

TEAM: GUCK MAL EIN KEKS (Cookieessss)



PROJECT: The Chaos Project





Charley & Lucas

is a loving dad currently enjoying his time during parental leave. Besides that he is a technology consultant. Lucas likes cookies and wants to become a coder



Avery

is a Data Science Student from Sydney and likes to play piano for the mental wellbeing of the group



Jane

is a Data Science Student from Sydney and we are confused in which language we should approach her. Maybe C++ or Python



Kelvin

is a consultant for cyber security based in Sydney. He wants to join a community garden. Hit him up for plant swaps



Antje

has a background in Marketing and Urban Developememt. She came all the way from Berlin to join GovHack Sydney. She has no clue about data and would rather go on hiking trips during the hackathon

Enhancing Wellbeing Measurement in ACT

We aim to improve wellbeing measurement in the Australian Capital Territory (ACT). Our goals include exploring external data sources, finding new ways to analyze data, and identifying multi-linked indicators.



5 Contributors

ACT Wellbeing Framework



The ACT Wellbeing Framework looks at 12 aspects of wellbeing – which we call ‘domains’ this is currently measured via 56 indicators. The domains reflect the key factors the community told us impact on the quality of life of Canberrans. The Framework also includes personal wellbeing, which is an overall measure of our life satisfaction. Canberrans generally have higher levels of wellbeing than people living in other parts of Australia – but wellbeing also differs for different people within our community.

Prior work and Readings

Human Flourishing Program's Institute for Quantitative Research



hfh.fas.harvard.edu



Research

The Human Flourishing Program organizes its research according to six different themes. If you would like to learn more or become involved with...

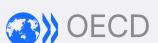


Global Wellness Institute



Statistics & Facts - Global Wellness Institute

Wellness Economy Statistics & Facts The Global Wellness Institute (GWI) is recognized as the leading source for authoritative wellness industry...



Measuring well-being and progress

GDP is a well-established tool for measuring economic output, but it does not tell us whether life as a whole is getting better, and for whom. The...



Measuring social connectedness in OECD countries

Social connections refer to the ways that people interact with and relate to one another. Their role in shaping well-being is increasingly recognised b...

Datasets used



ACT Wellbeing Framework



Domains and indicators

The ACT Wellbeing Framework comprises twelve domains of wellbeing, reflecting key factors that impact on the quality of life of Canberra residents. Indicators – the way we measure our progress – are grouped under each domain and will help us...



Regional Wellbeing Survey



Home - Regional Wellbeing Survey

The Regional Wellbeing Survey team measure wellbeing, resilience and liveability across Australia in surveys including the Regional Wellbeing Survey, Living Well in the ACT Region survey, and Carer Wellbeing Survey.



www.oecdbetterlifeindex.org



OECD Better Life Index

There is more to life than the cold numbers of GDP and economic statistics – This Index allows you to compare well-being across countries, based on 11 topics the OECD has identified as essential, in the areas of material living conditions and...



Made with Gamma

Personal Wellbeing Index Findings (ACT)

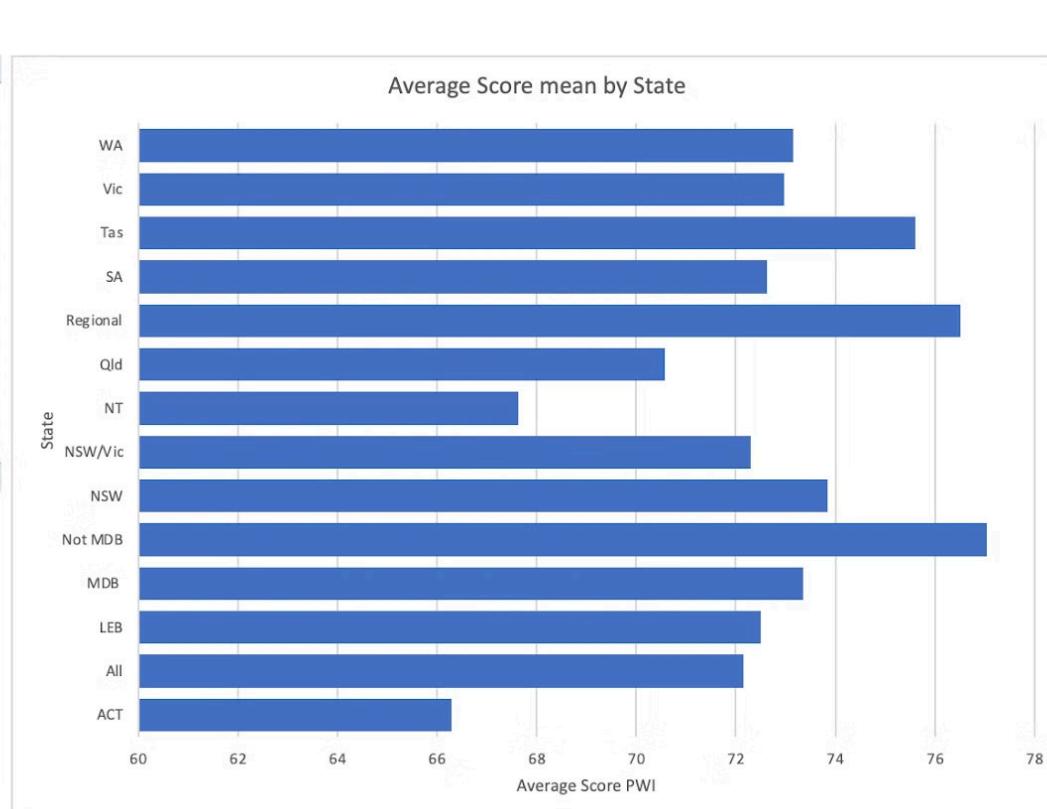
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Average Wellbeing

ACT adults scored 66.29 in 2023, below the national average of 72.16.

