

Use of Early Claims Management Activity as a Predictor of Scheme Duration

A Case-Study of Risk Model Co-Design and Integration

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Acknowledgement

I would like to acknowledge the Traditional Owners of the Land on which I am presenting today; the Jagera people and the Turrbal people as the Traditional Custodians of Meanjin (Brisbane) as well as the Wadawurrung People where TAC operates in Victoria.

I pay my respects to Elders past, present and emerging, and extend that respect to all Aboriginal and Torres Strait Islander people here today.



Enterprise Context

Our purpose

At the TAC, we are proud of our culture of genuine care. Our organisation thrives on an unwavering determination to care for the lives of everyone who travels on Victoria's roads – it is a collective force that helps us to make a difference to the community and clients we serve.

Victoria is a leader in road safety, yet sadly people continue to die or be seriously injured on our roads. Not only does road trauma have a devastating impact on people, it also costs our economy billions. We refuse to accept this as an inevitable cost of travelling on our roads. That is why, for almost four decades, the TAC has relentlessly pursued innovative strategies to prevent road trauma and support people injured on our roads.

We know much more needs to be done. We are motivated by our critical purpose, which has inspired the name of our strategy, **Make Every Day Matter**. We have set ambitious goals and targets over the next six years, which require all of us (the TAC, our clients, our partners, and the broader community) to focus on achieving better outcomes, every day.

Our four strategic goals are:

- 1. Safe to travel**
- 2. Best client outcomes**
- 3. High performing culture**
- 4. Scheme for now and the future**

Together with our road safety partners, we will lean in hard to the challenge of saving lives and reducing serious injuries. For those injured, we will help quickly connect them to the most effective services and supports based on their needs.



Supporting our clients

We are here to support those who have been injured on our roads and help them get their lives back on track. **Last year we supported 45,000 injured people.**

We cover the costs of injuries that are the direct result of accidents involving the driving of a car, motorcycle, bus, train or tram. This means we provide support to a variety of road users including drivers, passengers, pedestrians, motorcyclists and cyclists.

Under our 'no-fault' scheme, we pay for medical benefits and support services for any injured person – no matter who caused the accident.

We fund medical treatments for as long as necessary, whether it is over the short term, or for a lifetime. Our scheme is funded through the TAC charge, which is part of the annual vehicle registration Victorians pay through VicRoads.



Accident prevention

We work with road safety partners to reduce the incidence and severity of road trauma



Rehabilitation

We work with health and disability stakeholders to help injured people recover, get back to work and regain their independence.



Claims management

We empower our people to make the right decisions that best support our clients.



Financial management

We work with government to make sure our scheme is viable, sustainable and represents value for money.



Scheme design

We work with our stakeholders to make sure compensation is accurate, fair and provided as early as possible.

Background to Case Study

Simplified TAC Claims Management Journey

Lodgement

"I lodge a claim and provide evidence of my injury."

A claim is lodged via phone, online portal or by a Patient Liaison Officer in hospital.



Screening

"I answer questions about my situation."

Claim is managed and triaged within an initial support team and a needs-based assessment is completed.



Segmentation

"I am triaged to the right team, so I have support I need."

Claim segmented to relevant Claims Management Branch and Team.



Claims Management

"I receive the support I need to return to work and health."

Claims are managed and clients receive treatment. There is variation in how a claim is managed depending on segmentation pathway.

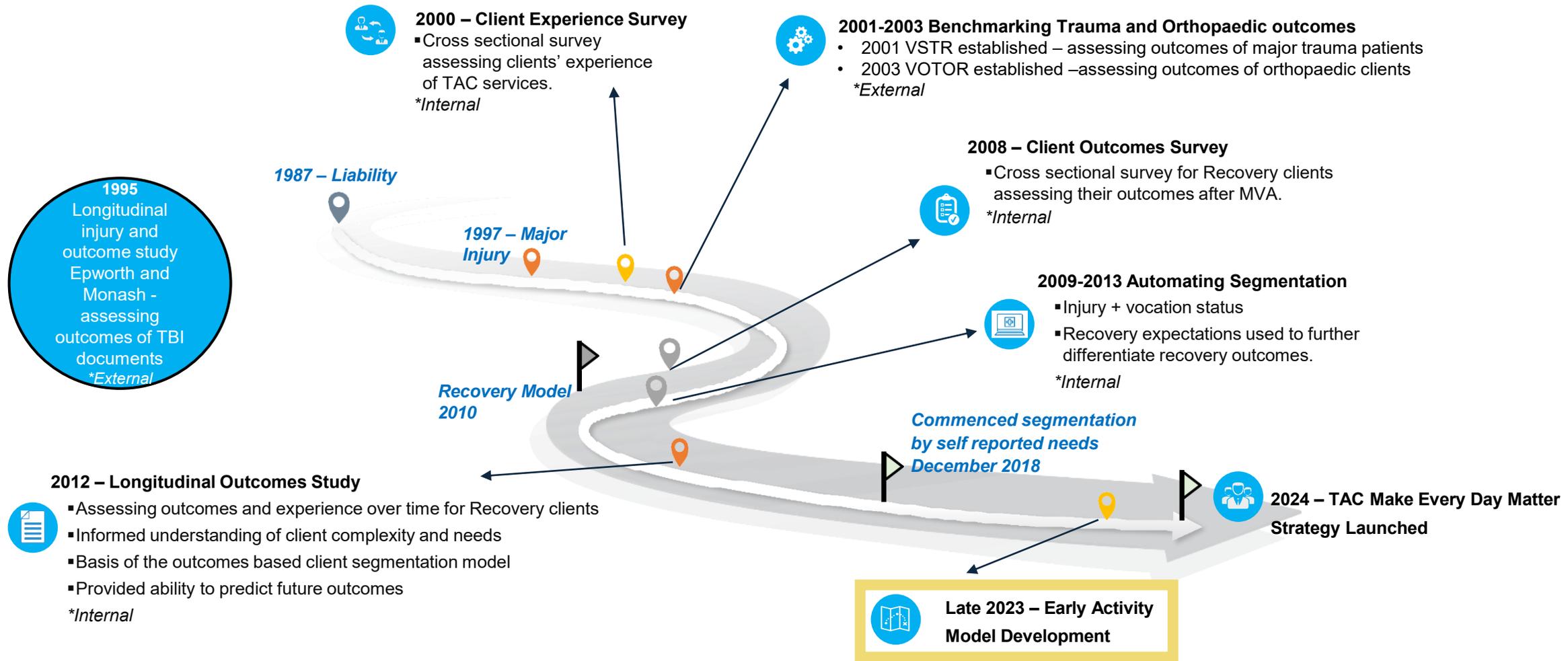


Client Outcome

"I have returned to work / I have returned to health."

