Using Artificial Intelligence to Improve Mental Health

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Acknowledgement
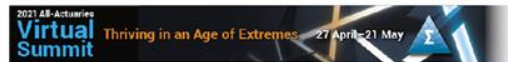
Chair for our session:

Lucy Hartley (Swiss Re Life & Health) – Claims Service Manager, Vice President, Life & Health Business Management

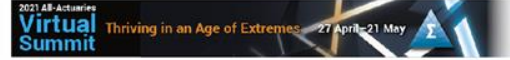**Peer Reviewer:**

Dr Mathew Paul (Munich Re) – Chief Medical Officer

Agenda

1. Mental Health in Australia – where are we now? How bad can it get?

2. MNC's Mental Health Research Project
   1. Scoping Literature Review
   2. Environmental Scan of Public Datasets
   3. Stakeholder Engagement

3. Voting and Q&A

Audience can join at slido.com with #5914

Mental Health in Australia Today

1 in 5 Australians suffer mental ill-health in any one year (2007)	An estimated 85% of people will suffer a mental illness in their lifetime	Half of all the mental health conditions experienced during people's lives have started by age 14	One in seven young people aged 4-17 experience a mental health condition in any given year
Every day in Australia, approximately seven men die by suicide.	1 in 6 women will experience postnatal depression.	The number of working age Australians received disability support pensions for psychiatric condition increase by about 50%	91% of employees believe mental health in the workplace is important. However, only 52% of employees believe their workplace is mentally healthy

Demand for Services has Increased
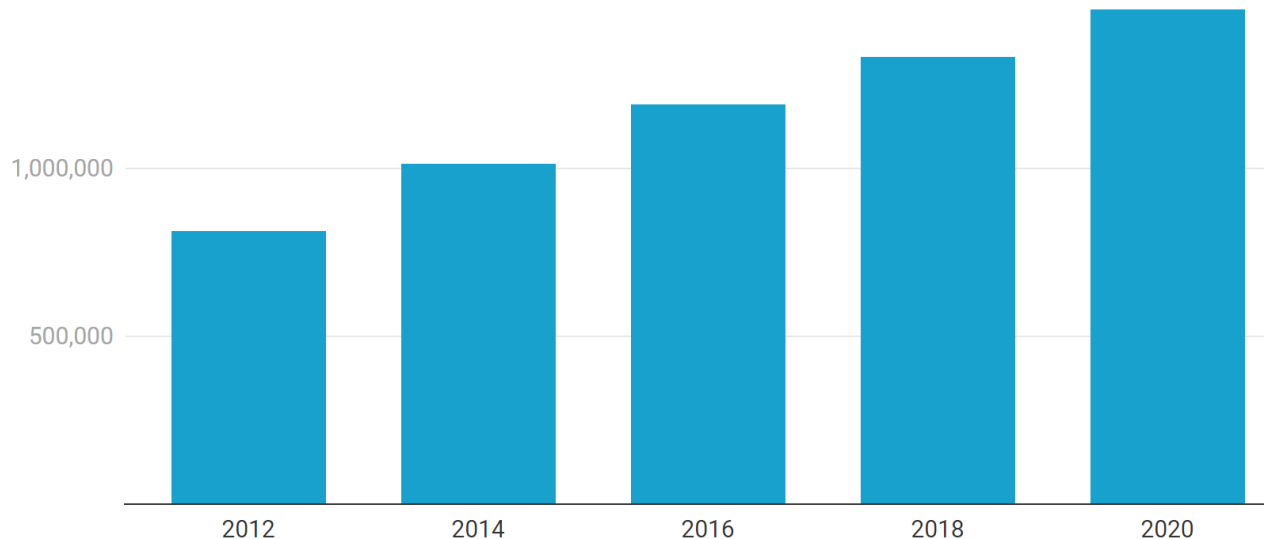
Medicare data showed GPs prepared record numbers of mental health treatment plans in 2020.

Number of Mental Health Treatment Plans created each year

The number of Mental Health Treatment Plans created by GPs has been steadily growing since 2012.

Source: AIHW analysis of Medicare data • Get the data

Insurers are feeling the financial cost

Net profit after tax by product for the life insurance industry in the year ended 31 December:

| Risk product	Year to Dec 2019 ($m)	Year to Dec 2020 ($m)	Dec 2020 quarter only ($m)
Individual lump sum	653.3	543.7	73.0
Individual disability income insurance	-1,472.8	-739.9	-97.5
Group lump sum	-240.6	-173.5	-7.8
Group disability income insurance	-270.9	-122.5	-108.0
Total	-1,331.0	-492.3	-140.3

Key ratios for the life insurance industry in the year ended 31 December:

	Year to Dec 2019	Year to Dec 2020	Yearly Change	Sep 2020 Quarter	Dec 2020 Quarter	Quarterly change
Return on net assets	-1.2%	-0.4%	0.9 percentage points	0.3%	6.6%	6.4 percentage points
Prescribed capital amount coverage ratio	1.66x	1.80x	0.13x	1.78x	1.80x	0.02x

