

# 18th Webinar Data Science Analytics

## 22 September 2026

### **Elevating Insurance Risk Assessment: Machine Learning for Underwriting & Risk Prediction**



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# Global highlights



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**1200**

Employees

**AA-**

Rated S&P  
global rankings

**1,970**

Reinsurance treaties

underwrite  
**4.2million**

Protection product  
applications processed through  
UnderwriteMe software

**967billion**

Life insurance policies in force

**100+**  
Key clients

**14.6 million**

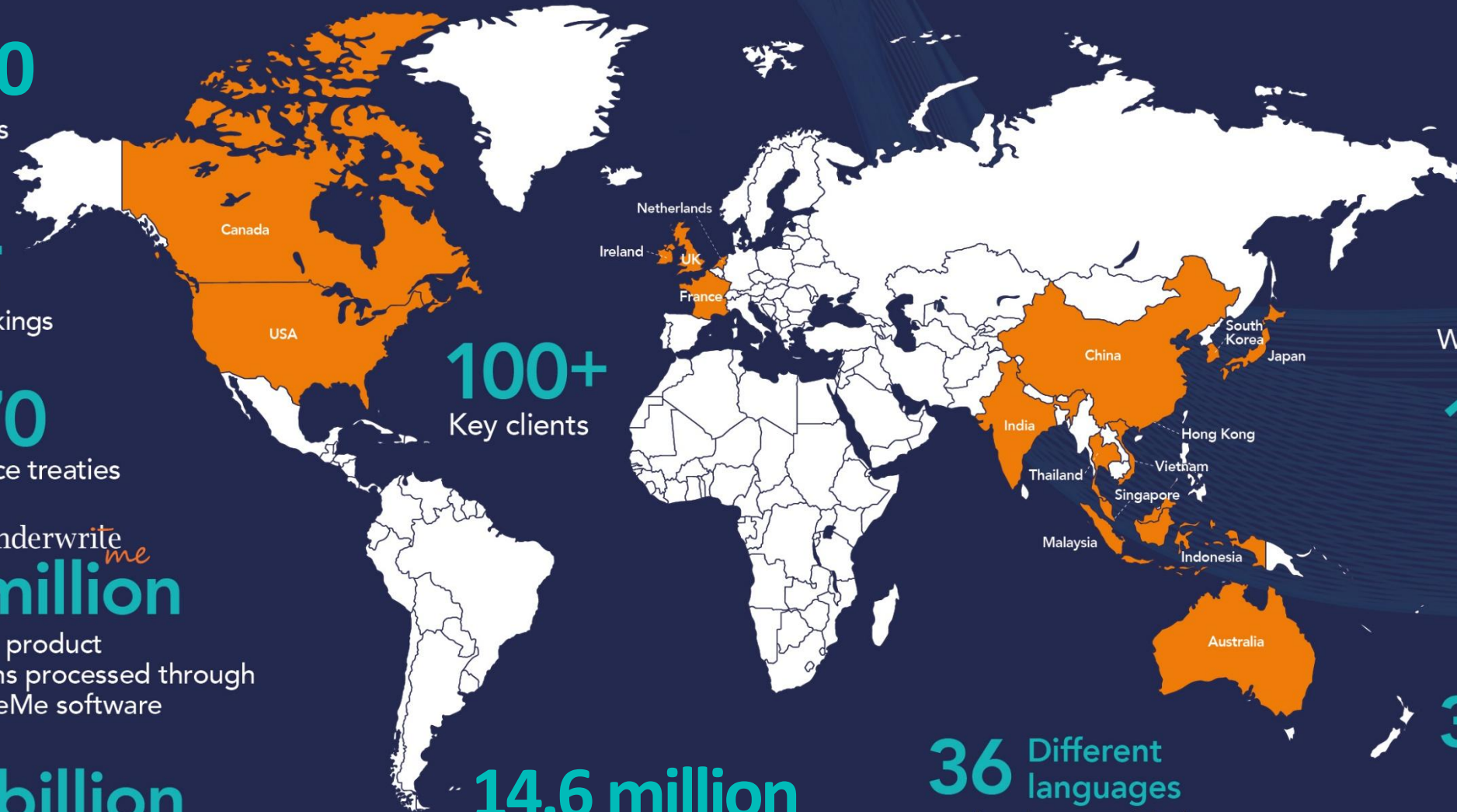
Lives protected

**36** Different  
languages  
spoken by our global  
PL Re employees

We are a  
global team  
spanning **18**  
time zones  
from Toronto  
to Sydney

We have an employee  
of every age from  
**18 to 65**  
bringing fresh  
perspectives and  
experience to  
everything we do

We have a diverse  
business with  
**38** nationalities  
& **13** religions  
recorded amongst  
our employees



## Pacific Life Re's Strategic Analytics team



We are a team of analytics actuaries, data scientists and data engineers with a global footprint.



We collect, maintain and utilise novel datasets to help derive new insights and sharpen actuarial assumptions.



We help our insurance clients develop and deploy data science solutions.

### What can we do for Indian insurers?

UW & Claim automation

Endorse & improve risk models

Experience study & data insights

Customer experience management

# What is Machine Learning / AI models?

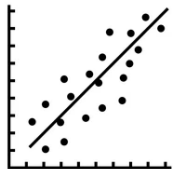
“AI models” span a broad spectrum of method, each with distinct strengths, limitations and use cases.

1970

## Statistical models

GLM • GAM • Survival

The model fits a statistical line through data points.

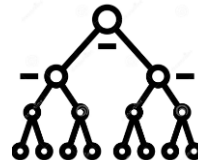


1990

## Classical ML

Trees • SVM • Clustering

The model learns patterns in tabular data without any constraints.



2010

## Deep learning

Neural Networks

The model learns hierarchical representations from high-dimensional data.



2020

## Foundation models

Transformers • LLM

Large-scale pretraining learns representations that transfer across tasks and modalities.



REPRESENTATION

mostly specified

DATA

structured / lower-dimensional

COMPUTE

modest

INTERPRETATION

transparent

increasingly learned

high-dimensional / unstructured

large-scale

black-box

*Different model families make different trade-offs in structure, data requirements, interpretability and compute.*



# In focus: ML applications through two distinct use cases

Real life projects done in the past creating actual business values



## Case 1: Underwriting Research

Use of ML models flexibly and interpretably to discover mortality risk factors, nonlinearities, thresholds and interactions in an assumption setting problem.

## Case 2: Accelerated Underwriting

Embedding machine learning models into live decision systems to automate routine assessments, support consistent risk decisions and reduce operational effort at scale.