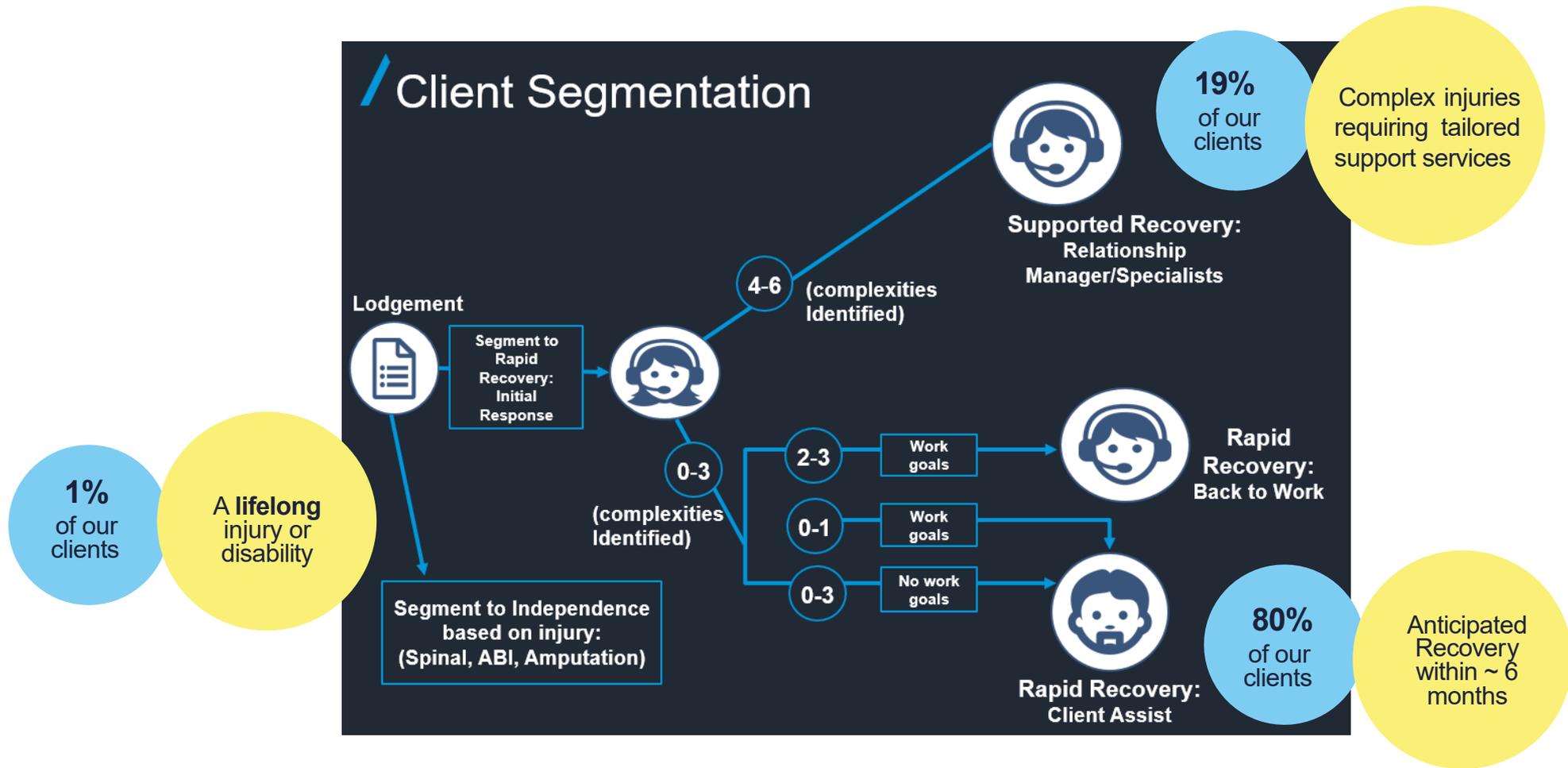
Claim becomes inactive once client meets their goals and recovers.

Client segmentation at TAC over the years



TAC Segmentation Model - 2023

- When work began, segmentation was driven by self-reported needs (called “NIDS”)



TAC Segmentation Model - 2023

- The 80/19 split was defined by 13 bio-psycho-social questions, of which 6 make up the core
- Claims scored as having 4 or more complexities are assigned a dedicated claims manager

Questions	Complexity Group
CH4. Usual activities	Pain Complexity
CH5. Pain or discomfort	
CH10. Persistent pain	
CH2. Mobility	Physical Health Complexity
CH3. Personal care	
CH6. Anxiety or Depression	Mental Health Complexity
DP2. Resilience	Recovery Expectations Complexity
PI7. Recovery Timeframe	
PI6. Expected Level of Recovery	Service Environment Complexity
PI3. Access to Treatment	
PI2. Treatment Helping Recovery	
DP3. Traffic Anxiety	Accident Response Complexity
DP4. Accident Response Issues	
DP5. Accident Response Issues Affecting Travel	
DP6. Accident Response Issues Mental vs Physical	

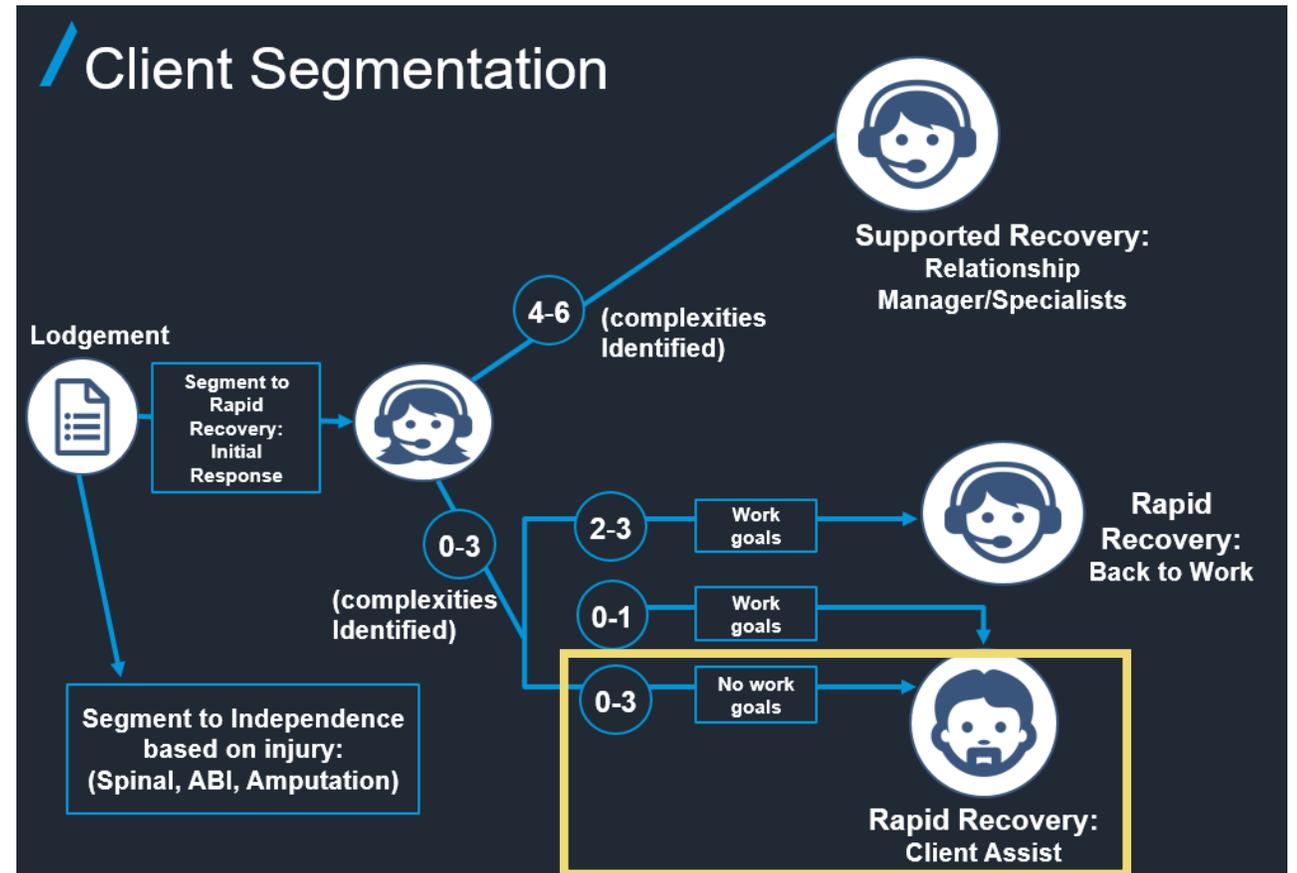
TAC Segmentation Model - 2023

A limitation to this approach was:

- Not all claims undergo screening
- Client needs can change over time
- There is high variability in outcomes among those who do screen “low complexity”

Case Study Objective:

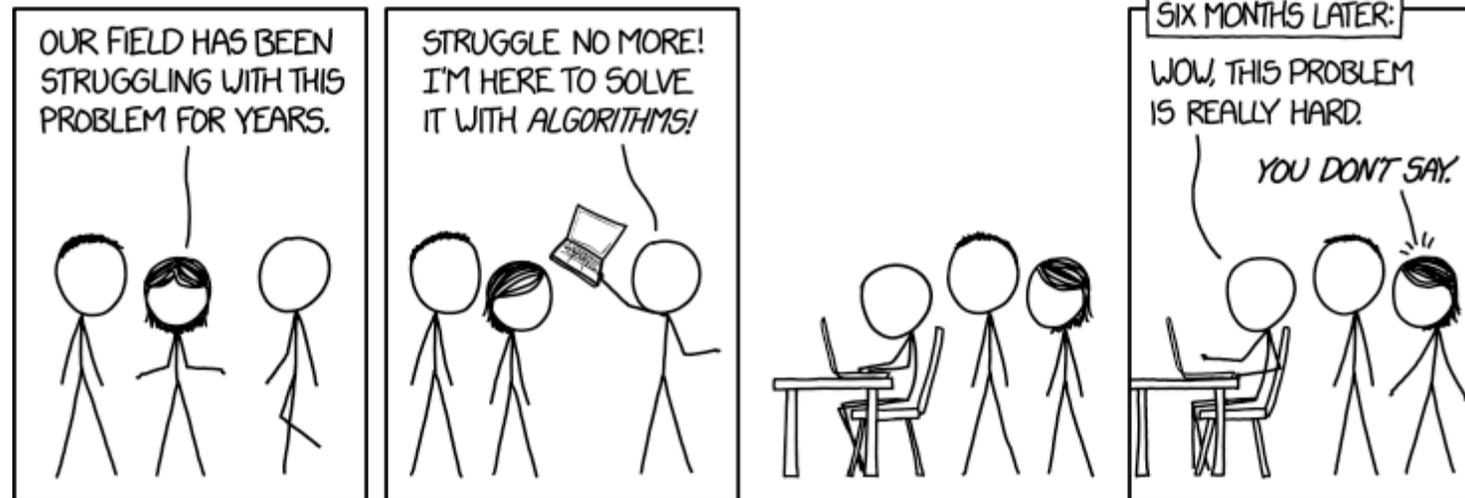
Can we further stratify the “low complexity” cohort?



The Analytical Model: From Idea to Implementation

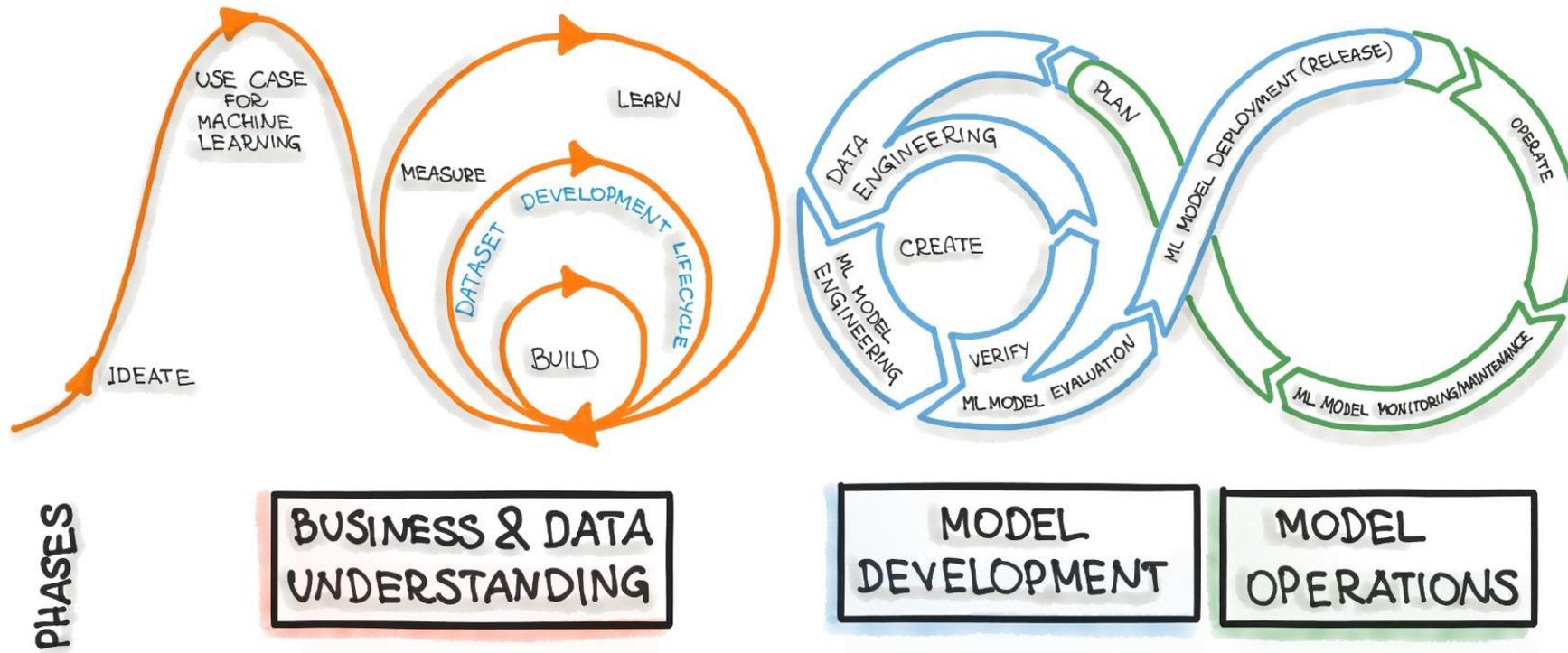
Why Machine Learning is Hard

- It's one thing to learn enough statistics and programming to train and test a model on static data...
- It's another thing to design and develop a new predictive tool on top of (imperfect) legacy data systems and embed it within business processes



Model Development Lifecycle

CRISP-ML(Q)



Step 1: Problem Formulation

- To build a model, we need to develop a concise definition of the problem that we are trying to solve.

Problem Statement

- Each year, ~12,000-13,000 clients screen “Low Risk”, but there is **high variability** within this cohort
- Another ~1,900 clients go unscreened while ~400 clients undergo only partial screening

Objective

To develop a predictive model that can forecast scheme duration for clients at 30 days post-lodgement, so that we can match “at-risk” clients with a tailored response that will improve outcomes