% of total 'Mean PWI' by 'State'

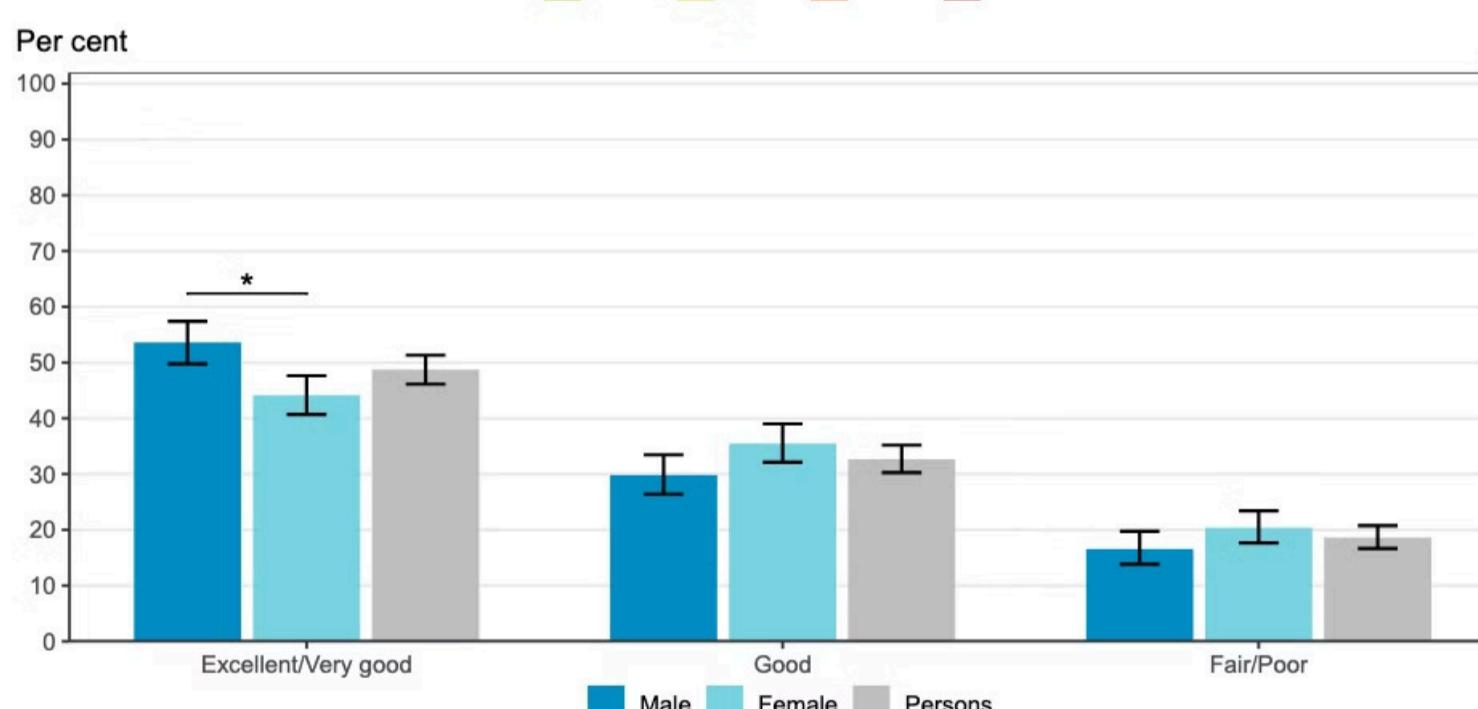
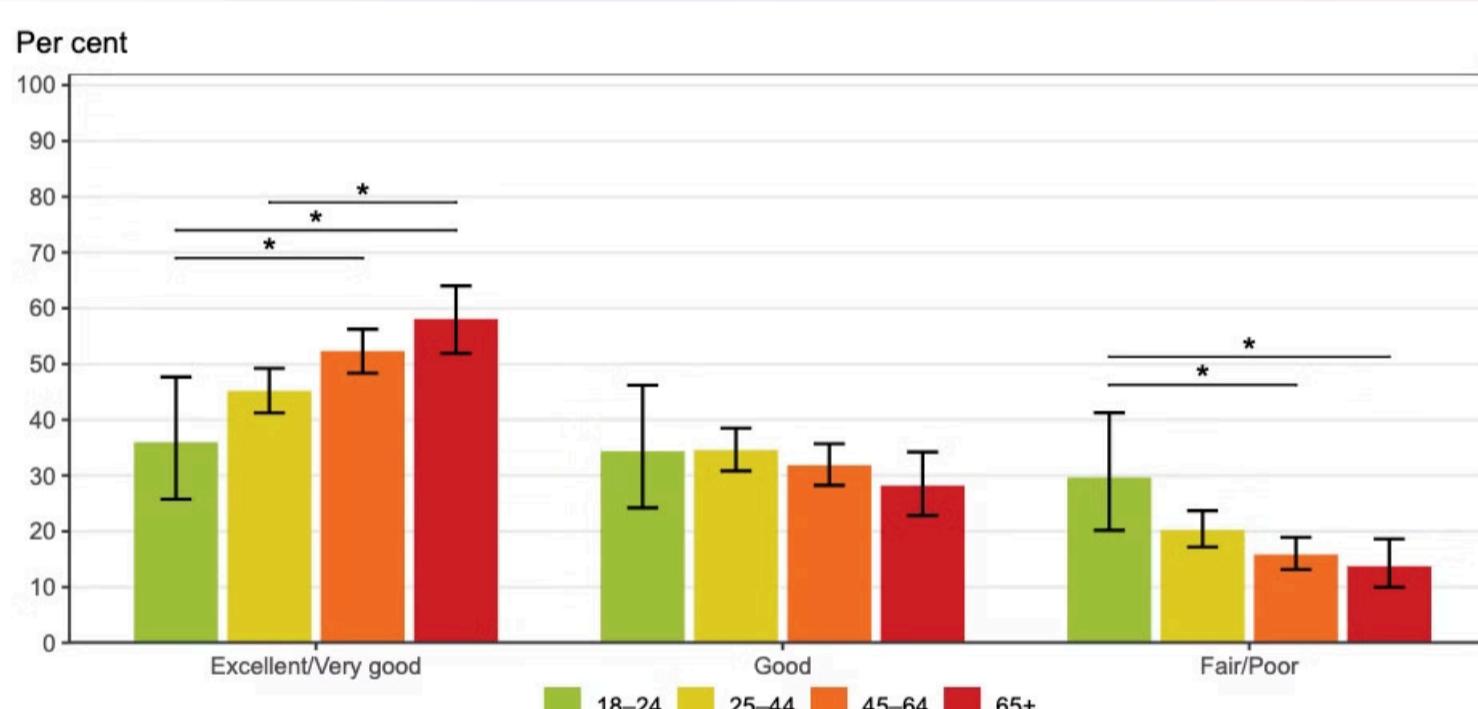
State	Average of Average score (mean 0-100)
WA	73.16013708
Vic	72.96647518
Tas	75.60939758
SA	72.628448
Regional	76.51053434
Qld	70.57119334
NT	67.62618357
NSW/Vic	72.30820009
NSW	73.85136789
Not MDB	77.04762362
MDB	73.36072648
LEB	72.50135523
All	72.1627835
ACT	66.29652083
Grand Total	72.60554824