After the two cases, we return to one broader question - **Where do tree-based models fit in today's wider AI toolkit?**



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# Case Study 1 – Underwriting Research

# (Re)insurers need philosophy on how to price for impaired lives



In UK, approx. 20% of life covers are rated with an average of 50%-75% extra mortality loading for policy lifetime. Accurate ratings can improve price competitiveness whilst maintaining profitability.

Typical assessment framework:

Current Health Measures | Lifestyle Habits | Condition History | Family History → Elevated Claim Risk

Philosophy development:

## COMMON APPROACH

### Scan and synthesize public medical literatures

- **Basis mismatch** Clinical / general-population evidence may not resemble an insurance applicant pool.
- **One risk factor at a time** May miss the joint effect of correlated health risks
- **Coarse evidence** Published results often use broad categories and predefined cut-offs inconsistent with desired ranges
- **Different definitions** Disease definition and follow-up time period can differ to the insurance setting

## DATA APPROACH

### Get the data and model the risk structure in-house

- **Insurance-shaped question** Model the exact variables, ranges and combinations relevant to philosophy.
- **Multivariate by design** Choose all variables of interest and let them interact in one framework.
- **Flexible risk shape** Results in exact granularity as desired
- **Sensitivity testing** Test different approaches and scenarios for risk tolerance

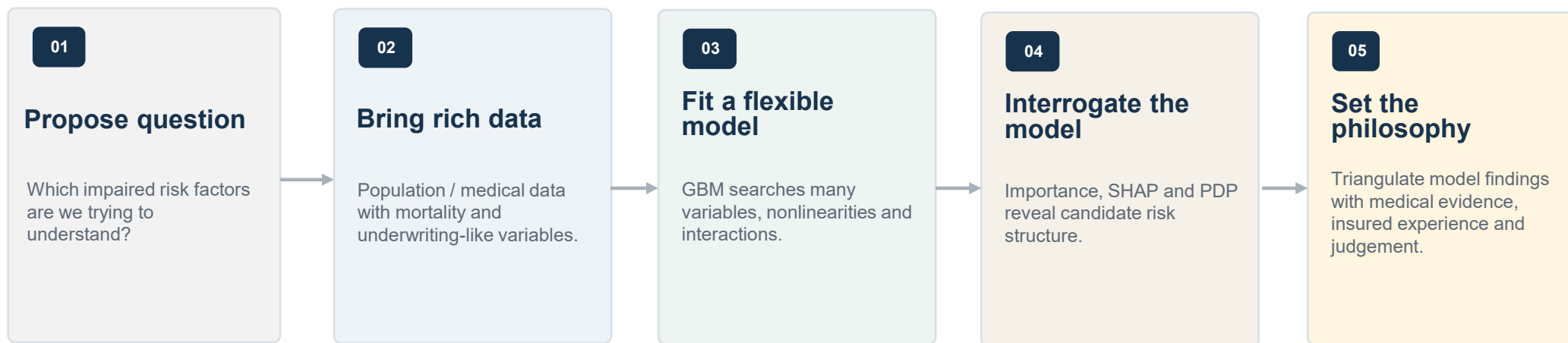


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# Process Overview

It can be framed as an assumption setting problem with underwriters and medical experts



## 01 Propose question

### How should we rate cardiovascular risk?

- **BMI, blood pressure, lipids and blood glucose:** these are the most commonly available objective health measures in health checkup.
- Large number of applicants present with elevated cardiovascular risk, which has been clinically proven to have a clear link to mortality.
- The factors are correlated. Their combined effect may differ from assessing each factor individually.
- Small improvements in rating can materially affect pricing competitiveness and new business volumes



# NHANES: public US population health dataset



A freely available, real-world health and mortality dataset, well suited to experimentation and production

## National Health and Nutrition Examination Survey

A survey research program conducted by the US National Center for Health Statistics (NCHS).

It was run in multiyear phases from 1971 until 1999, after which it became an annual, continuous, survey.

It is not a longitudinal study. Each iteration covers a new selection of participants, constituting a representative sample of the US population.

Data summary:

**140k**  
participants

**1,000+**  
variables

**23 years**  
Longest follow up

**31,000**  
deaths

[CDC download: NHANES datasets & documentation](#)

### CAVEAT

The official data source are high modular. Data definition could vary across different NHANES cohorts. Effort required for data collection, merging and normalization.

Open-source, analysis-ready versions of NHANES are available to download.

### VARIABLE EXAMPLES

#### Demographics

- Gender
- Race/Ethnicity
- Income
- Marital Status
- Age
- Occupation
- Health Insurance

#### Body Measurements

- BMI
- Waist circumference
- Blood Pressure
- Heart rate

#### Medical History

- Asthma
- Bronchitis/Emphysema
- Diabetes
- Heart Attack
- Hepatitis
- Kidney disease
- Cancer
- Stroke
- Thyroid

#### Family History

#### Labs: Blood and Urine

- Albumin
- Aspartate aminotransferase
- Bilirubin
- Blood Urea Nitrogen
- Cholesterol
- Cotinine
- Creatinine
- Gamma glutamyl transferase
- Globulin
- HDL
- Haemoglobin
- LDL
- Protein
- Red Blood Cell Count
- Triglycerides
- Urine pH
- White Blood Cell Count

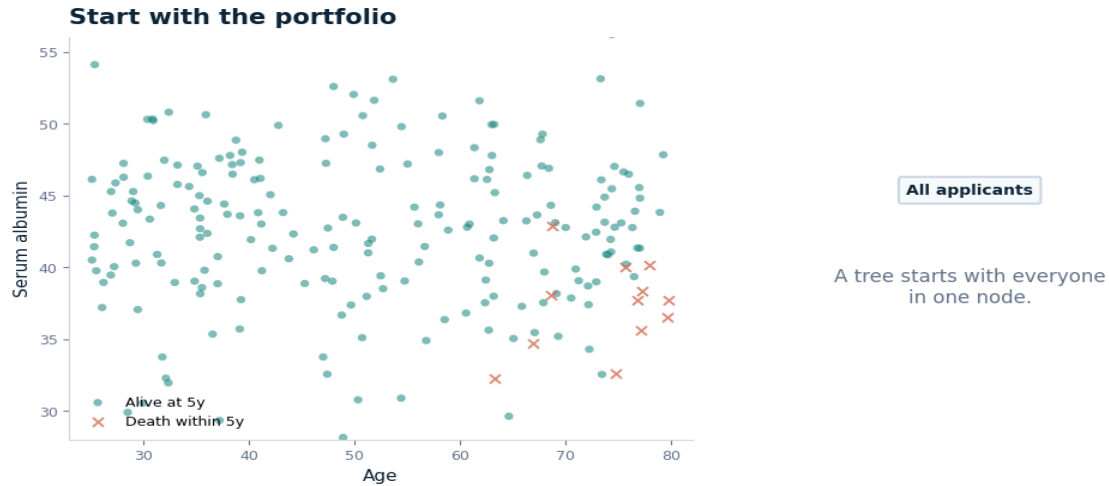
#### Mortality Data

- Mortality Status
- Cause of Death
- Time and age of death
- Time since NHANES contact