Dependent Variable

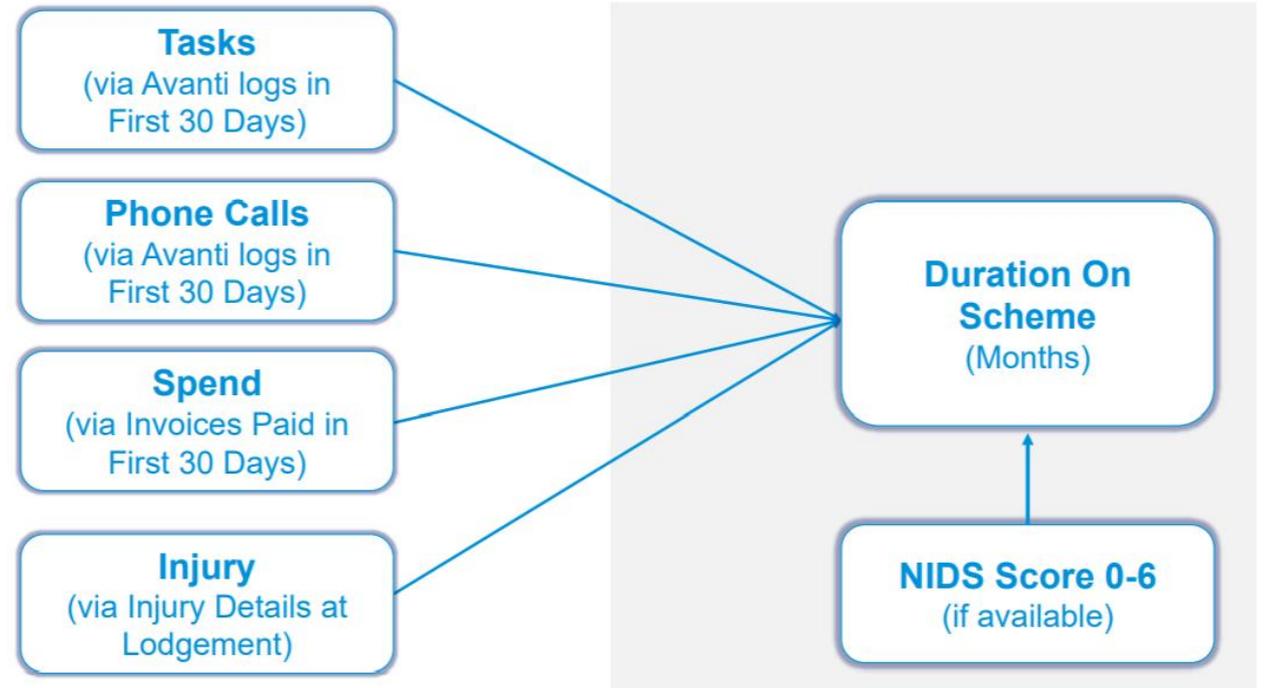
- When this work began, there was no consensus about what a model would actually *predict* to support our goal of client recovery at the earliest opportunity
- Business sponsors speak about client “complexity”, but complexity is not easily defined as a numeric measure available for most clients
- Ultimately, we agreed on *time on scheme* as the primary dependent variable because:
 - It is reasonable to assume a client who is on scheme for many months is “complex”
 - It rank-order correlates with the “Big 6” questions which are widely trusted
 - It aligns with corporate KPIs and strategic objectives
 - It is a reasonable proxy for client outcomes

Independent Variable

- We ran working groups with claims experts and business analysts to identify data domains that are:
 - Collected passively
 - Available within first month of lodgement
 - Likely associated with poor outcomes (based on expert opinion)
- Through this work, we arrived at a common understanding about:
 - What data is available when
 - The limitations of each data domain
 - Why a data domain would or would not be carried forward into hypothesis testing

Conceptual Model

After identifying the dependent and (potential) independent variables, we can build a simple conceptual model to test with data



Step 2: Exploratory Data Analysis (EDA)

- With the data domains identified, we can begin an analysis of the nature of the underlying data.
- Sharing early findings with business sponsors can help build a common understanding about what might and might not work.
- Early findings may challenge assumptions!

Category	Measure	Correlation
NIDS^	Final Score	45.9%
Phone	Total	40.7%
Task	Total	35.1%
Spend	Total	29.9%
Injury	Character Length	18.5%
Injury	Total	12.3%

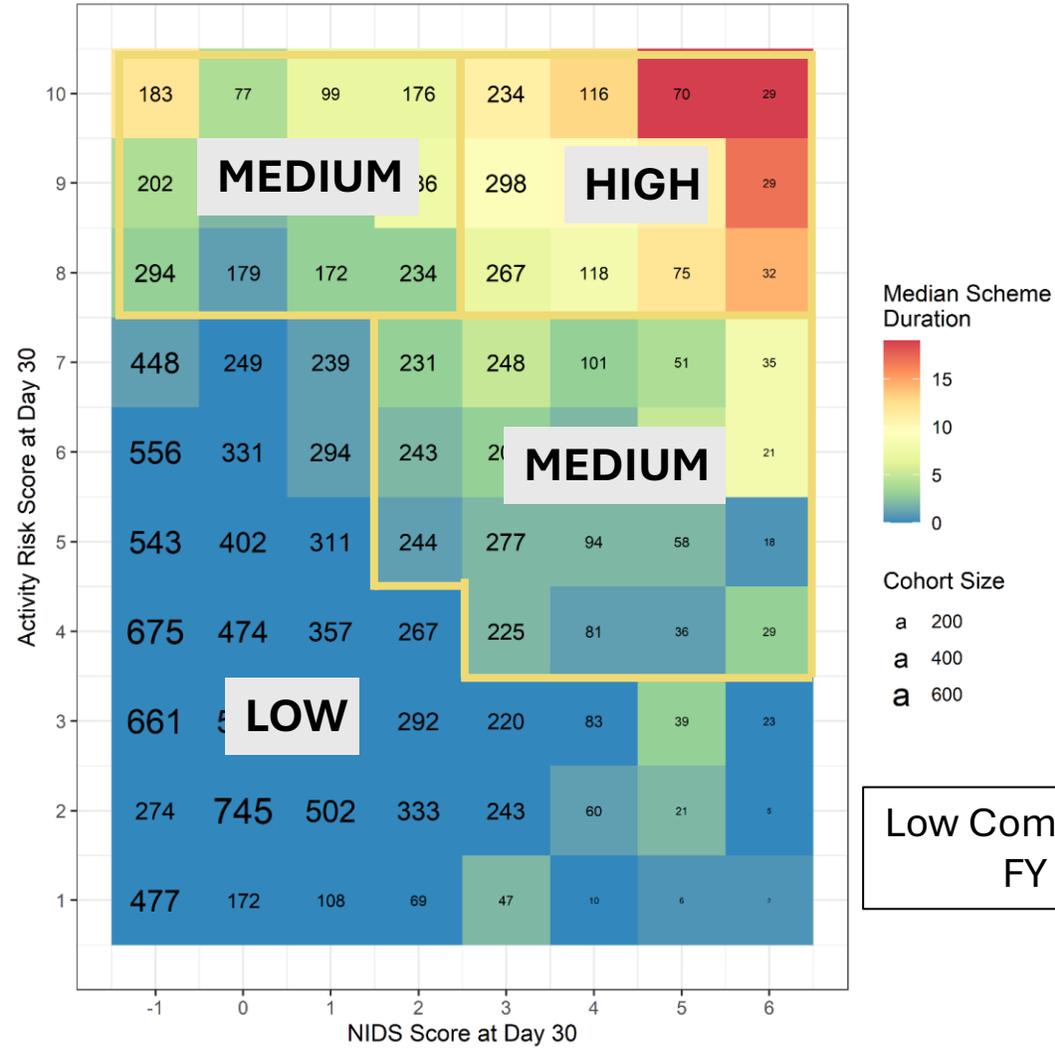
^NIDS refers to our Complexity Survey and serves as a baseline.