The December 2020 Quarterly Life Insurance Performance Statistics publication is available on APRA's website at: Quarterly Life Insurance Performance Statistics.
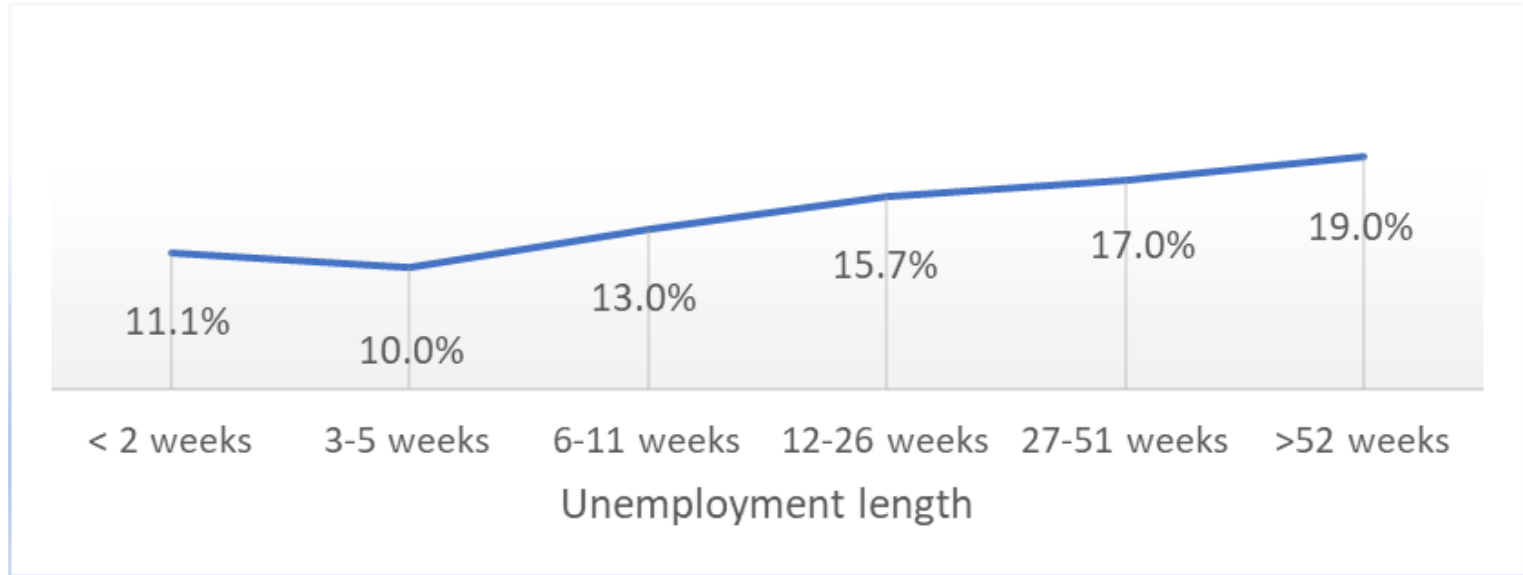
Australia's Seasonally Adjusted Unemployment Rate
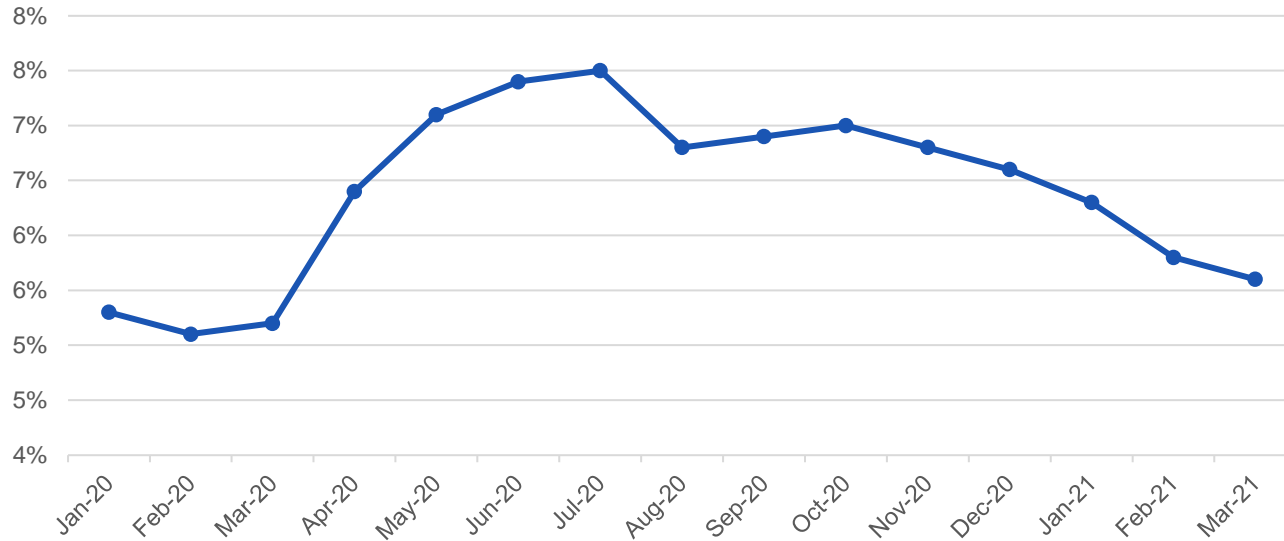
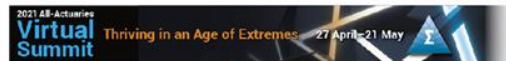Source: Australian Bureau of Statistics, Labour Force, Australia March 2021

Length of unemployment and socioeconomic status are important

Steve Crabtree (9 Jun 2014) "In US, Depression Rates Higher for Long-Term unemployed"

Why is this research important?

- Through MNC's previous consideration of the impact of COVID-19 on mental health and implications for the insurance and super industries[1] it is widely accepted there could be a potential in the increase of incidence and severity of mental ill-health in Australia.

- There has been an increasing trend in mental health claims.

- Uncertain outcomes for mental health claimants may drive the insurance industry to exclude mental ill-health from cover.

- Funding for mental health organisations is limited, it needs to be directed to areas where it can have the most impact

- Mental health data is currently not well connected. There are opportunities to use new data sources such as publicly available social media feeds to connect the dots and to enable early interventions for people with mental ill-health.
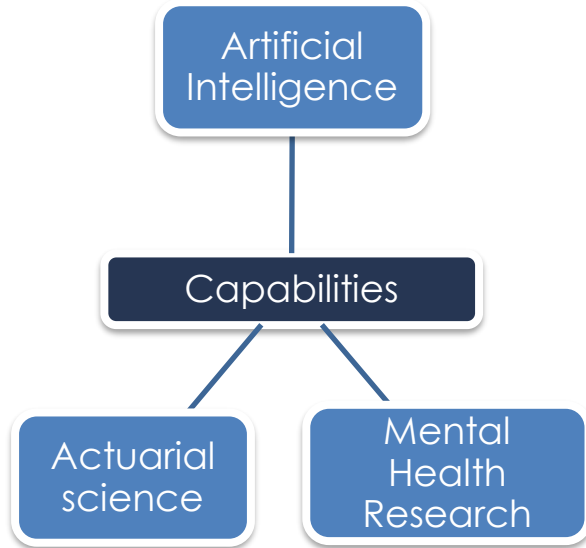
- AI is a powerful tool to determine when mental health is deteriorating

