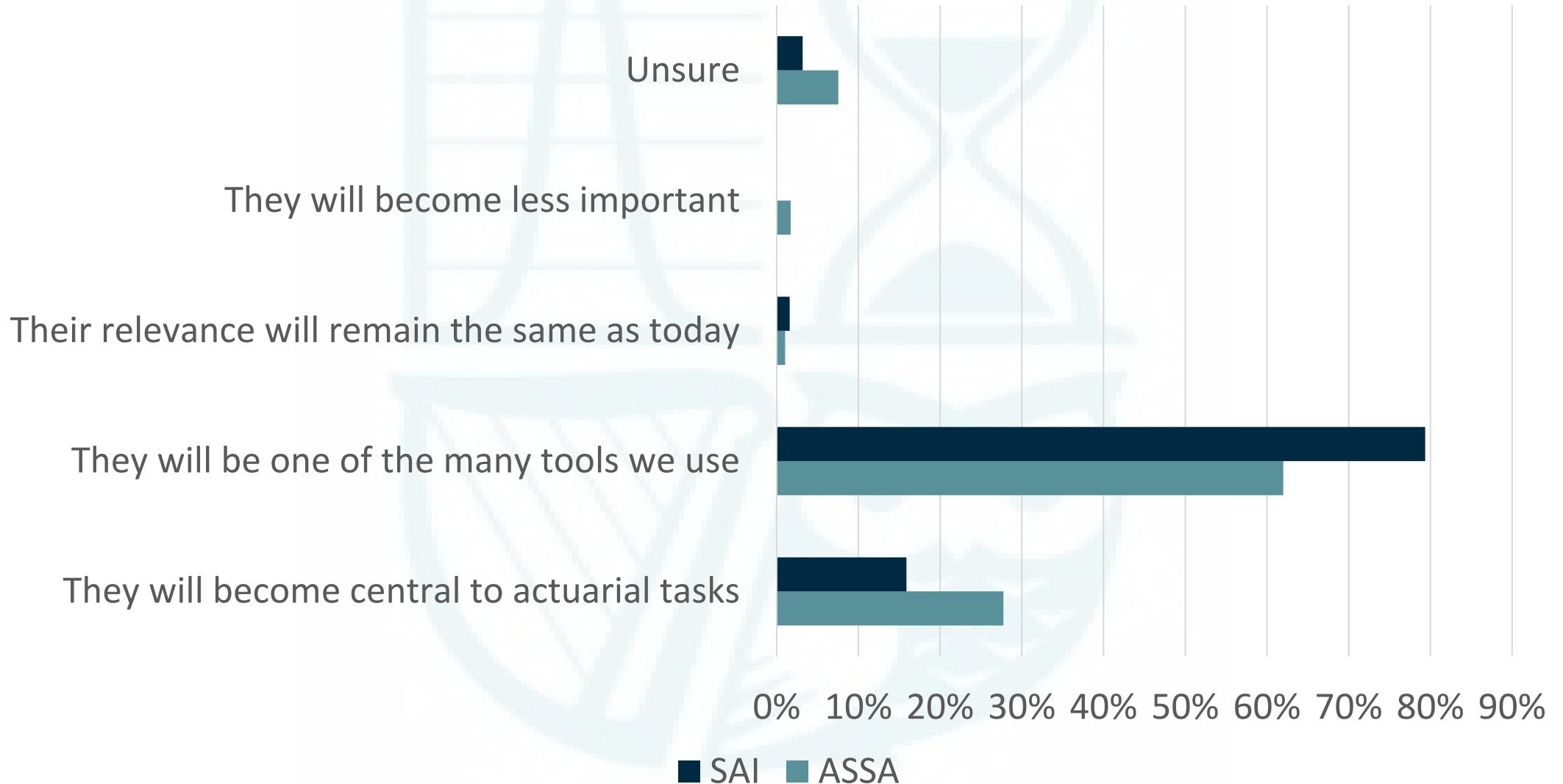


What challenges or concerns do you face when using LLMs in your actuarial tasks?