Step 3: Build Prototype

- After the problem is defined and the data are understood, it becomes relatively straightforward to train a model prototype.
- The only missing piece is an agreed upon definition of model *performance* such as accuracy, F1-score, MSE, etc.
- We chose *accuracy of predicting scheme independence at 12 months* because it aligns with corporate KPIs, but also monitored precision and recall.
- The Prototype was developed on a local machine as the organisation was transitioning from on-prem to cloud

Quantitative Evaluation

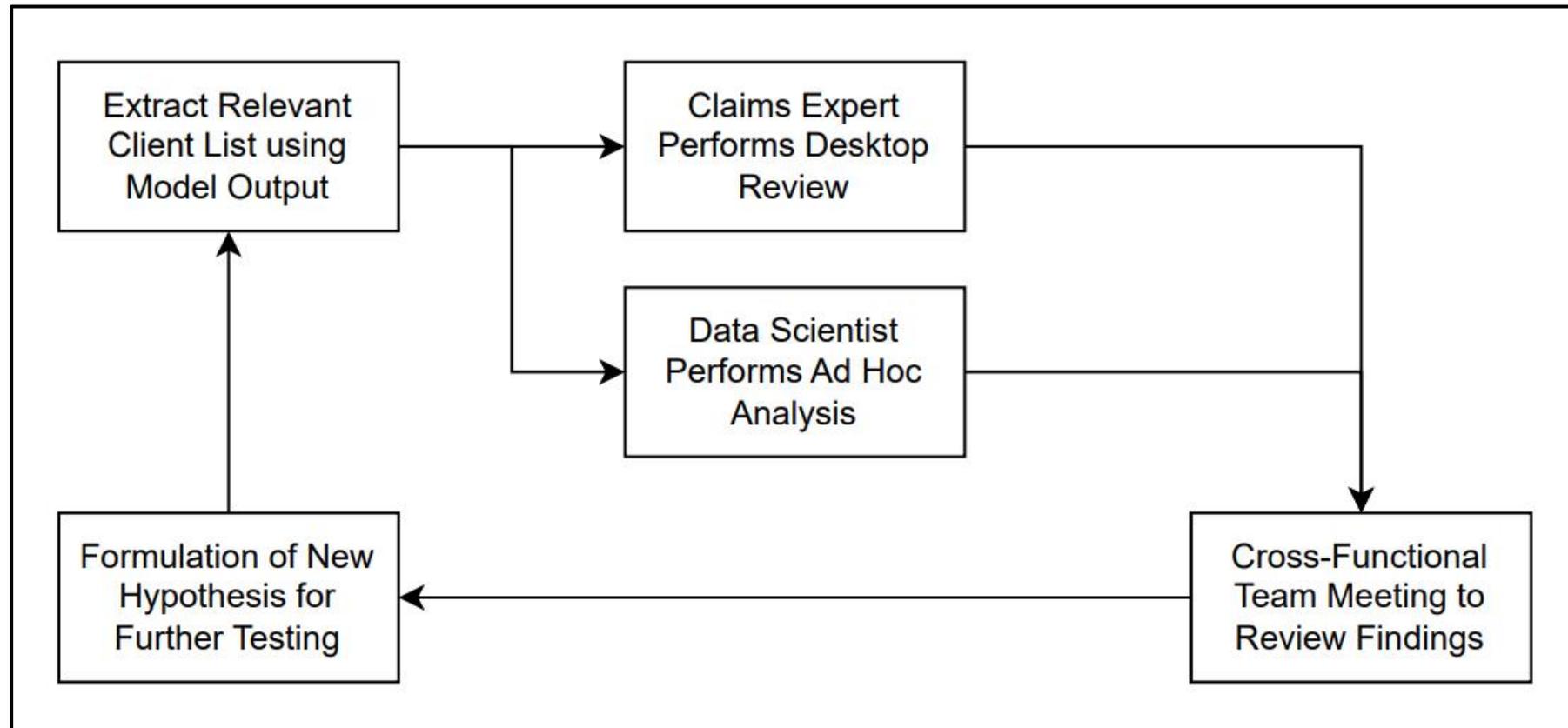
Model Output, Converted to Deciles



Low Complexity Only, FY 20-21

Step 4: Domain Expert Evaluation

- During this work, we developed a collaboration framework between data science and claims management experts, creating a feedback loop between analytics and operations



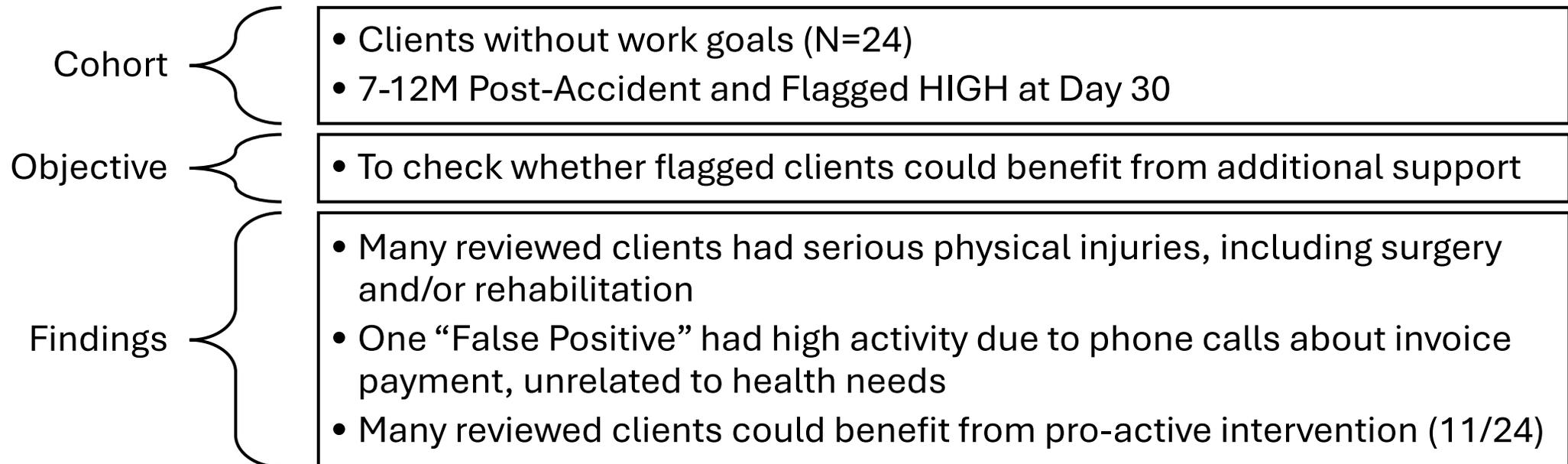
Learnings

Why this helped? *A tale of two errors...*

- For data scientists, a model is an algorithm that produces an output based on input
 - The model is correct if the output it produces agrees with the output it was trained to produce
- For the business, the model is a tool to identify claims that require a specific action
 - The model is correct if the output flags a claim for an action who needs an action
- The data science *false positive rate* is not the same as the operational *false positive rate*

Learnings

- We use desktop reviews to assess the operational false positive rate
- A claims expert reviews claims flagged by the new model and labels whether they believe the model flagged the “right” claim or not.
- Each review cycle was summarised, e.g.,:

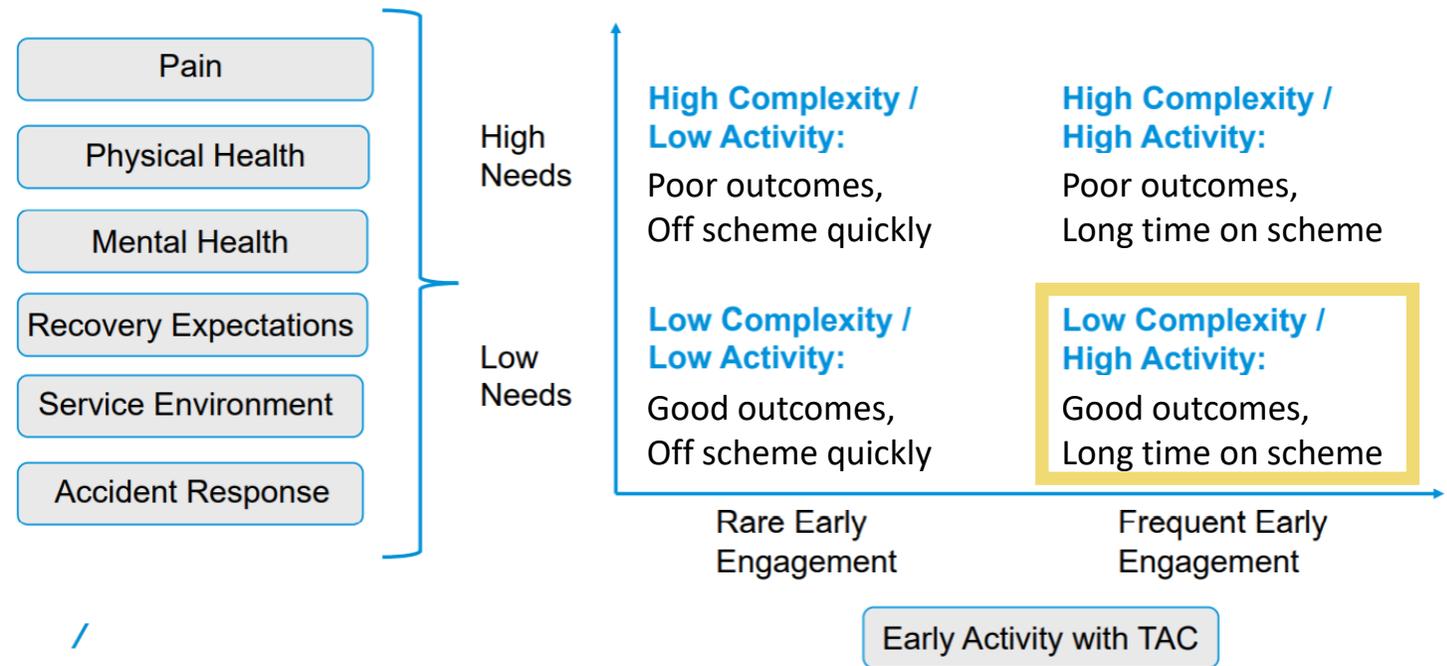


Learnings

- The benefits of desktop reviews are two-fold:
 - Data scientists gain a qualitative assessment of model output, identifying opportunities for continuous improvement
 - Domain experts gain a deeper understanding of the types of claims identified by the model, informing decisions about how the model gets used within business operations

Cohort Evaluation

- From the quantitative evaluation and desktop reviews, we conceptualised 4 cohorts
- The yellow box represents an under-serviced cohort that could benefit from proactive intervention (covered in next section)

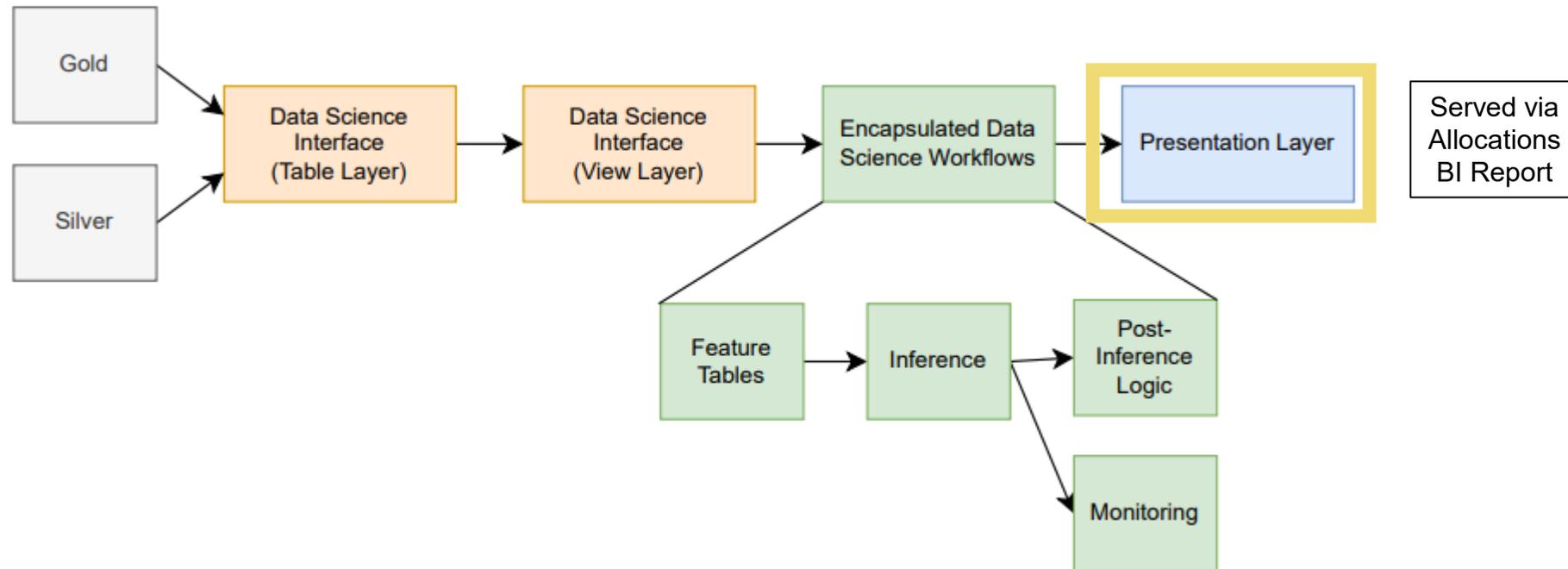


Step 5: Live Piloting

- Once the model is set up to run (manually) on old data to produce output for desktop reviews, it is straightforward to adapt the model to run (manually) on new data to produce output for live piloting – e.g., testing a new work practice

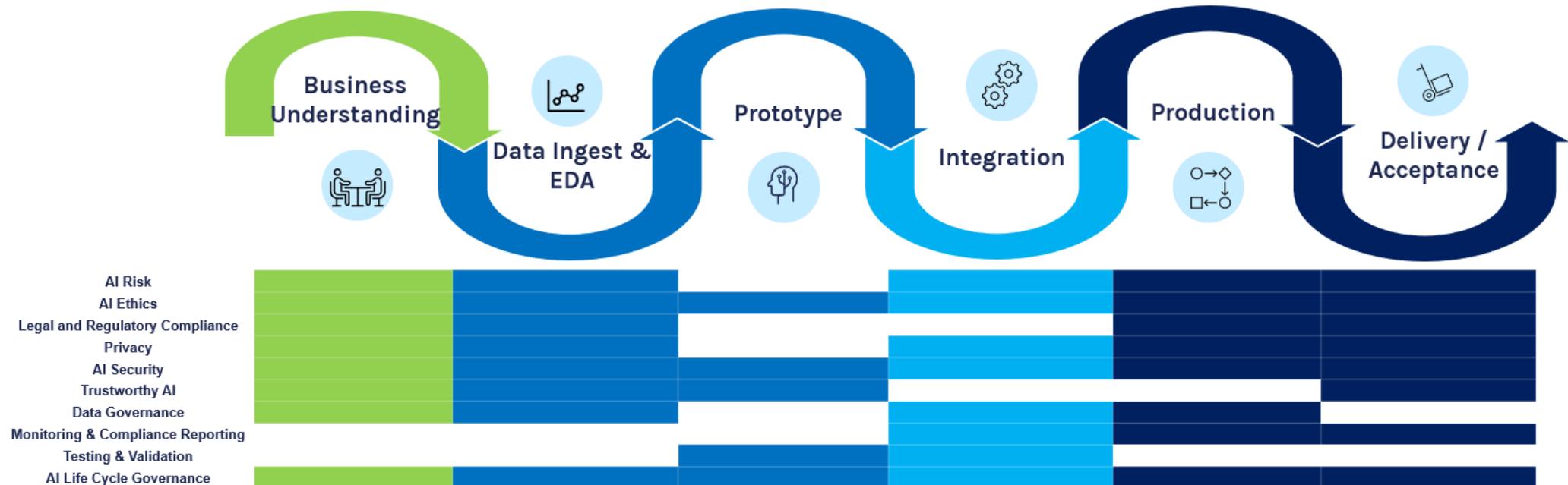
Step 6: Automation

- TAC analytics have transitioned to DataBricks, upon which we apply a Medallion Architecture to build Data Marts that then feed predictive models