[1] Matt Noyce Consulting, (2020) COVID-19, Mental Health & the Life Insurance Industry

2. MNC's Mental Health Research Project

Project Proposal

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        ┌──────────────────┐
        │   Artificial     │
        │   Intelligence   │
        └──────────────────┘
                 │
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        │   Capabilities   │
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  │ Actuarial  │  │   Mental   │
  │  science   │  │   Health   │
  │            │  │  Research  │
  └────────────┘  └────────────┘
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- Identify trends of mental ill-health in the community and sign-post to appropriate care

- Direct mental health resources to the areas of most impact

- Provide evidence-based research to assist funding proposals

- Improve overall customer experience from the research and purchasing stage through to insurance claim stage.

- Offer superior insurance products appropriate for people who already experience or may impacted from mental ill-health at a later stage

- Create affordable and sustainable insurance products using our enhanced understanding of risk drivers

Current Project Phase
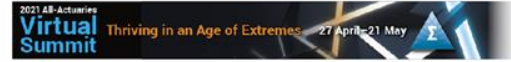
➤ Scoping review (evidence-based)

➤ Environmental Scan (public datasets & models)

➤ Engaging stakeholders (insurance, mental health, and research sectors)

Scoping: Literature Review

A scoping review was performed to identify the research literature on AI using mental health and insurance data.

- Three main concepts: **Artificial Intelligence**, **Mental Health**, and **Insurance**
- Search for published articles between **2015-2021**
- **Six** peer-reviewed databases were searched (see below)
- Website searching
- Other sources from suggested by stakeholders

Health Sciences	Finance and Actuary Sciences	Multi-disciplinary
PubMed	*ProQuest*	*Web of Science*
PysInfo	*EBSCO (Business Source Corporate, Business Source Premier, TOC Premier)*	*Scopus*

Scoping: Literature Review
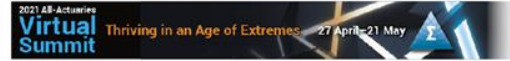
Focus area 1: Developing AI predictive models using mental health and insurance data.

Focus area 2: Observing factors in mental health and insurance data using AI techniques.

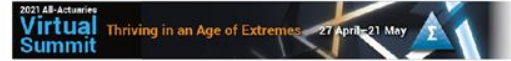**Focus area 3:** Industry and commercial research of AI using mental health and insurance data.

Focus area 4: Methodological and ethical consideration of AI using mental health and insurance data.
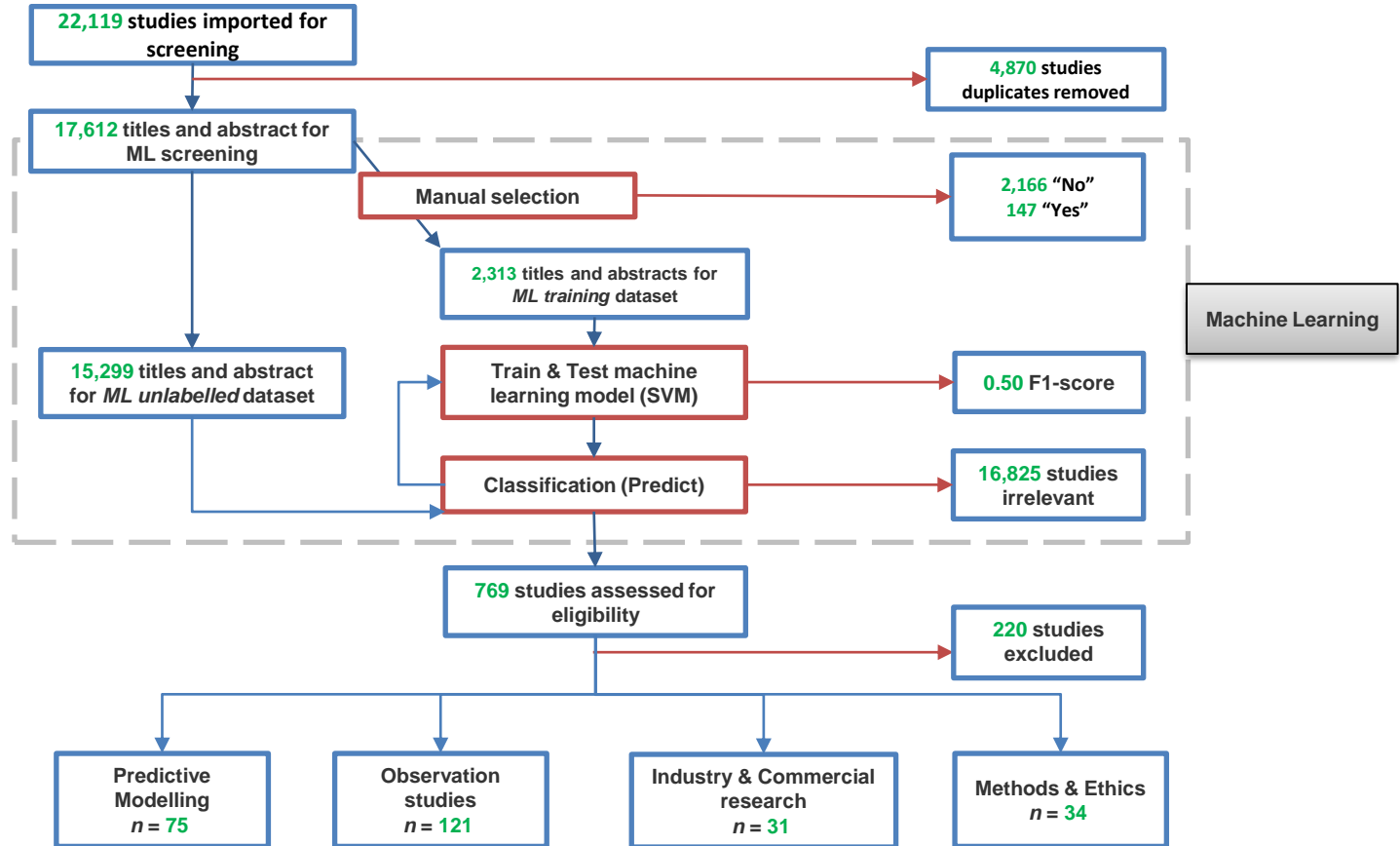
Scoping: Literature Review

- We used machine learning and natural language processing to efficiently screen **22,119** articles based on two classes (*Yes* = Relevant Papers, *No* = Not Relevant).