2. Risk groups- People with disabilities, carers, and unemployed individuals had lower wellbeing scores.

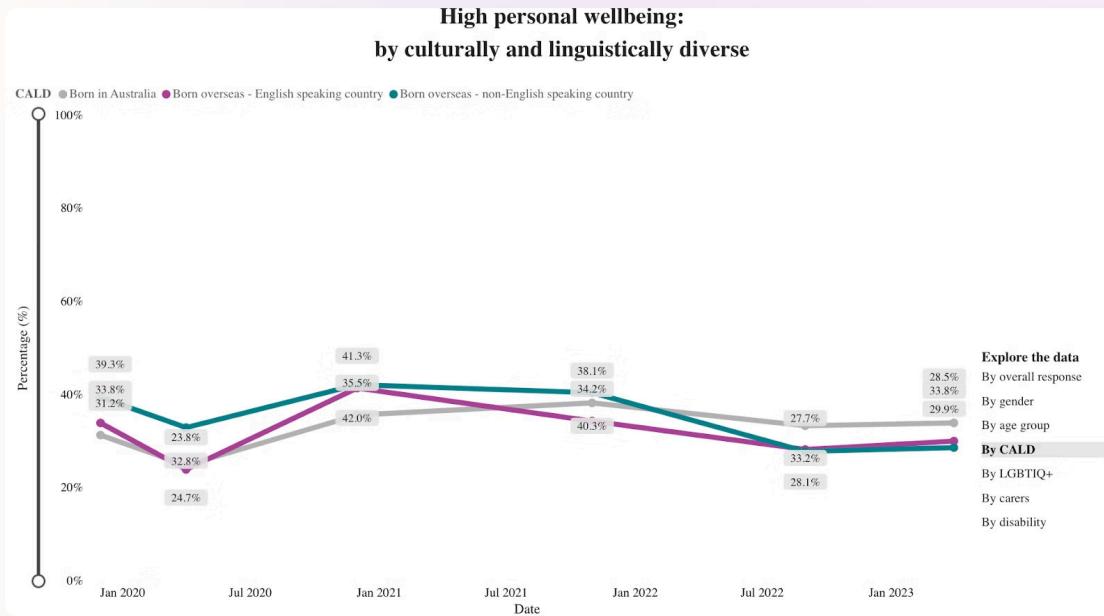
Groups with highest rates of low wellbeing, Oct/Nov 2021	% with LOW wellbeing	Groups with highest rates of sufficient/high wellbeing, Oct/Nov 2021	% with SUFFICIENT or HIGH wellbeing
Person with mental health disability	73.4%	Couple, no children at home	92.7%
Carer with 15 + per week caring obligations	38.2%	Aged 65+	89.7%
Person with any type of disability	36.3%	One or more children aged 0-4 in household	89.0%
Carers (all)	34.9%	Freestanding house	86.9%
<i>Unemployed and looking for work</i>	33.0%	Home owned outright	86.7%
Person with physical disability	30.5%	Home has mortgage	86.0%
Sole person household	29.9%	Born overseas - non-English speaking country	85.6%
<i>One or more children aged 15-17 in household</i>	29.3%	No children in household	85.3%
Carer with < 15 hours per week caring obligations	27.2%	One or more children aged 5-14 in household	85.3%
Unit/apartment	23.1%	Not LGBTIQA+	85.2%
Adult residents of ACT	17.6%	Adult residents of ACT	82.4%

3. Higher Wellbeing- Older adults, couples without children, and homeowners reported higher wellbeing.



Error bars indicate 95% confidence intervals.
Asterisks indicate statistically significant difference between estimates (non-overlapping 95% confidence intervals).