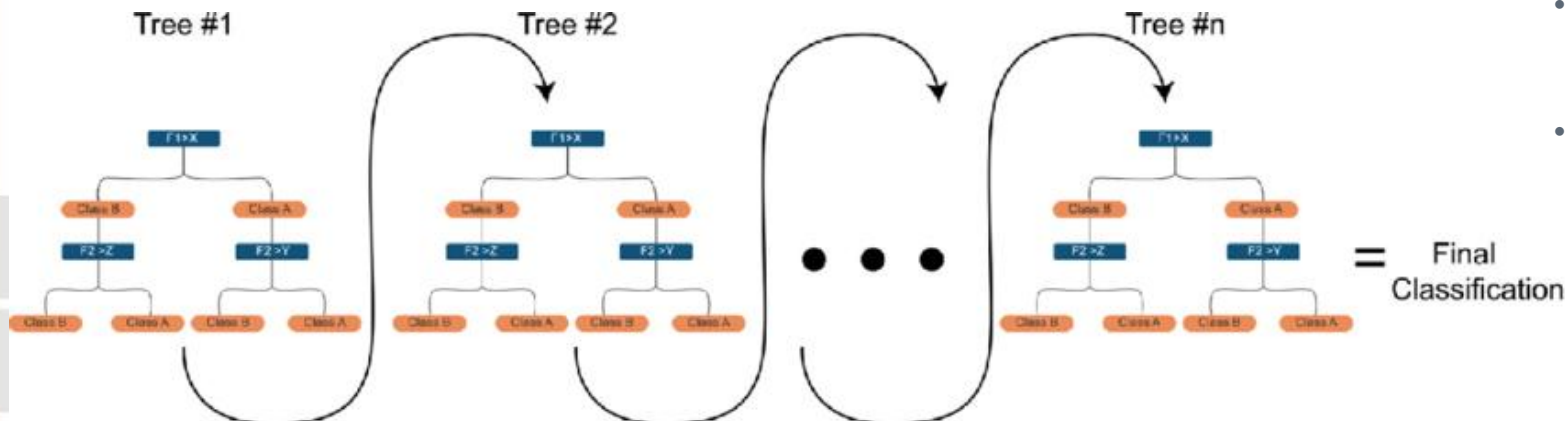
# What is Gradient Boosting Model?

From a decision tree:



- Each split creates more homogeneous risk groups; later splits automatically create interactions.
- A tree learns by repeatedly splitting the portfolio

To a series of trees, each improving on previous:



- Each tree learns from errors of previous trees
- Many shallow trees combined together improve performance

# What is Survival GBM?

Same survival framework; a different function for the log hazard ratio

## 1 Cox proportional hazards

Hazard = baseline hazard  $\times$  relative risk

$$h(t | x) = h_0(t) \cdot \exp(\beta^T x)$$

### Interpretation

- $h_0(t)$ : underlying mortality pattern over time
- $\beta^T x$ : log relative-risk score from covariates
- $\exp(\beta_j)$ : hazard ratio for a 1-unit increase in  $x_j$

Example:  $\beta_{\text{BMI}} = 0.04$

HR for +5 BMI units =  $\exp(0.04 \times 5) \approx 1.22$

$\approx 22\%$  higher instantaneous mortality hazard, holding other covariates fixed



## 2 XGBoost with Cox loss

Replace the linear predictor with the tree ensemble

$$h(t | x) = h_0(t) \cdot \exp(f(x))$$

where  $f(x) = \sum_k \text{tree}_k(x)$

What changes?  $\beta^T x \rightarrow f(x)$

The Cox framework stays; the risk function becomes flexible enough to learn patterns present in the data

Training objective: Cox partial likelihood

At each death time, increase the score of the person who died relative to everyone still at risk.

**Key  
Interpretation**

$$\text{HR(A vs B)} = \exp[f(x_A) - f(x_B)]$$

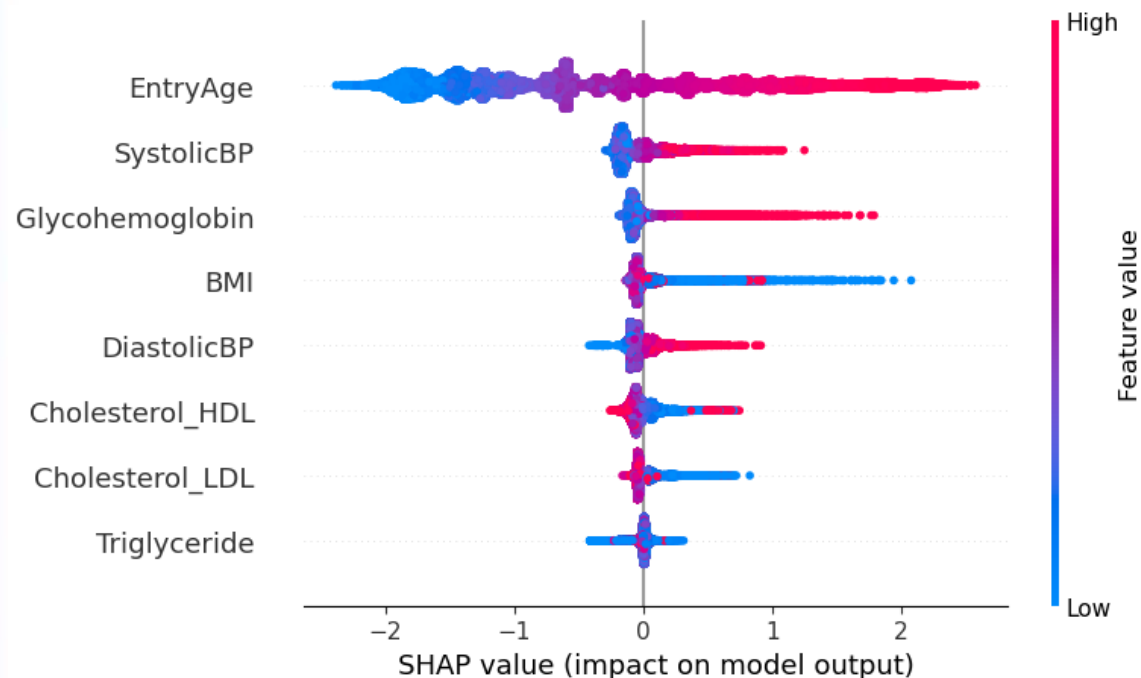
The model outputs relative risk, not an absolute mortality probability. Absolute survival requires an estimate of  $h_0(t)$ .