- Two team members manually coded **2,313** titles and abstract with a good inter-reliability (labelled dataset – training/test set).

- Our best model was using **TF-IDF** (words per document in corpus) and **Support Vector Machines (SVM).** We able to produce a **F1-score of 0.50** (after *hyperparameter tuning* the model to get the best performance).

- We applied the model to the unlabelled dataset (**15,299** articles), Yes = **769** studies and No = **16,825** studies.

Scoping: Literature Review

22,119 studies imported for screening

4,870 studies duplicates removed

17,612 titles and abstract for ML screening

Manual selection

2,166 "No"
147 "Yes"

2,313 titles and abstracts for *ML training* dataset

15,299 titles and abstract for *ML unlabelled* dataset

Train & Test machine learning model (SVM)

0.50 F1-score

Machine Learning

Classification (Predict)

16,825 studies irrelevant

769 studies assessed for eligibility

220 studies excluded

Predictive Modelling
n = 75

Observation studies
n = 121

Industry & Commercial research
n = 31

Methods & Ethics
n = 34

Case Study 1: Social Media Datasets

Paper: Deep neural networks detect suicide risk from textual facebook posts
Authors: Yaakov Ophir, Refael Tikochinski, Christa S. C. Asterhan, Itay Sisso & Roi Reichart

A total of 1,002 Facebook users completed a well-established, clinically valid screening tool of suicide risk and volunteered to disclose a year of their Facebook activity, resulting in a dataset of 83,292 postings. These postings were used to predict the risk of suicide for each of the users.

The _two modelling approaches_ used showed a material improvement over current methods of suicide prediction which are on average no better than chance in term determining if someone is at risk of suicide.

A key benefit of using Facebook data is it is "in the moment" daily discussions between people and can provide much more timely information then other sources that have been used historically. Although, more research is needed to determine _specificity and sensitivity_ of these types of models.

Case Study 2: Medical & Claims Datasets

Paper: Medical comorbid diagnoses among adult psychiatric inpatients
Authors: Goldman, ML, Mangurian, C, Corbeil, T, Wall, MM, Tang, F, Haselden, M, Essock, SM, Frimpong, E, Mascayano, Radigan, M, Schneider, M, Wang, R, Dixon, LB, Olfson, M, Smith, TE.

The study aims to describe the prevalence of medical diagnoses among individuals with psychiatric diagnosis using _insurance claims_ and _clinician data_ linked with hospital- and system-level data.

A _modified Elixhauser Comorbidity Index (ECI)_ score was used on insurance claims and medical records for patients aged 18-64 admitted to an inpatient psychiatric unit during 2012-2013. Predicators included patient-, hospital-, and system-level variables. _Logistic regression and generalized linear models_ were used to perform clustering.

Majority of individuals had significant comorbidity, including young people. Higher medical comorbidity were associated with older age, female, non-schizophrenia patients, and prior help-seeking behaviour.

Case Study 3: Insurance Datasets

Paper: The Importance of Unresolved Fatigue in Depression: Costs and Comorbidities
Authors: Robinson, RL, Stephenson, JJ, Dennehy, EB, Grabner, M, Faries, D, Palli, SR, Swindle, RW.

The study aimed to investigate the cost outcomes of patients with significant fatigue and depression. The objectives is to assess the association of fatigue with costs for mental health care use.

6 months patient surveys linked with 24 months of insurance claims data was used. Surveys capture demographics and patient-reported outcomes. Claims data include demographic, provider specialty, treatment patterns, and health plan cost. Linear regression models were used to perform the outcome analysis.

Patients with fatigue reported higher scores in depression, pain, sleep difficulty and anxiety. High medication use was associated with lower socioeconomic status. Cost were greater for patients with fatigue.

Data Considerations

Datasets are key to the success of research projects, particularly with respect to:

- **Challenges** in accessing datasets (ethics concerns, acquiring resources etc.)

- **Types** of datasets (insurance claims, calls to helplines etc.)

- **Quality** of datasets

- **Links** between datasets

- **Timing** of datasets

- **Logistics** of obtaining and storing datasets

Modelling

Mental Health Services Data

Insurance Data

Social Media Data
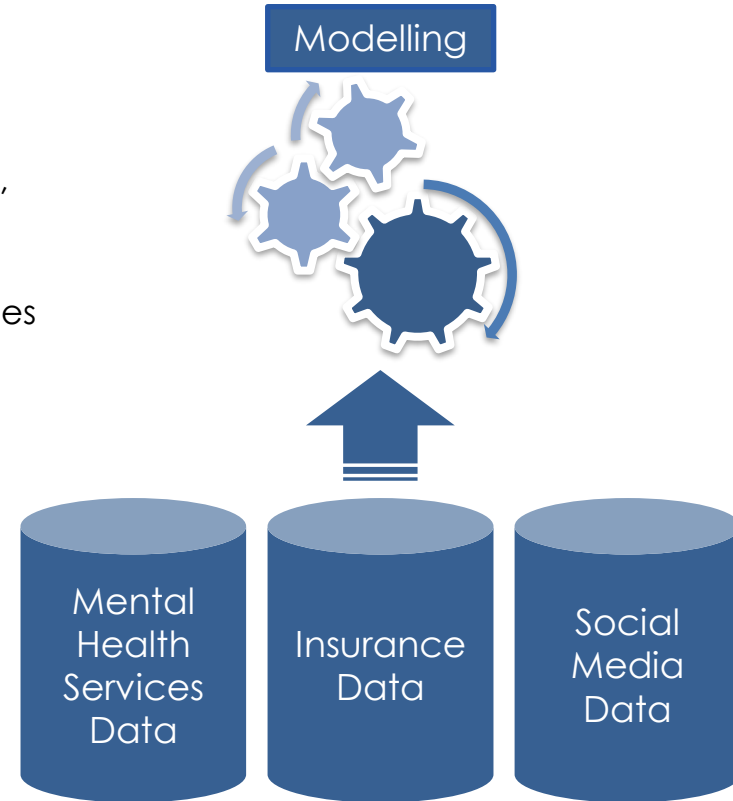
- Conduct an Environmental Scan (ES) that examines **public mental health datasets.**

- ES aim to understand different **indicators** and **measurements** of mental well-being across various research datasets.