People who
are born
overseas - non
English have
better
wellbeing
index score



Regression on regional Wellness survey: Quantifying influences by domain

```
: import pandas as pd
import statsmodels.api as sm

# Sample data based on your provided information
data = {
    'Household Financial Wellbeing': [4.5596, 4.4015, 4.3776, 4.3191, 4.6414, 4.4031, 4.5750, 4.9172],
    'Community Economic Wellbeing': [3.8521, 4.0835, 4.0415, 3.8050, 4.3094, 3.6765, 3.9554, 4.5623],
    'Equity and Inclusion': [4.2944, 4.5417, 4.4054, 4.7291, 4.5977, 4.3569, 3.4118, 4.4227],
    'Access to Roads': [3.3155, 3.4120, 3.8856, 3.3785, 4.3164, 3.5938, 4.1125, 4.8386],
    'Access to Financial Services': [4.35, 4.33, 4.37, 4.05, 4.32, 3.89, 4.23, 4.94],
    'Access to Telecommunications': [4.5215, 4.5652, 4.8070, 4.6262, 5.0129, 4.9051, 5.1655, 5.2009],
    'Crime and Safety': [4.3, 4.1, 4.4, 3.8, 3.9, 4.0, 5.8, 3.7],
    'Landscape and Aesthetics': [5.7486, 5.7300, 5.7609, 5.9246, 5.7607, 5.6953, 5.3064, 5.6199],
    'Getting Involved in the Community': [3.1, 3.2, 2.9, 3.2, 3.3, 2.8, 3.3, 2.9],
    'Sense of Belonging': [5.5016, 5.6939, 5.5117, 5.7591, 5.3530, 5.5000, 5.2001, 5.6199],
    'Access to Health and Education': [4.0525, 4.4114, 4.6058, 4.3063, 4.4466, 3.7678, 3.9903, 4.5936],
    'Perceived Environmental Health': [3.9224, 4.2058, 4.3769, 4.2476, 4.2760, 4.4614, 4.3909, 4.5936],
    'Loneliness Index': [3.055, 2.875, 2.995, 2.890, 3.025, 2.890, 2.905, 3.070],
    'Wellbeing Index': [5.26, 5.29, 5.18, 5.23, 5.37, 5.24, 4.85, 5.19]
}

# Creating DataFrame
df = pd.DataFrame(data)
|
# Defining dependent and independent variables
X = df.drop(columns='Wellbeing Index')
y = df['Wellbeing Index']

# Adding constant for intercept
X = sm.add_constant(X)

# Performing regression
model = sm.OLS(y, X).fit()

# Displaying the regression results
print(model.summary())
```

OLS Regression Results

Dep. Variable:	Wellbeing Index	R-squared:	1.000			
Model:	OLS	Adj. R-squared:	nan			
Method:	Least Squares	F-statistic:	nan			
Date:	Sun, 08 Sep 2024	Prob (F-statistic):	nan			
Time:	10:37:22	Log-Likelihood:	240.89			
No. Observations:	8	AIC:	-465.8			
Df Residuals:	0	BIC:	-465.1			
Df Model:	7					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.1116	inf	0	nan	nan	nan
Household Financial Wellbeing	0.2761	inf	0	nan	nan	nan
Community Economic Wellbeing	0.7812	inf	0	nan	nan	nan
Equity and Inclusion	0.6732	inf	0	nan	nan	nan
Access to Roads	-0.4144	inf	-0	nan	nan	nan
Access to Financial Services	-0.1211	inf	-0	nan	nan	nan
Access to Telecommunications	0.1403	inf	0	nan	nan	nan
Crime and Safety	0.1895	inf	0	nan	nan	nan
Landscape and Aesthetics	0.1962	inf	0	nan	nan	nan
Getting Involved in the Community	-0.2082	inf	-0	nan	nan	nan
Sense of Belonging	-0.3799	inf	-0	nan	nan	nan
Access to Health and Education	-0.3013	inf	-0	nan	nan	nan
Perceived Environmental Health	0.1480	inf	0	nan	nan	nan
Loneliness Index	0.2254	inf	0	nan	nan	nan
Omnibus:	2.100	Durbin-Watson:	0.028			
Prob(Omnibus):	0.350	Jarque-Bera (JB):	0.077			
Skew:	-0.129	Prob(JB):	0.962			
Kurtosis:	3.404	Cond. No.	334.			