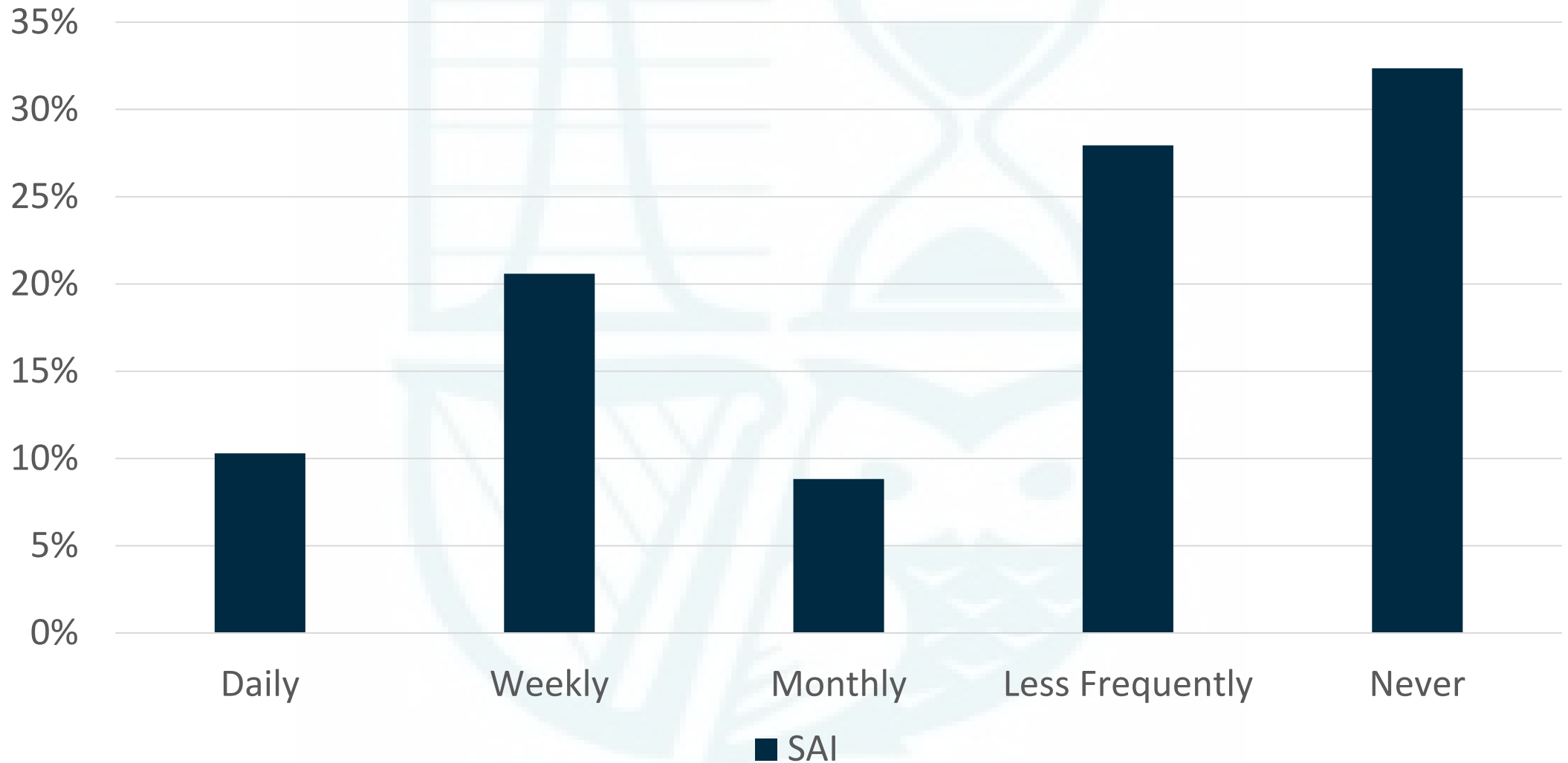


How do you see the role of LLMs in actuarial science evolving in the next 5 years?



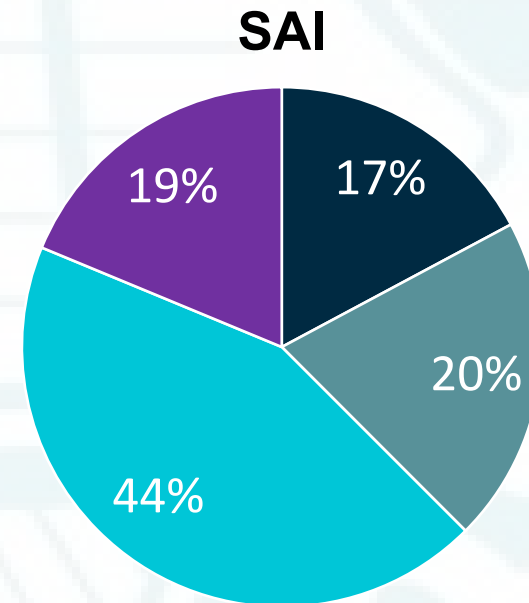


How often do you collaborate with other data science or analytics professionals?





My organisation has invested in a POC machine learning exercise and is now considering deploying the model to support decisions.



- I would not get involved in the decision over whether or not to deploy the model
- I would feel confident in recommending controls around deployment, but not in challenging the model design or findings
- I would feel confident in seeking a high-level understanding of the model
- I would feel confident in testing or challenging all aspects of the proposed model



Q&A

Please raise your hand to ask a question,
and wait for a mike to get to you



Society of Actuaries in Ireland

Panel Discussion

Compere Roz Briggs - incoming President



Society of Actuaries in Ireland

DEAI committee has put together the below survey to help plan their year ahead agenda. Please complete at your convenience

Thank You