- **Eight** dataset repositories searched in March 2021.

- **74** individual datasets related to mental well-being.

- **792** measures were identified (grouped into **34** categories).

- **358** demographic and **398** mental health measurements.

Scoping: Environmental Scan

Figure 1. Dataset indicators across region
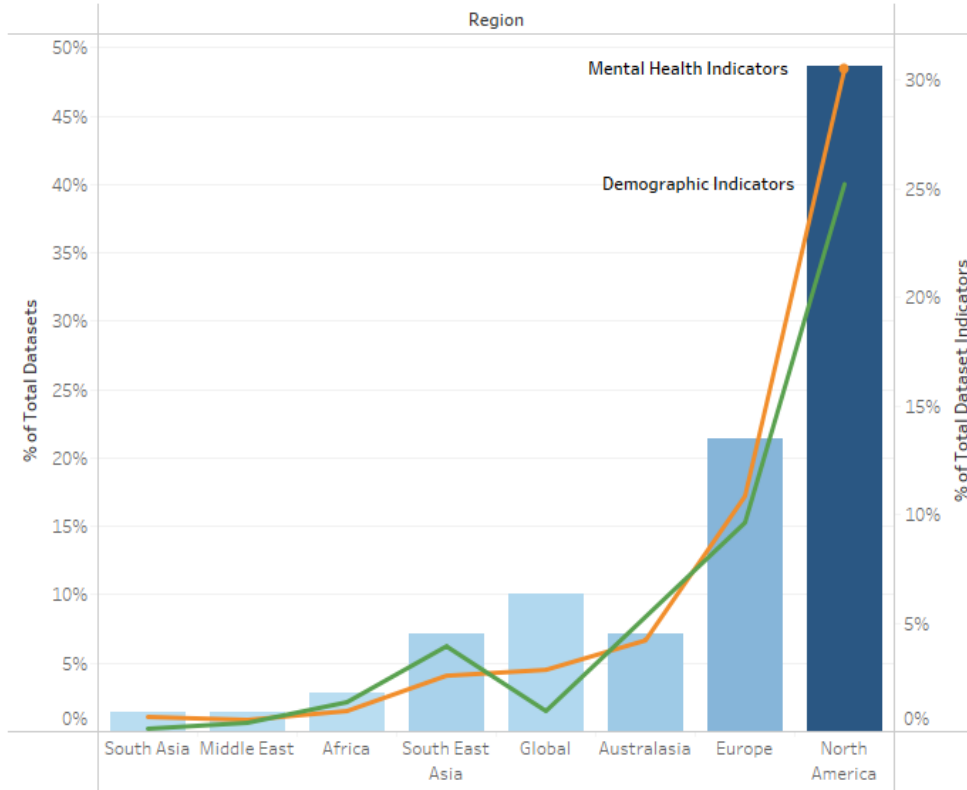
- This graph illustrates that the 74 datasets were heavily focused on North America (48%) and Europe (21%) data.

- The % of total dataset indicators shows that the proportion of mental health indicators and demographic indicators has a similar pattern by geographical location.

Scoping: Environmental Scan

Figure 5. Units of analysis of mental health datasets

Unit of Analysis (Categories)
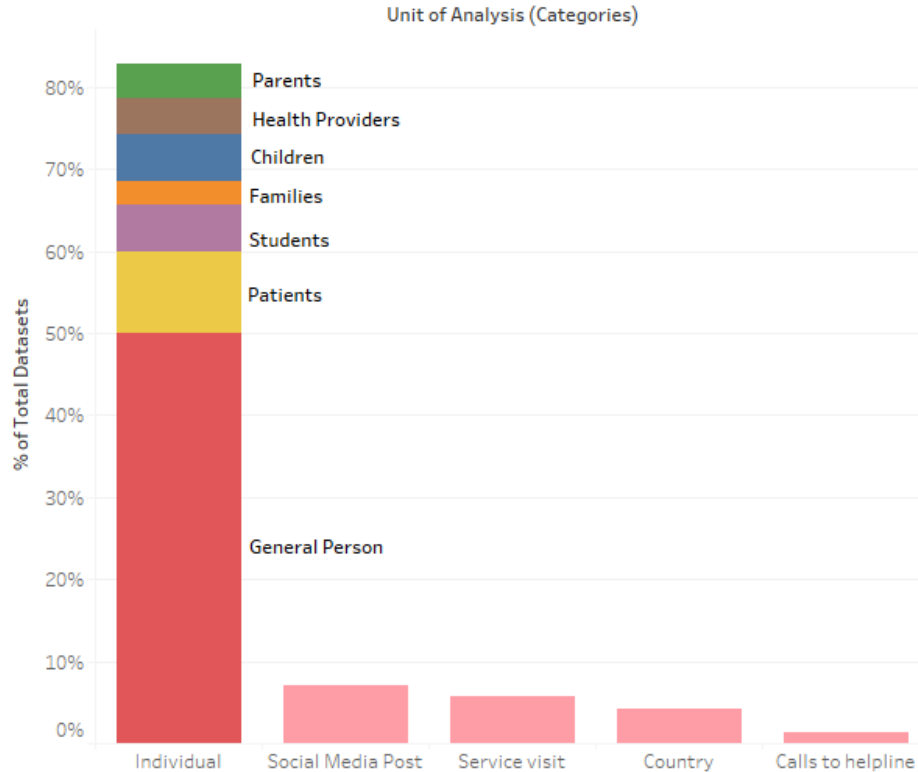
- The unit of observation by mental health dataset is examined in this graph. For individuals – 50% of datasets look at the general population, 10% consider patients in medical facilities.