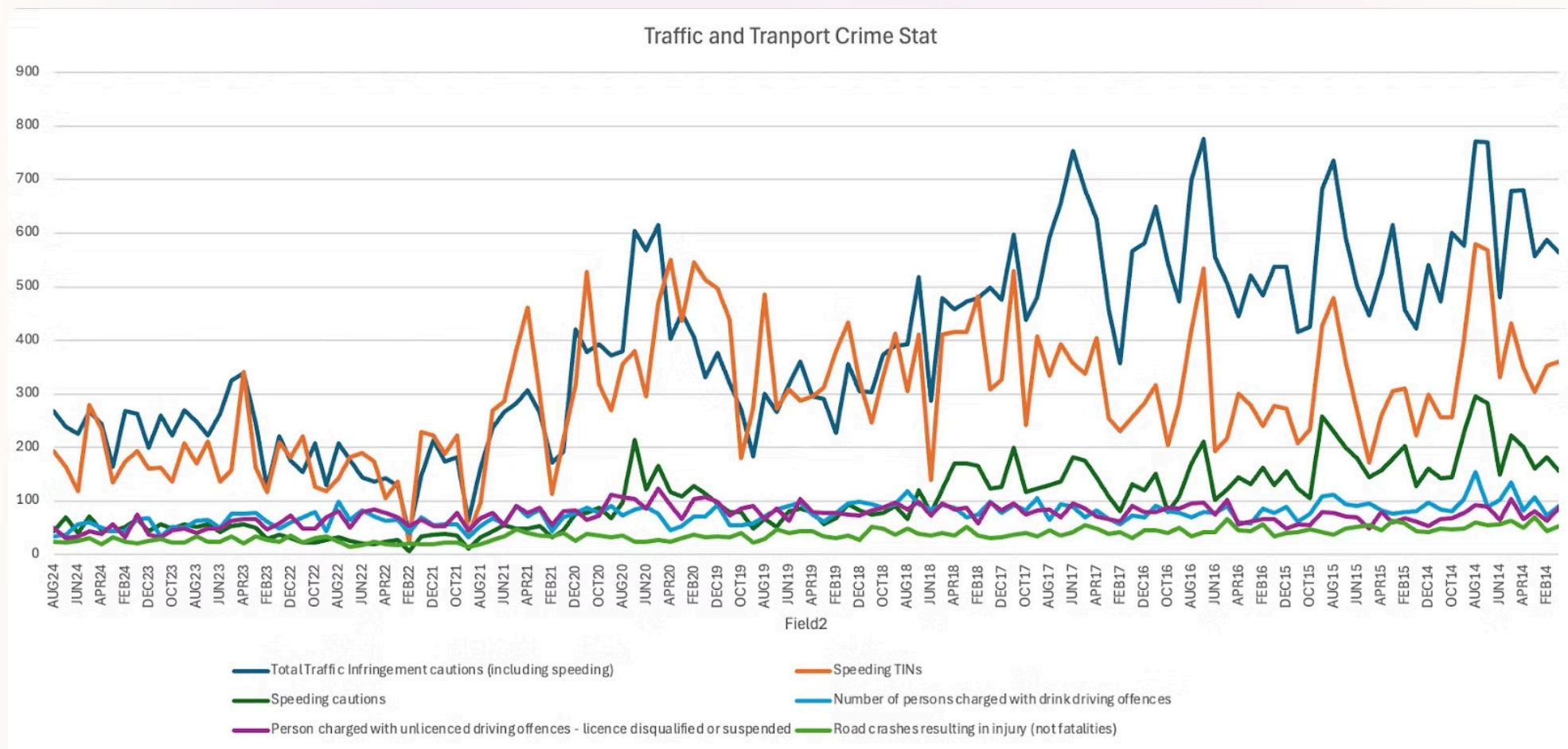
Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The input rank is higher than the number of observations.

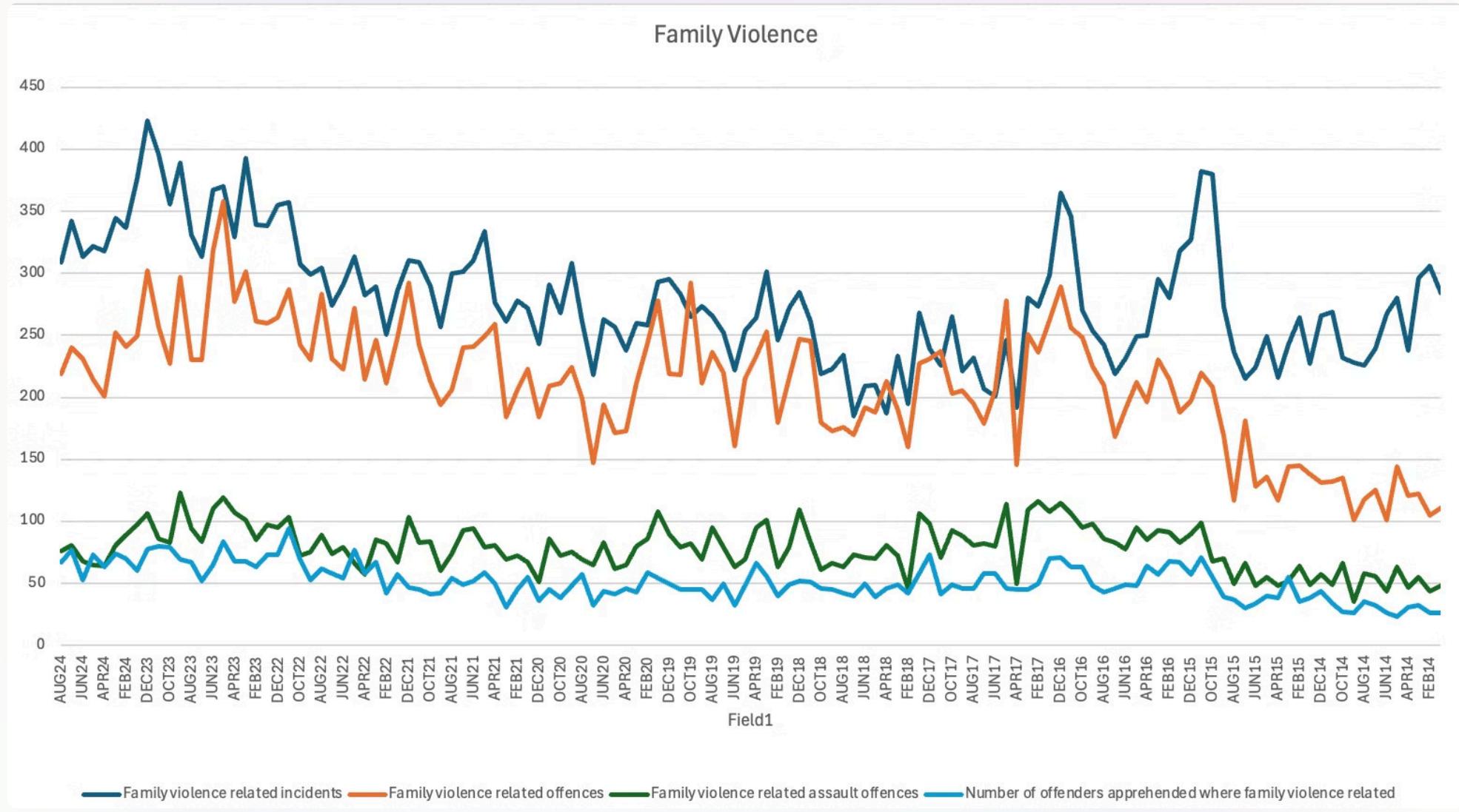
Domain Focus: Community Safety and Domestic Violence