# What does the model say?

SHAP values – powerful model explainer based on game theory

**SHAP Beeswarm Plot – what variables are important and how they drive prediction**



## How to read the plot

- Dot = one individual
- Right of vertical line = higher predicted hazard
- Left of vertical line = lower predicted hazard
- Colour = feature value
- Order = variable importance

## Takeaways

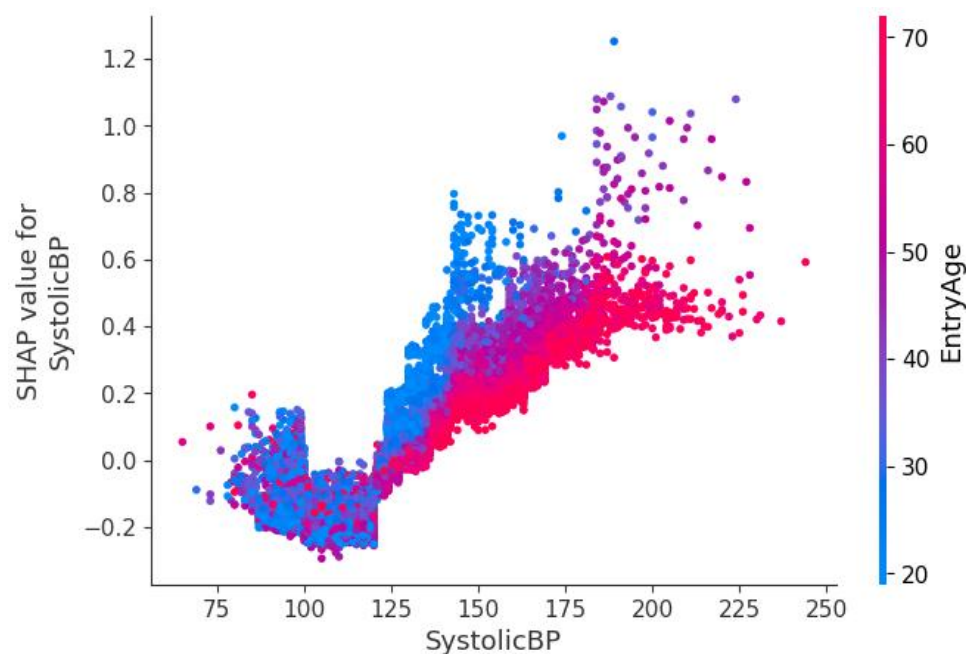
1. For entry age, lower values are associated with lower predicted hazard (less risk), obviously.
2. For systolic blood pressure, higher values are associated with higher risk, but lower values does not drive lower mortality
3. Triglyceride does not show strong link with mortality



# What does the model say?

SHAP values – powerful model explainer based on game theory

## SHAP Dependency Plot – interactive effect of two variables



### How to read the plot

- Dot = one individual
- X-axis = range of values for variable A
- Y-axis= higher values => higher model predicted risk
- Colour = range of values for variable B

### Takeaways

1. Model predicted a J-shape for systolic BP: high or low SBP is associated with high mortality.
2. There is an age interaction at increased BP: older people's mortality is less affected by elevated BP than younger people

### Caveats

SHAP values explain the fitted prediction function, it is not model predicted values. Correlated measurements can redistribute attribution.

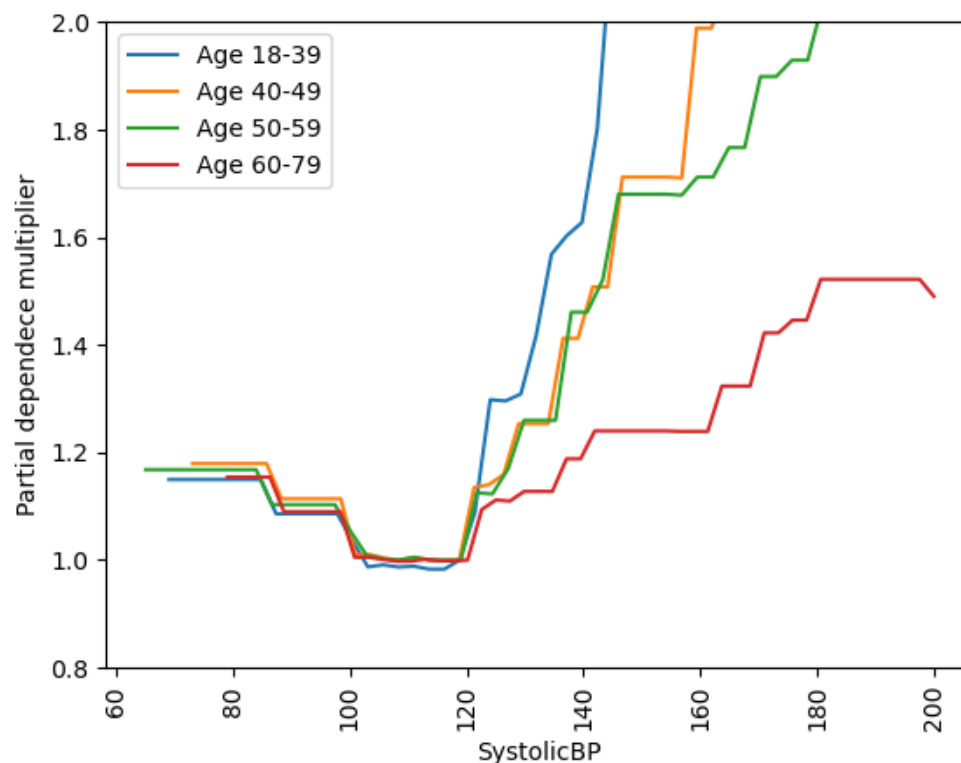
Many more plots available: [SHAP documentation](#)