- The remaining datasets looking at individuals are fairly evenly spread by unit of observation between parents, children, families, students and health providers.

- Other units of observation include social media posts (blog posts, Twitter, Facebook etc.)

Scoping: Environmental Scan
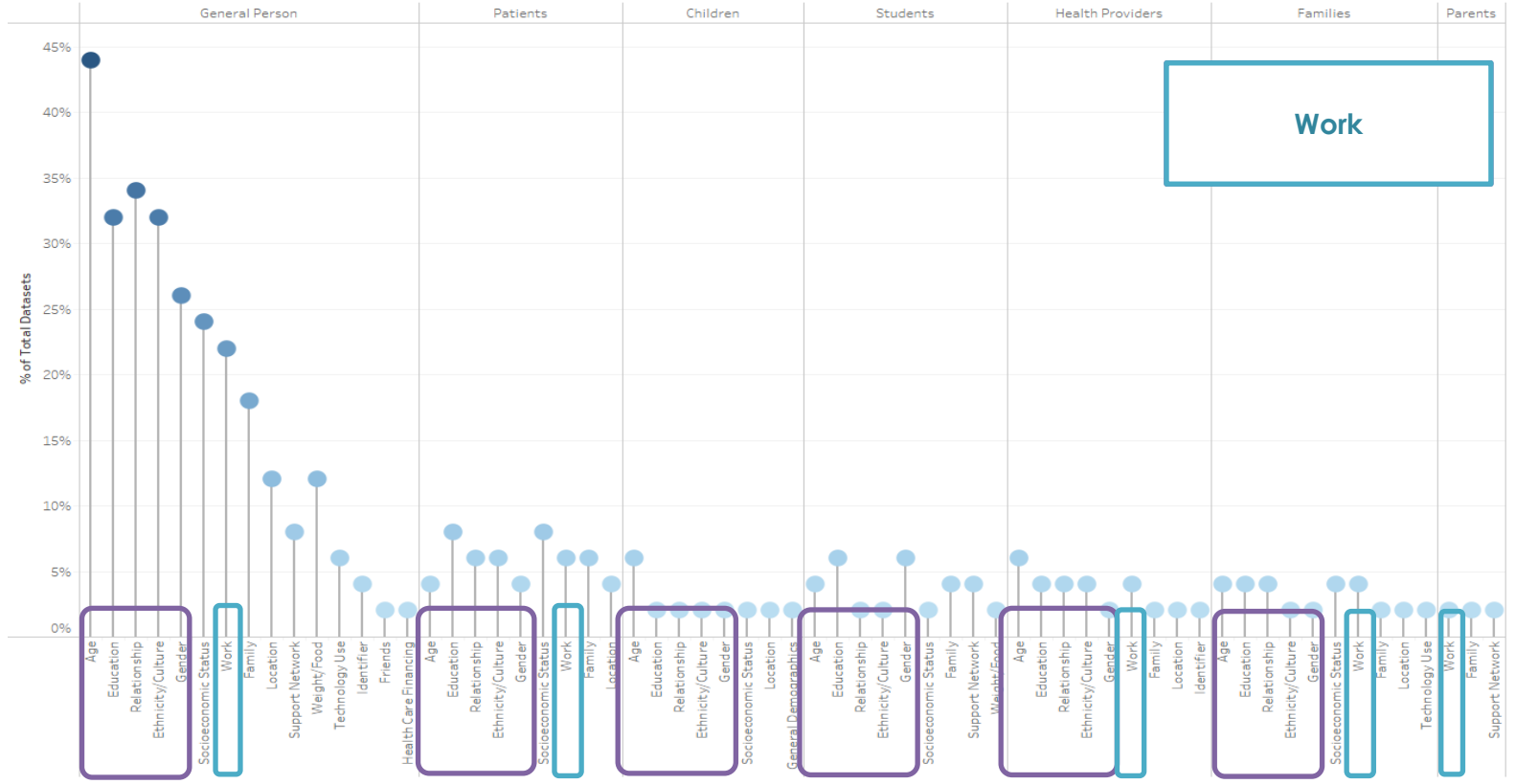
Table 1. Common mental health indicators

Indicator		%
Feelings		44.12%
Depression		39.71%
Physical Health		33.82%
Anxiety		30.88%
Mental Well-being		29.41%
Services		20.59%
Treatment		19.12%
Substance Use		16.18%
Personality Disorders		14.71%
Social		13.24%
Sleep		11.76%
Suicide		11.76%
Developmental Disorders		8.82%
Eating Disorders		7.35%
Mental Disorders		5.88%
Addictions		4.41%
Victimization		4.41%

Table 2. Common demographic indicators

| Indicator		%
Age		62.50%
Education		48.44%
Ethnicity/Culture		48.44%
Relationship		48.44%
Socioeconomic Status		37.50%
Gender		35.94%
Family		31.25%
Work		31.25%
Location		29.69%
Support Network		10.94%
Weight/Food		10.94%
Technology Use		6.25%
General Demographics		4.69%
Health Care Financing		4.69%
Identifier		4.69%
Friends		1.56%

Scoping: Environmental Scan

Figure 6. Demographic indicators by unit of analysis (person/individual)
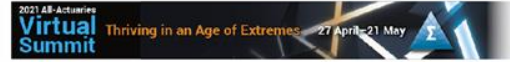
Scoping: Environmental Scan

Figure 7. Mental health indicators by unit of analysis (person/individual)