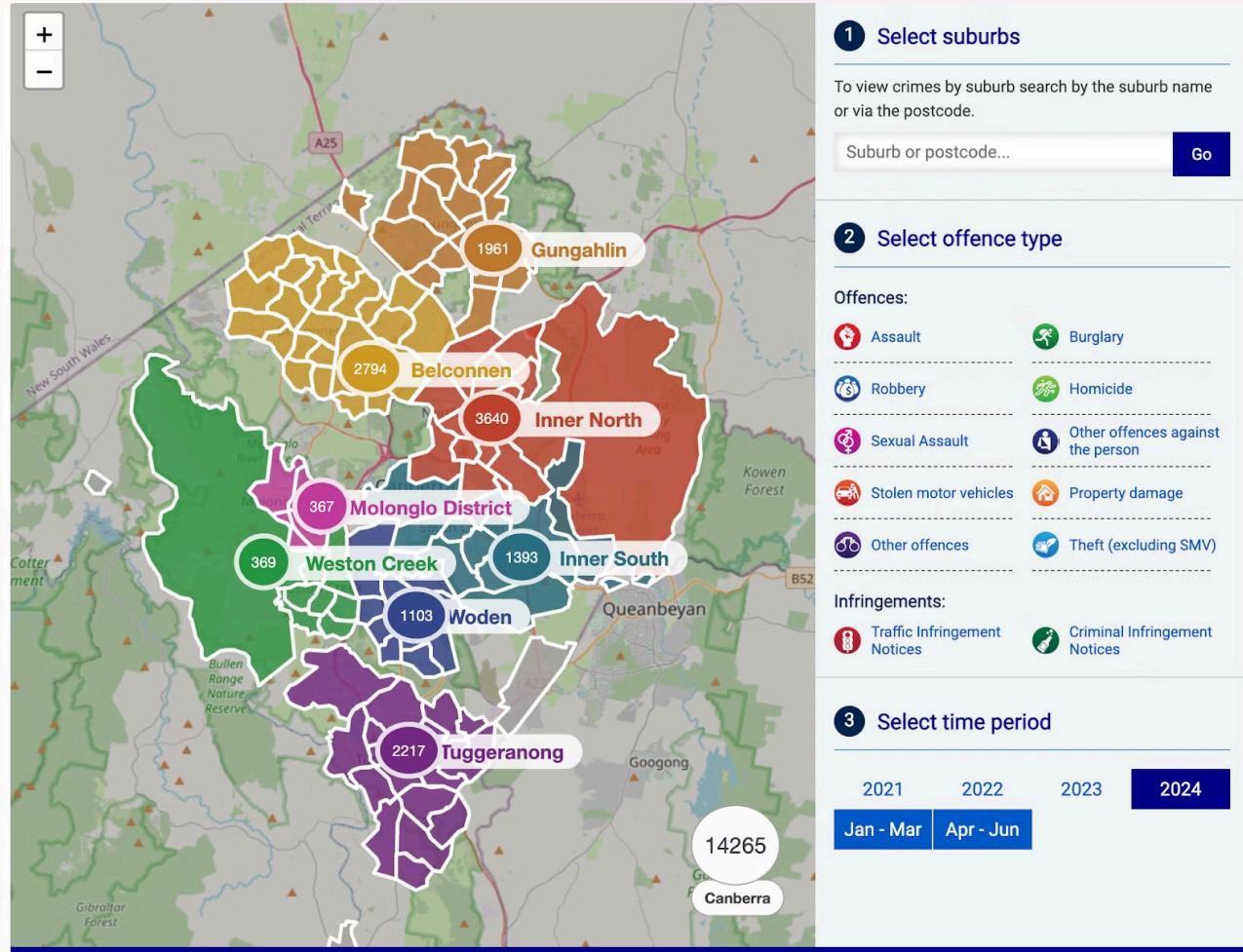
- Explore the **interaction between safety indicators** (e.g., crime data, domestic violence reports) and other wellbeing domains like **mental health and housing stability**.
- Integrate **data from domestic violence helplines, police reports, and emergency services** to map trends in domestic violence over time. Highlight the role of socioeconomic factors, employment status, and housing situations in predicting vulnerability to domestic violence.
- Apply **machine learning algorithms** to predict **high-risk periods or areas** for domestic violence, using data from environmental stressors (e.g., economic downturns) and the availability of community support services.