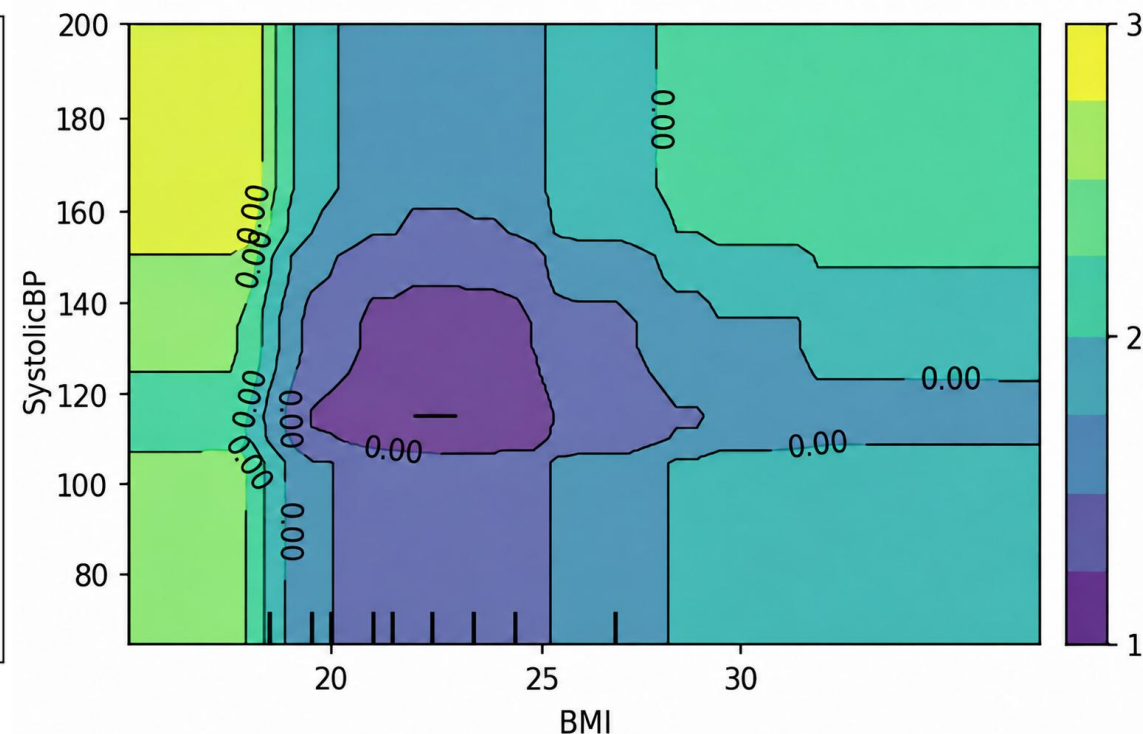
# What are the model predicted loadings?

ML model predictions are revealed by averaging over many predictions of samples.

Partial dependency plot



2D Partial dependency plot



## What does the plot say

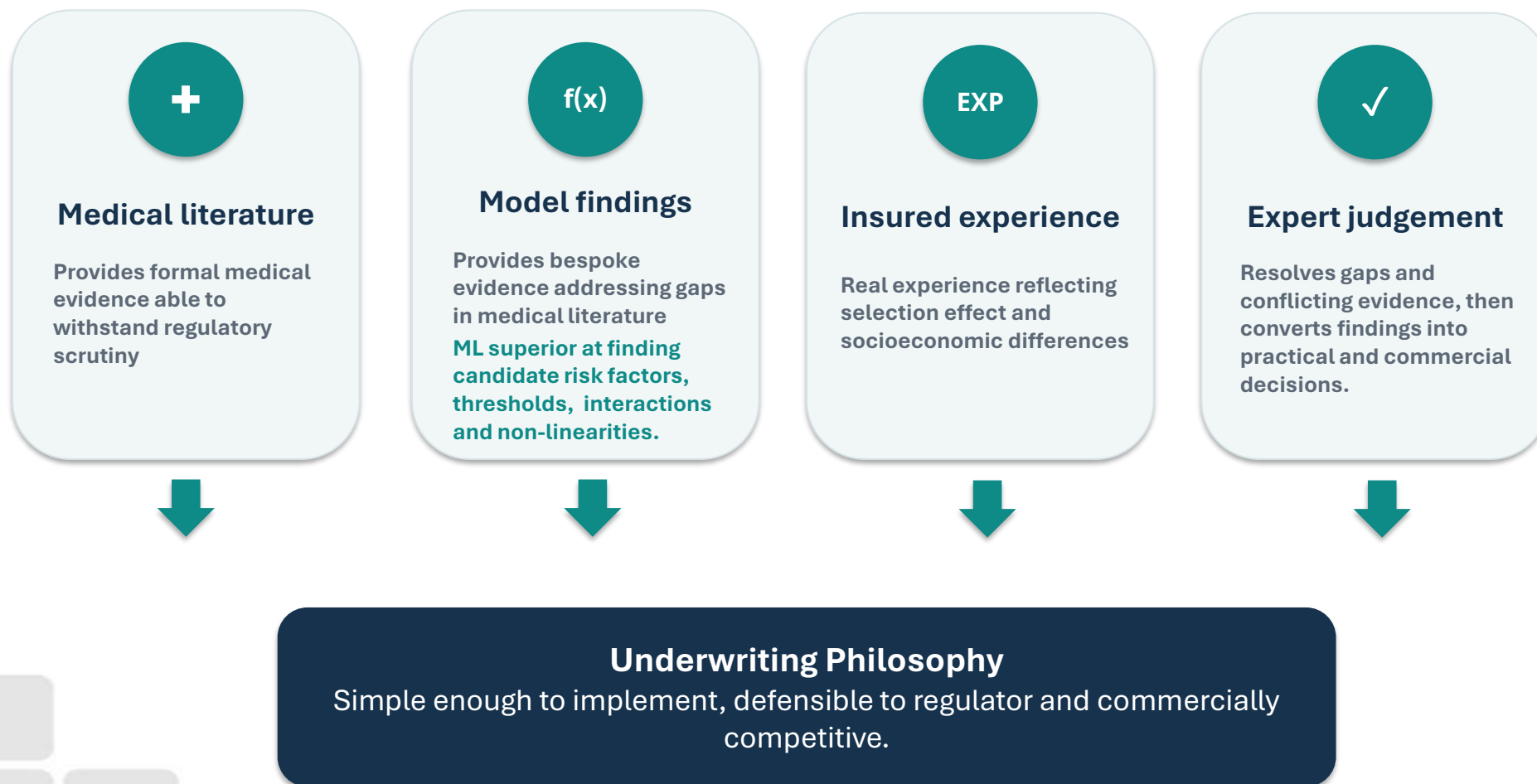
1. **J-shaped systolic BP** consistent with SHAP plot. Low BP are associated with up to 20% extra mortality, compared to BP of 100-120.
2. SBP=140 is associated with 60% EM for age 18-39 whereas for 60-79 it's only about 20%

## What does the plot say

BMI interacts with SBP, the effect of BMI on mortality changes across blood-pressure levels, so assessing either factor independently may misstate the combined risk.