Physical Health
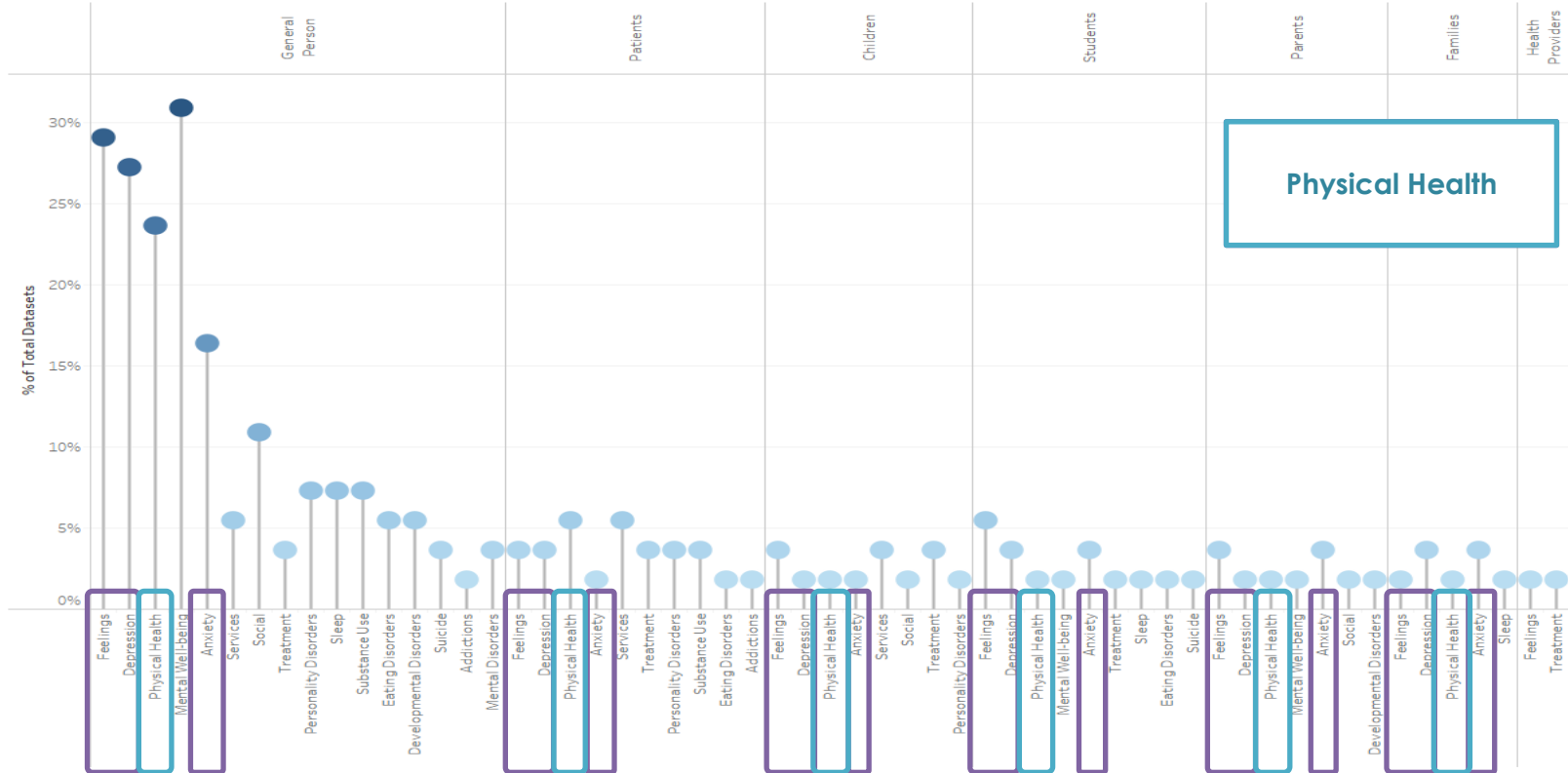
Stakeholder Engagement: Overview

We engaged with insurance companies, superannuation funds, mental health organization during **February 2021- May 2021**.

- **Nine** insurers and re-insurers
- **Three** superannuation funds
- **Eight** mental health organisations
- **One** research organisation

The purpose of the stakeholder engagement was to understand issues and needs of organisations across the sectors.

Stakeholder Engagement: Common Themes

Health System:
- GP not well trained to detect mental illness symptoms early
- Lack of co-ordination and poor integration of care in the Health System
- People not using the Health System due to poor experience

Risk factors & models:
- Understand why some people claim but not others with the same mental health condition
- Identify people with mild symptoms who will develop into more severe conditions
- Co-morbidity risk factors
- Bio-psychological model vs Psycho-social model
- Improve UW questions and claims management practice
- Understand linkage between UW and claims outcome
- Factors for sustained mental good health (or resilience)

Diagnosis:
- 'Erosion of Normal' - More work is needed to improve the diagnosis of mild conditions verses more severe conditions.
- Diagnosis of mental health condition is subjective
- Diagnostic criteria changes over time

Treatment & Outcome:
- Mental illness is unavoidable – should we focus on recovery and resilience?
- Understand why treatment helps some people to recover but not others?
- Not enough evidence on how treatment is linked to RTW
- Need to address problem at root cause – reliance on employer to collaborate
- Difficult to measure impact and effectiveness of services – what are real benefits to community and business

Mental Health Org.
- How to direct government funding to most needed areas
- How to get people who need help to access/use the services
- Measure impact/effectiveness of services/programs – is early intervention effective to avoid development of severe conditions?

Super Fund
- Members' best interest – how to help members achieve best retirement
- Work with employers to improve mental well-being of employees

Insurer/ Reinsurer
- Claims occur at the late notification stage– early intervention opportunity is missed
- Treatment plans prepared by GP are not linked to RTW
- UW and claims management are not at appropriate level to handle mental health cases
- Need to understand diagnostic validity and reliability

Longitudinal Study:
- Longitudinal Study is useful in understand how people develop from mild symptoms to more severe conditions

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What do you think are the key problems?

ⓘ Start presenting to display the poll results on this slide.