Road safety

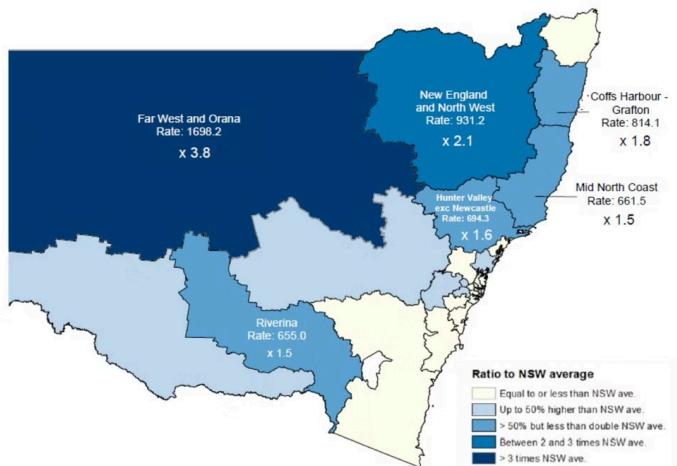


Domestic Violence





Regional trends in domestic violence



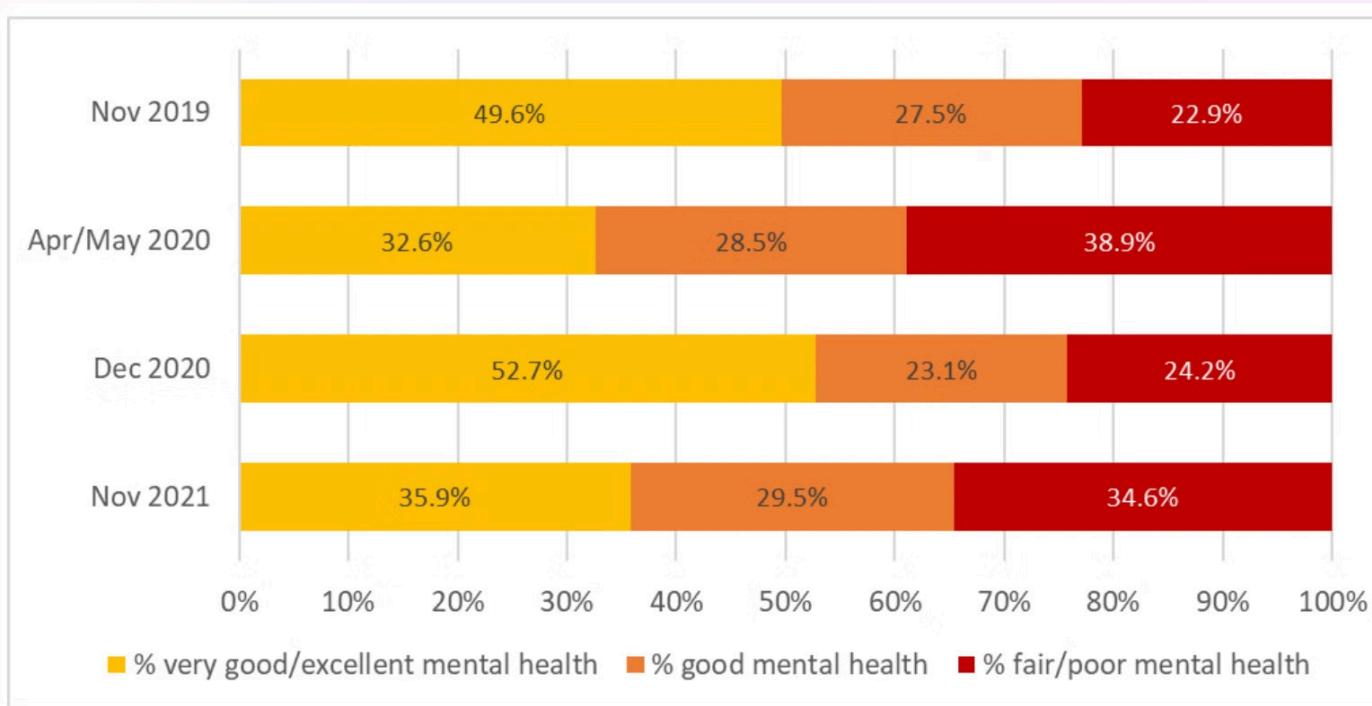
Rate map of DV assault in NSW: April 2023 to March 2024

Rates of domestic violence related assault vary across NSW with higher per capita rates in remote and regional areas.