# Model findings are just one piece of the puzzle



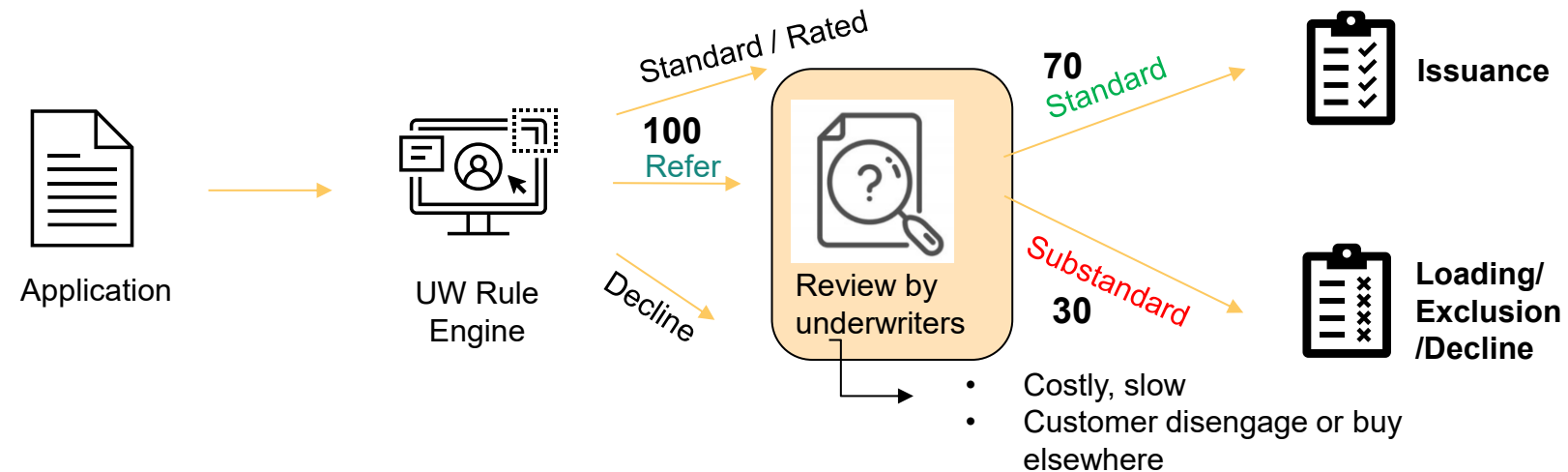


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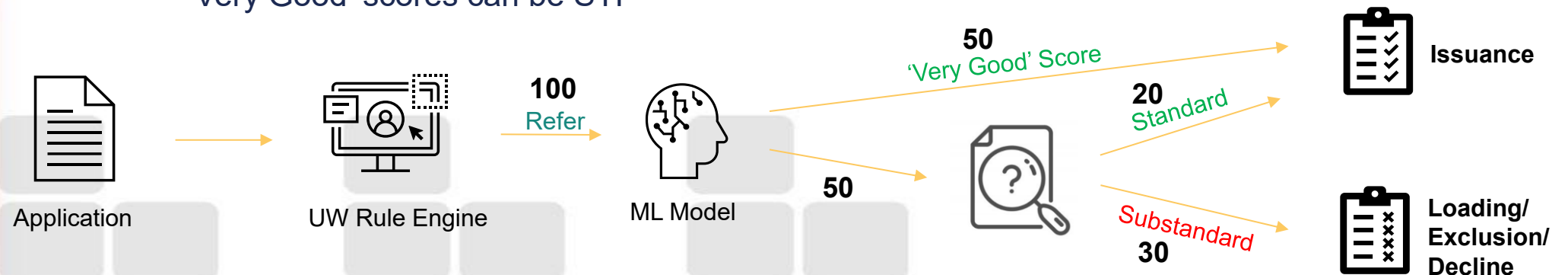
# Case Study 2 – Accelerated Underwriting

# UW Decision Workflow Overview

**As-Is:** Applicants classified as 'Refer' (non-STP) by UW Rules Engine will go through manual underwriting by underwriters