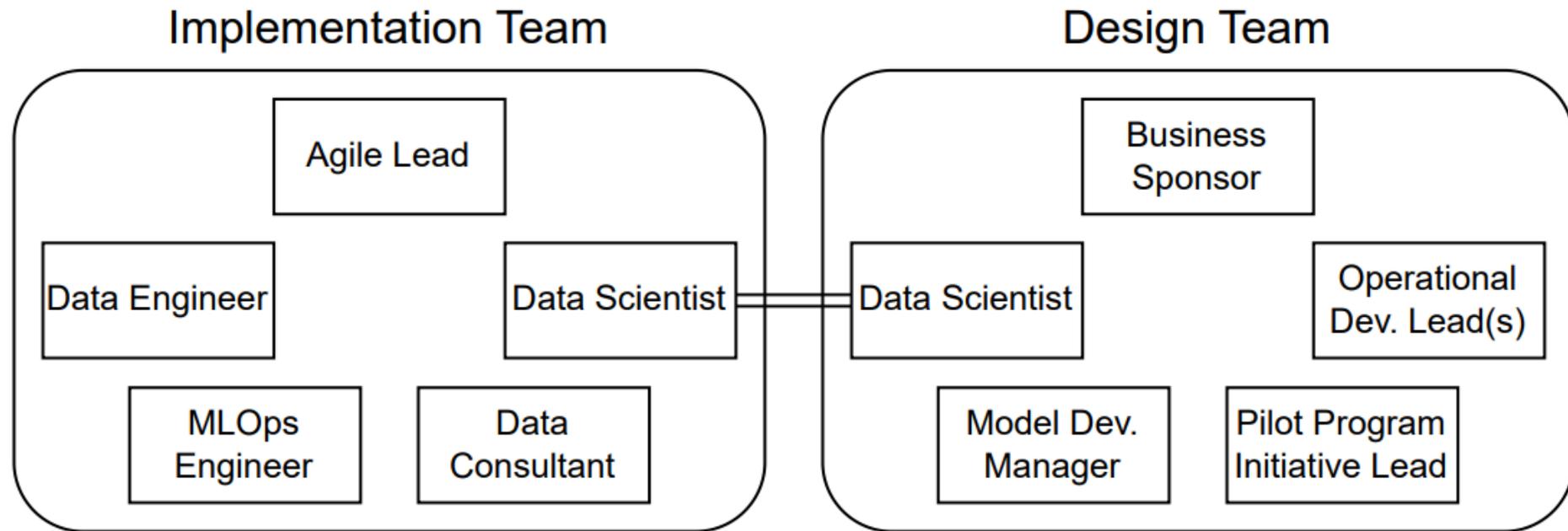
Stage 7: Final Approval

- Decision to accept model is based on quantitative (model performance) and qualitative (end-user feedback) data
- All models undergo multiple stages of Governance and Risk Assessment



Team Configuration

- When the work began, it was not entirely clear what roles were needed to implement and embed a model start-to-finish. Since then, we have arrived at an arrangement that is working:



Using the Model

Using the Model

- The model output was aligned to identify claims for potential enrollment in TAC's Injury Support Program pilot that commenced in May 2024.

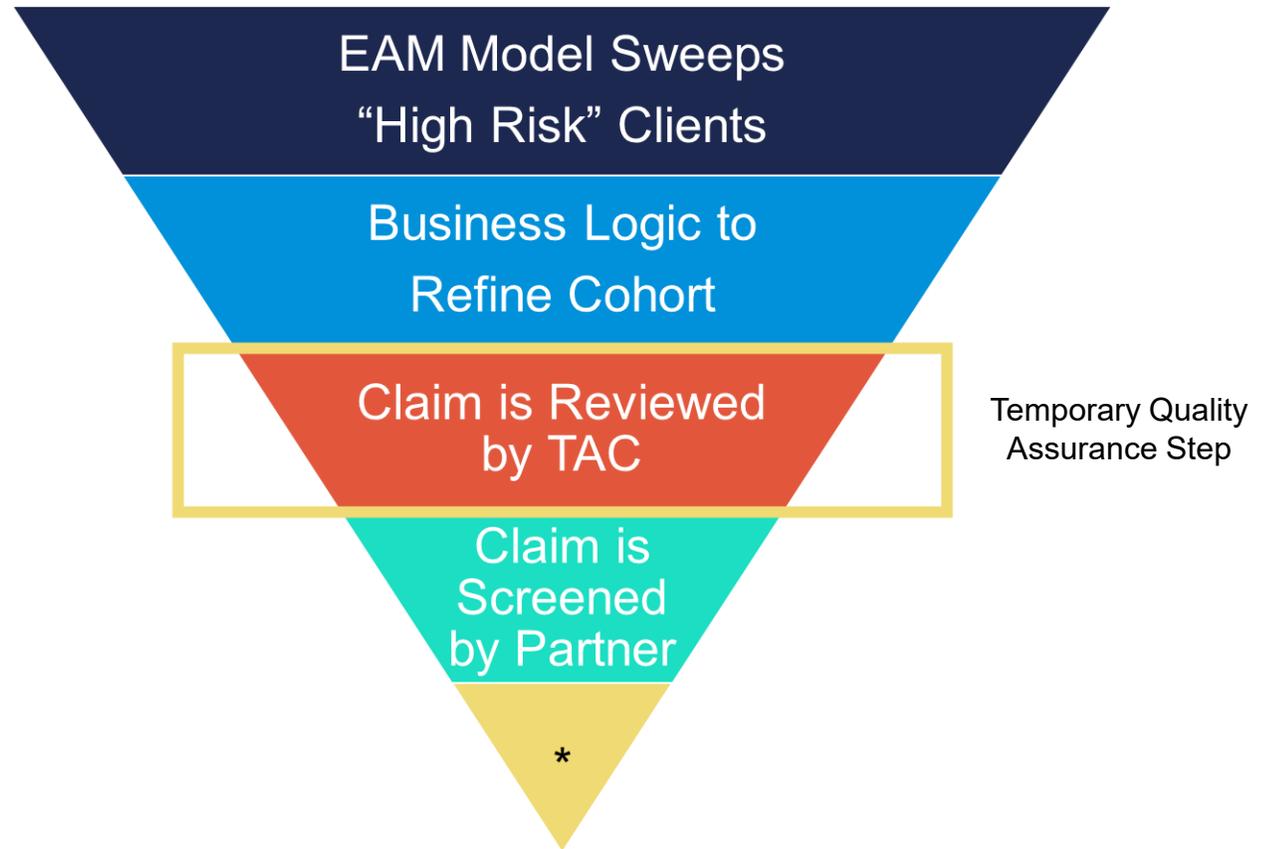
What is the Injury Support Program (ISP)?

- ISP is an **early intervention**, phone-based program delivered by Honeysuckle Health (HH)
 - ISP provides early intervention for clients at risk of delayed recovery.
 - Offers **nurse-led care coordination** for 16 weeks, bringing together care, treatment access and recovery planning.
 - Delivers **personalised, holistic and multidisciplinary** support that helps clients achieve both functional, psychological and recovery goals.
- 
- An illustration of two healthcare professionals, a man and a woman, standing and talking. The man is on the left, wearing a light blue shirt and has a dark bag slung over his shoulder. The woman is on the right, wearing a blue nurse's uniform with a stethoscope. Above them are two speech bubbles, indicating a conversation. The entire illustration is enclosed in a light grey circular frame.