Data file

[Domestic Violence Assault Regional Comparison tool](#) (XLS, 299.5 KB)

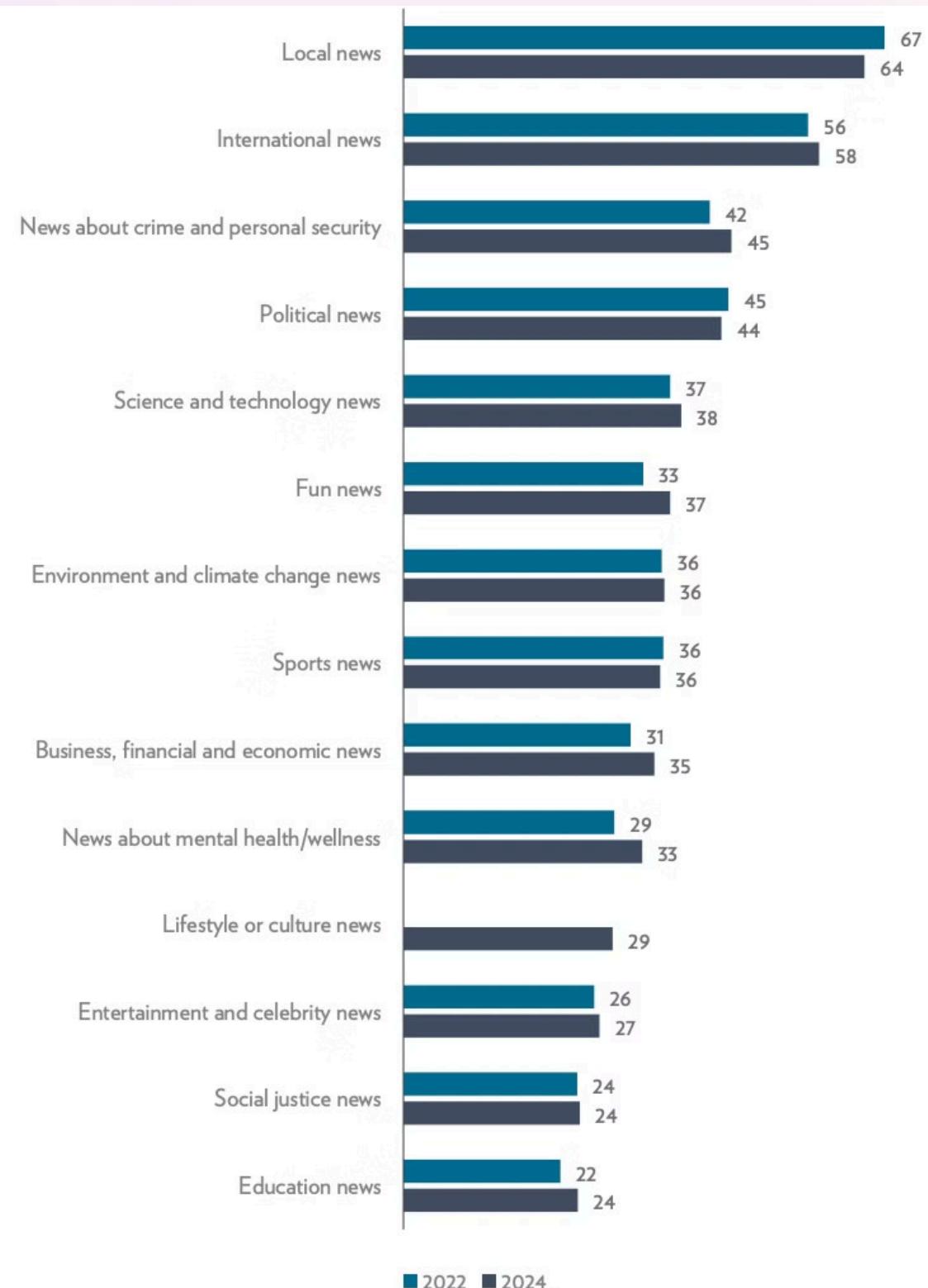
This tool provides information on domestic violence assault incidents reported to, or detected by, the NSW Police. It contains regional data for NSW, Greater Sydney, Regional NSW, Statistical Areas and Local Government Areas, for the past five years



SOCIAL MEDIA IMPACT ON WELL BEING

The research demonstrated real social impact as evidenced by its presence and discussion on social media. —> Use **natural language processing (NLP)** techniques to analyze **social media data** and **news articles** to detect emerging wellbeing trends (such as changes in community sentiment or mental health trends related to specific events, such as economic crises or natural disasters). Link these insights to ACT's Wellbeing Framework domains.

Effect of social media usage



→ There is an increment of people interested in mental health/wellness.

Limitations

The data collection period coincided with societal restrictions due to Covid-19 between 2020 and 2023.

Tried to map regional indexes **Access to local government services**, **Getting involved in the community**, **Sense of belonging** and **Access to telecommunications** with the ACT wellbeing domain framework **Governance and institutions**, **Social connections**, **Identify and belonging** and **Access and connectivity**

We also tried to link the ACT with other external wellness surveys, however methodology varies significantly with other data sets.
The ACT wellness has far more indicators than other data sources.

Comparisons



Social Determinants of Health Literature Summaries - Healthy People 2030 | health.gov

Social determinants of health affect nearly everyone in one way or another. Browse our literature summaries to learn about the latest research related to specific social determinants of health.



Future Directions

Machine Learning

Develop predictive models for high-risk periods of domestic violence.

Data Integration

Combine datasets on civic participation and wellbeing for deeper insights. Ideally this would need to be aligned with other data collection methods (US, OECD, Private Sector) so that information can be compared appropriately

Continuous Improvement

Regularly update measurement methods to capture evolving wellbeing factors.

Additional Data Points

Effect of Social Media usage on wellbeing