**To-Be:** ML model generates individual scores for these customers and 'Very Good' scores can be STP

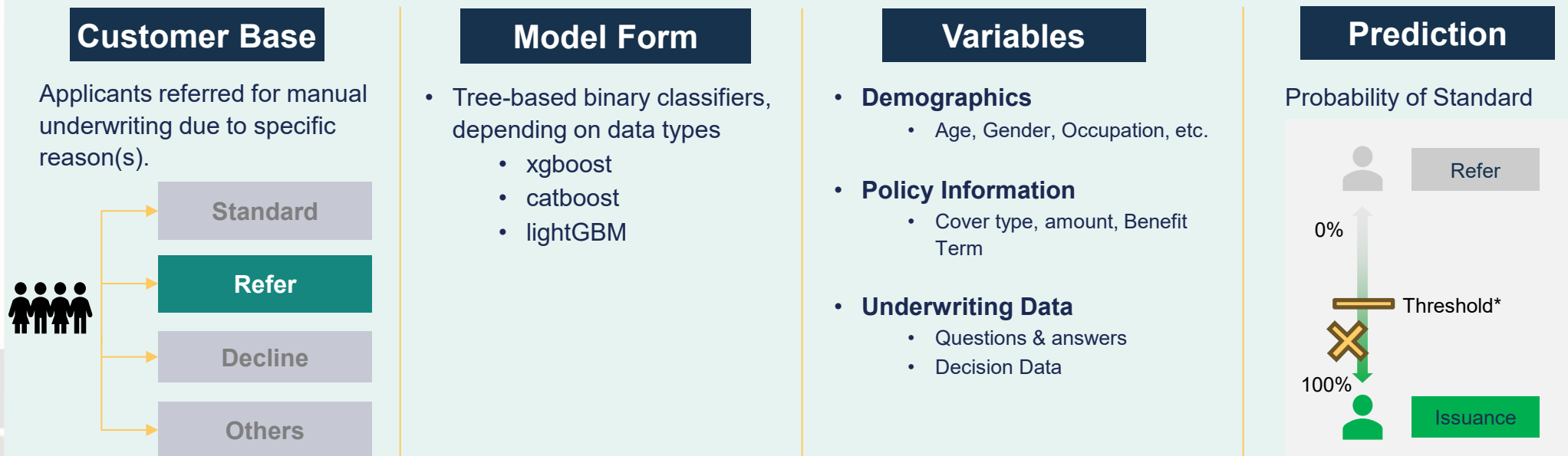


# Predictive Model Solution Overview

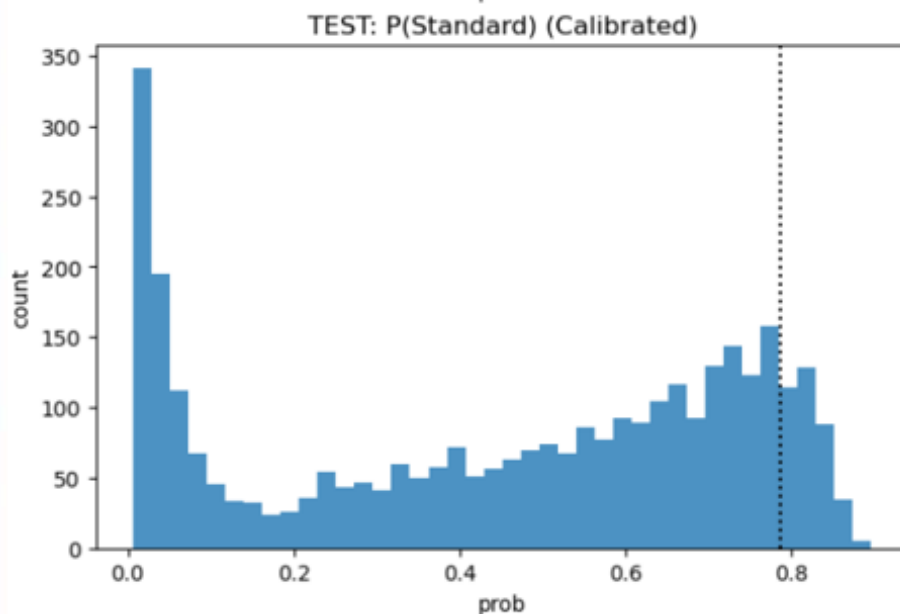
## Model Overview

|                  |                                                                                        |
|------------------|----------------------------------------------------------------------------------------|
| <b>Objective</b> | To predict the underwriting outcome (Standard vs Sub-standard) of targeted applicants. |
| <b>Solution</b>  | Develop ML model that learns from past underwriting records.                           |

## Model Content



# Choosing The Threshold



|        |              | Predicted         |                    |
|--------|--------------|-------------------|--------------------|
|        |              | Standard          | Non-Standard       |
| Actual | Standard     | Good              | Missed opportunity |
|        | Non-Standard | Mortality leakage | No Impact          |

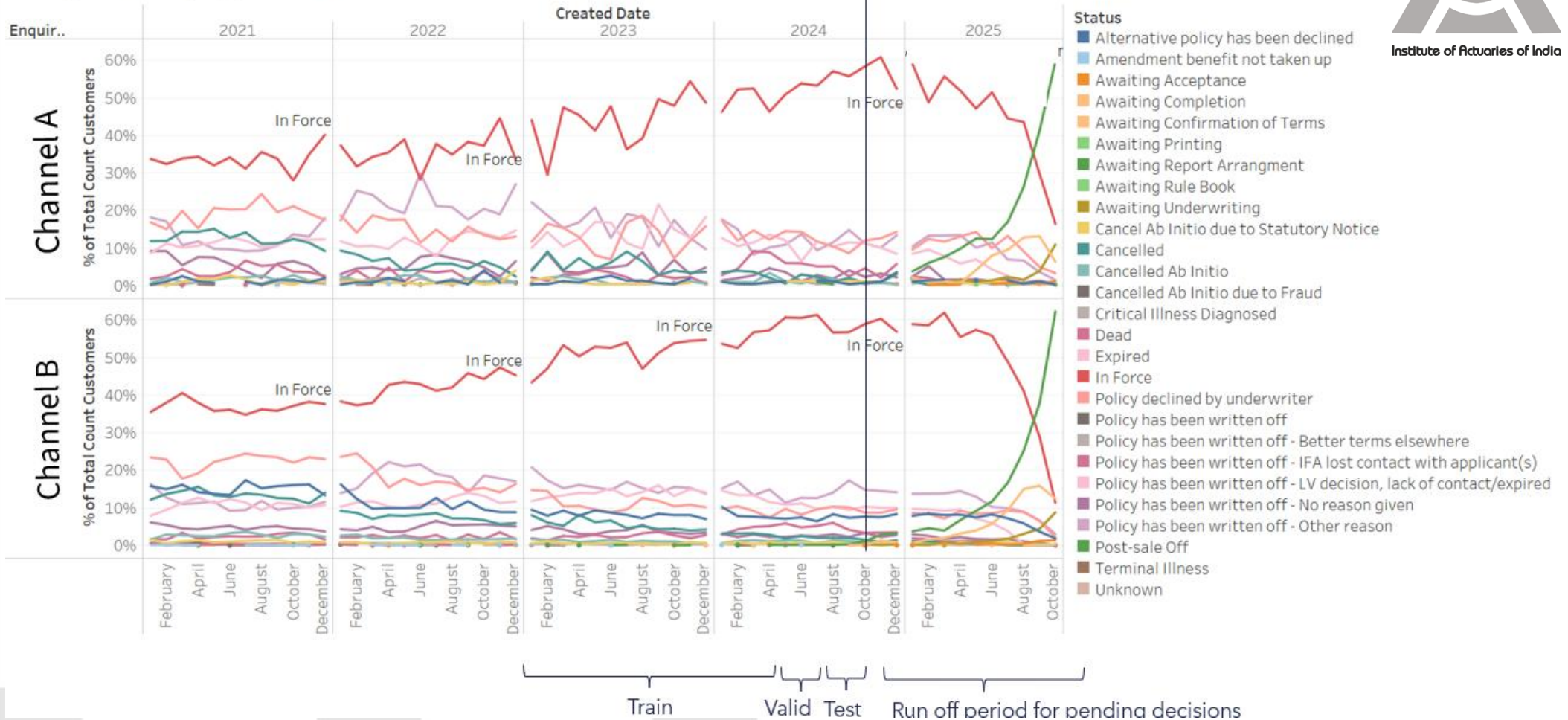
- In choosing the threshold, we want to maximise the **Good**, whilst minimising the **Mortality Leakage**
- There is no “right” answer, it’s up to the business risk appetite
  - lower threshold leads to:
    - more efficiency & policy take-up, but
    - higher risk cost.
- In practice, it is a collective decision involving many different stakeholders.