Scope Idea - A

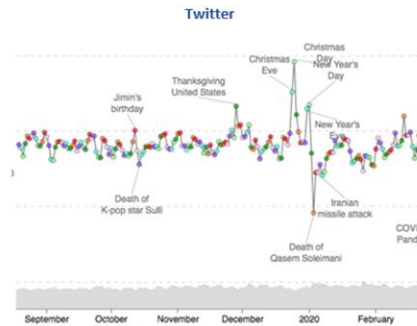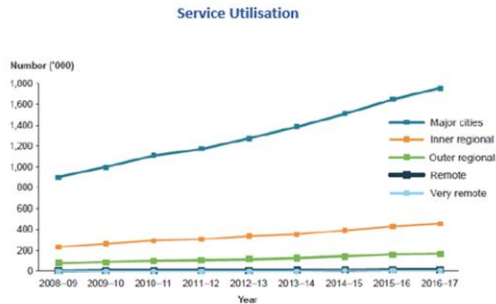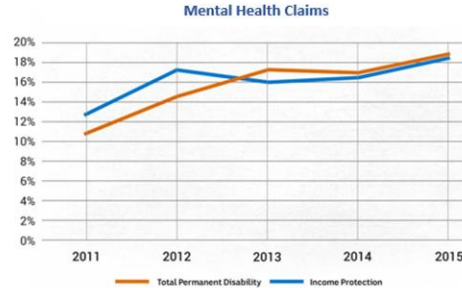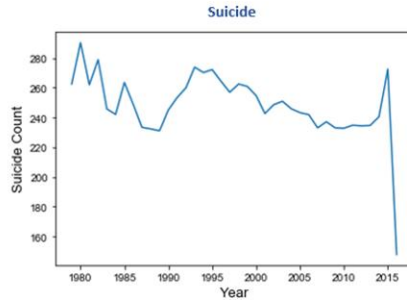|	
Idea A:	**Understanding Suicide Clusters among Young Workers in New South Wales**
Cohort:	People aged 20-40 in NSW
Aims:	Proposal to understand suicide clusters among young workers and their families.
Datasets:	• *Electronic Medical Records* • *Customer Relationship System (Mental Health Services)* • *Claims Management System (Insurance Company)* • *Social Media*

Scope Idea A
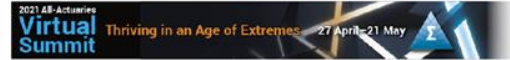
Idea B:	**Targeting Depression and Anxiety in the Australian Population**
Cohort:	People aged 20-40 with depression and anxiety
Aims:	Identify people early in their lives and to ensure appropriate care thus reducing more severe mental ill-health issues.
Datasets:	• *Wearables* • *Social Media* • *Workplace data* • *Wellness portal* • *Insurance data* • *Mental health service usage (calls to helpline)*
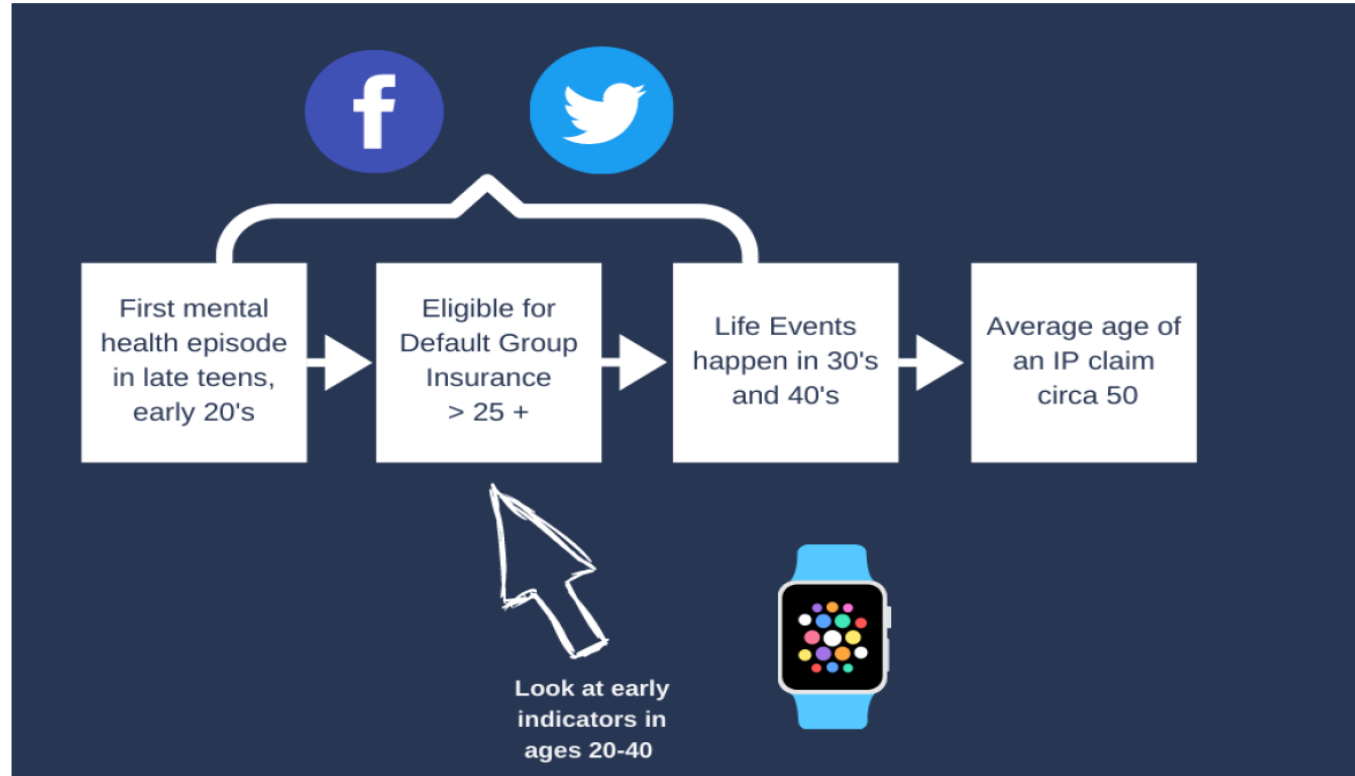
Idea C:	**Developing a mental health index that can be used as an early warning indicator**
Cohort:	People of working age (employed and unemployed)
Aims:	Provide insurers with an indicator they can use as a benchmark.
Datasets:	• Social Media • ABS data • Claims data • Mental health service data • Workplace data

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Which proposal idea do you consider most valuable?

ⓘ Start presenting to display the poll results on this slide.

Q&A

If you are interested in finding out more about this project, please contact us at **research@mattnoyceconsulting.com.au**