- The goal was to create an automated, data-driven referral process so claims managers in highly operational pool-based roles didn't need to identify suitable clients

Business Rule Overlay

The model (called “EAM”) became the first step in a multi-step screening process between TAC and HH



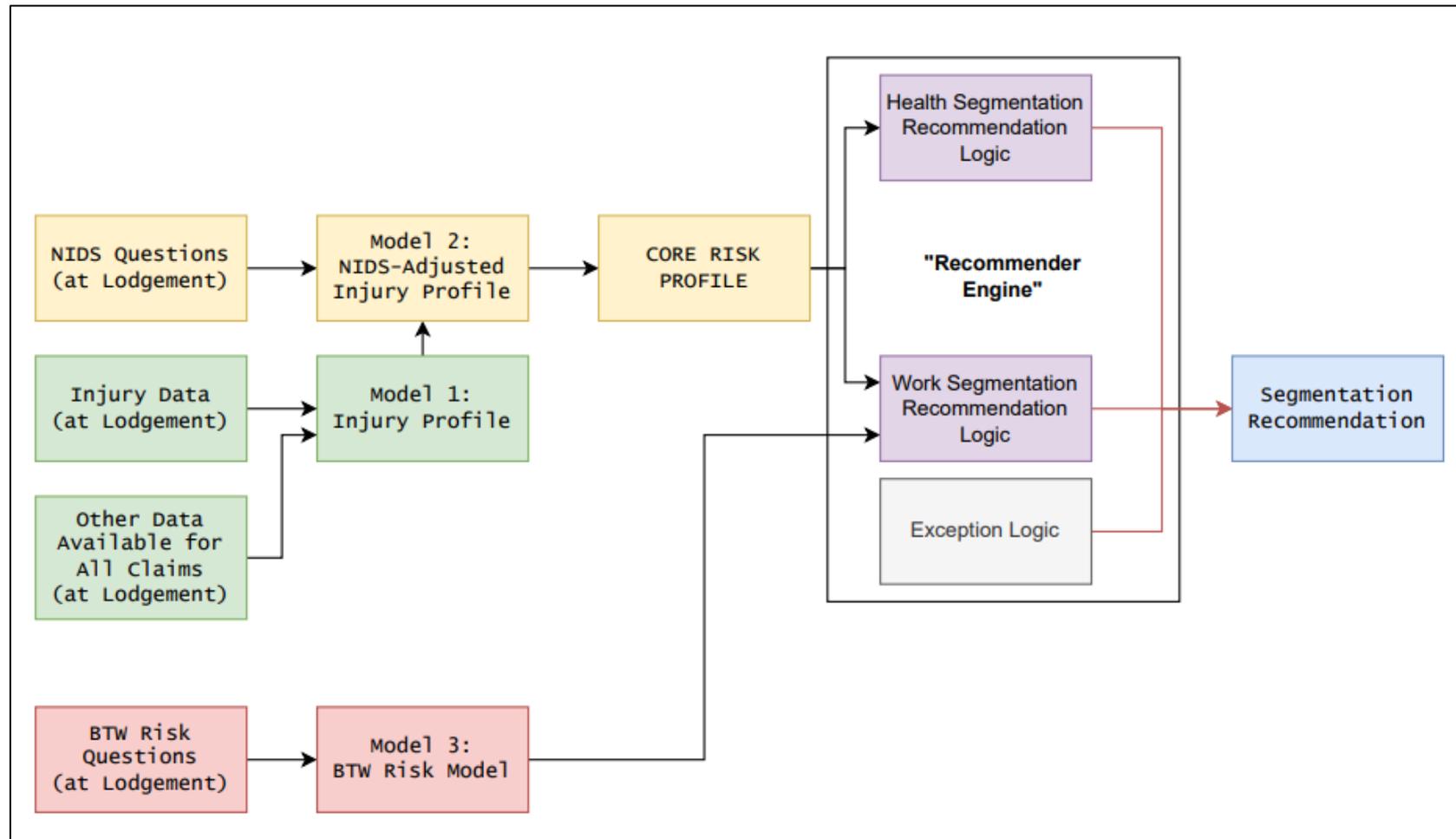
Results

- As of November, the model has identified **2,631** pool managed clients for screening by HH
- Referred clients received a subsequent injury-based risk score by HH via the ODG Tool, which confirmed the risk status assigned by the New Model
 - Referred clients had an average ODG Risk Assessment Score of **61**, giving confidence the model can consistently identify clients who would benefit from a more proactive approach
- **66%** enrolled in the HH program
 - Of those who didn't, most declined because support was not required
 - Enrollment rates match expectations set by desktop reviews, where we opted to lower the model threshold to increase sensitivity at cost of precision

Future Vision

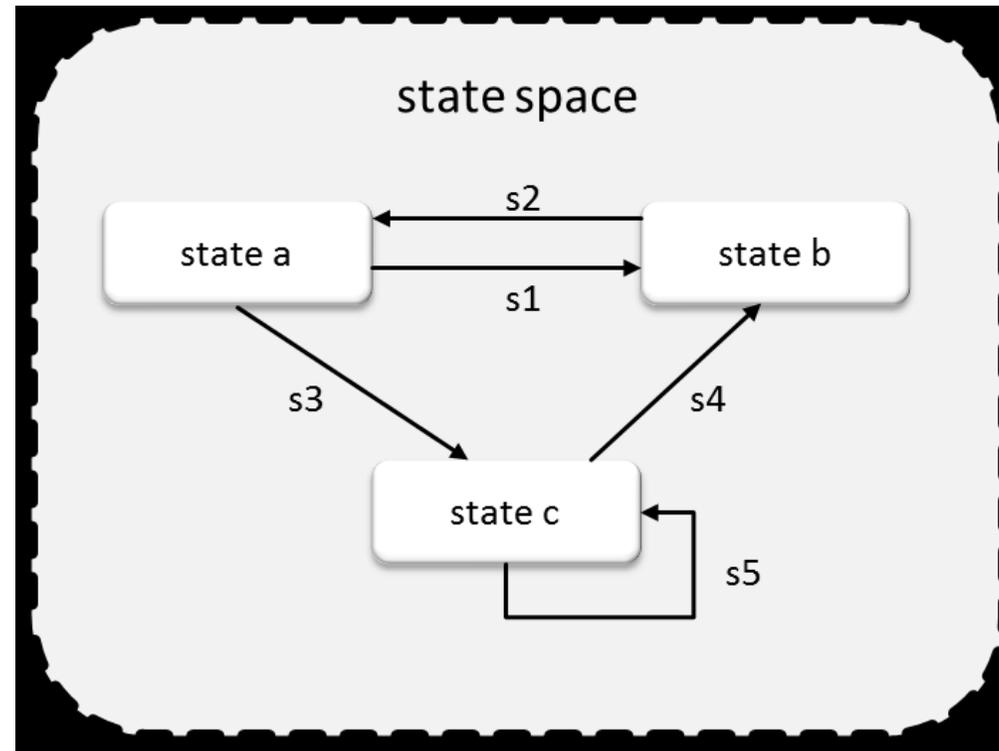
Direction 1: Many-Models, 1-Decision

- We are now building out a model ecosystem that will work together to segment clients into tailored Work and Health service pathways



Direction 2: Dynamic Segmentation

- We know there is an upper limit to the predictive performance of models within the first month.
- We are beginning to scope how to best use predictive models dynamically over the life of a claim, for example to escalate and de-escalate claims as client needs change



Reflections

Lessoned Learned



What Worked Well

Regular meetings between data science and operational teams

Evaluating models not only by accuracy, but desktop reviews

Live piloting of model prototype before full implementation



What Didn't

Knowing at the beginning what roles were needed for end-to-end solution delivery

Aligning priorities between data science and other technical teams

Moving from Prototype to Production



Opportunities for Future

Incorporate other data to improve model further

Combine multiple existing models into single decision-making tool

Automate model monitoring that covers both analytical and operational needs