*Example metrics we looked at when deciding the threshold*

| Threshold | Referral Reduction % | Precision | Overall STA Uplift | Risk Cost | Medical evidence saving | FTE saving | Volume increase |
|-----------|----------------------|-----------|--------------------|-----------|-------------------------|------------|-----------------|
| 85.0%     | 15.1%                | 94.6%     | 4.2%               | 0.5%      | £210k p.a.              | 0.5-1      | 3.4%            |
| 90.0%     | 10.0%                | 96.6%     | 2.8%               | 0.2%      | £140k p.a.              | 0.5-1      | 2.2%            |
| 95.0%     | 7.6%                 | 97.5%     | 2.1%               | 0.1%      | £105k p.a.              | <0.5       | 1.7%            |
| 98.0%     | 2.6%                 | 99.2%     | 0.7%               | 0.0%      | £35k p.a.               | <0.5       | 0.6%            |

# Determining Analysis Period

Policy Status by Application Created Date



- UW rules change over time, we want the model to be most representative of current and near future
- Most recent data have pending UW decisions. Incomplete information makes this period unusable.
- Time-based train/valid/test split is used, whereby test period is set to the most recent usable period to be most accurate of the future expected outcome.

# Key Considerations for Live Deployment

## Model Monitoring

Performance can degrade over time as the portfolio shifts in:

- the underlying insured population
- prevailing underwriting rules
- distributor behaviour, among other factors

### Solution

Track model performance and business outcome continuously and recalibrate/retrain the model if performance diverges materially.

## Regulation

More stringent control when customer's outcome is directly decided by model. Company needs to demonstrate:

- adherence to data privacy laws
- non-discriminatory practices
- explainability
- human accountability

### Solution

- Exclude sensitive attributes from training
- Implement hard rules for model routing
- Evidence equal outcomes across key attributes
- Use interpretation techniques to explain each case



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# Future Outlook

# Can LLM replace tree-based ML models?

## 1 Repeatability

Same input, same output in trees. LLM can produce a distribution of outputs, or answers can even with a slight change in semantics in prompt.

## 2 Predictable cost and speed

Tree models are cheap and fast. LLM cost and latency depend on tokens, context and tool calls — hard to budget at scale.

## 3 Auditability

Tree models can be frozen, versioned and re-run to explain any decision to regulator. LLM setups add prompts, retrieval and vendor versions to validate.

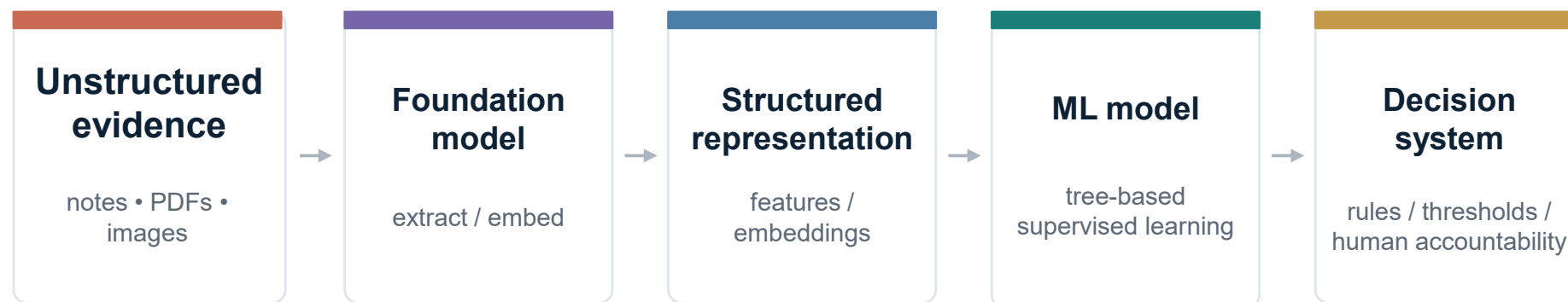
## 4 Security and data control

Insurance data is personal and sensitive. An outside LLM service adds privacy, vendor and data-leak risk that in-house models avoid.



# Foundation models may make tree-based ML more useful

Foundation models can expand the inputs; Tree-based models remain the structured risk engine.



## Medical notes

LLM extracts conditions →  
underwriting features

## Claims descriptions

text classifier → cause / fraud  
/ triage signals

## Documents

OCR + LLM → structured  
underwriting evidence

*Modern AI can sit upstream of tree-based ML rather than replace it.*

*Model building has never been easier with AI coding assistant*



To help you get started, I have created a github repo showcasing end-to-end ML survival modelling:  
[iai-webinar-demo](#)



C: > Users > zzhou > AppData > Local > Temp > 913df4d9-4e2c-4de4-85e1-68487c84d748\_iai-webinar-demo-main.zip.748 > iai-webinar-demo-main > underwriting\_research.ipynb > M4 Interpreting mortality associations for underwriting research

Generate + Code + Markdown | Run All | Outline ...

## Interpreting mortality associations for underwriting research

This analysis estimates adjusted mortality associations for underwriting research using clearly defined comparisons. Including more variables can change that comparison, even when prediction improves.

1. Choose coherent measurements and remove strong redundancy.
2. Estimate smooth, adjusted HR curves with spline Cox.
3. Use XGBoost with all selected measurements to investigate nonlinear relationships.
4. Check data support and interpret model contributions before drawing UW conclusions.

We investigate conditional associations, not causal effects or ready-to-use loadings. No curve is constrained to match an expected U-shape.

Run the cells from top to bottom. Each code cell performs one part of the analysis; later cells use objects created earlier. Cells that define a function prepare a reusable operation and do not produce a result until the function is called.

### 1. Data prep

Import packages. Load the libraries used for data preparation, survival models and plots.

```
[1] from pathlib import Path
import json, hashlib, warnings
from urllib.request import urlopen
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from IPython.display import display
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import SplineTransformer
from threadpoolctl import threadpool_limits
import xgboost as xgb

warnings.filterwarnings("ignore", message="IPProgress not found.*")

import shap
from survival_helpers import LinearCox, signed_labels, concordance
```

Set paths and reproducible settings. Create the output folder and use a fixed random seed. The plotting function saves each figure before displaying it.

```
ROOT = Path.cwd()
OUT = ROOT / "results"
OUT.mkdir(exist_ok=True)

SEED = 2026
np.random.seed(SEED)

thread_limit = threadpool_limits(limits=4)

plt.rcParams.update(
    {"figure.figsize": (10, 5), "axes.spines.top": False, "axes.spines.right": False}
```

# Thank you!

We don't sell models; we build capabilities with your teams.

Let's continue the conversation.



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