Escalating Depression Trends in Australia: An Analysis of Increasingly Severe Mental Health Challenges

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Abstract. Since the 1990s, de-pression has been a prevalent mental health issue in Australian society, causing significant harm to its people. This study utilizes data from authoritative health and statistical agencies, employing ARIMA models to forecast Australia's depression rates, severity, and approximate suicide probabilities among depression patients. The forecasts indicate that Australia's depression situation is expected to worsen over the next decade. According to model predictions, the proportion of the population in Australia suffering from depression will remain around 4.6% overall in the future. However, with the growth of the total population in Australia, the absolute number of people with depression will be visibly increasing, leading to a rise in the number of depression-related suicides. However, the development of artificial intelligence technology may significantly help alleviate Australia's persistently high depression rates. The Australian government should continuously increase funding for mental health services to ensure more people can access timely and appropriate mental health support. This includes funding for public and private mental health services, such as psychotherapy, counseling, and mental health hotlines. Efforts should also be made to raise public awareness of depression and other mental health issues, reducing the stigma and discrimination associated with these problems. These activities include mental health education in schools, communities, and workplaces.

Keywords: Depression, Australia, ARIMA model, Forecast, AI.

1 Introduction

The latest edition of the Mental State of the World Report has been released by Sapien Labs in the United States, which reveals that Australia is the sixth most depressed country in the world [1]. According to the latest survey by the Australian Bureau of Statistics (ABS) released on Thursday, at some point in their lives, a mental disorder has been encountered by over two-fifths (42.9%) of Australians aged 16-85. In the past 12 months alone, one in five (21.5%) Australians experienced a mental disorder. Linda Fardell, Head of Health Statistics at the Australian Bureau of Statistics, announced that the findings of the National Study of Mental Health and Well-being were unveiled today. This study, encompassing nearly 16,000 Australian participants, provides a

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comprehensive snapshot of mental health across Australian society from 2020 to 2022, highlighting anxiety disorders as the most prevalent mental health issues during this period. In the past year, 17.2% of Australians encountered anxiety disorders like social phobia or post-traumatic stress disorder. Additionally, 7.5% experienced affective disorders such as depression, and 3.3% grappled with substance use disorders [2].

In 2018, antidepressants were taken by 3 million Australians, and depression was suffered by one in eight people. Among those affected, depression was experienced by over 300,000 young adults aged 18-27, and by more than 400,000 individuals aged 28-38 [3]. Between 2007 and 2015, the volume of psychotropic medicines dispensed in Australia surged by 23.5%, as reported by the Pharmaceutical Benefits Scheme (PBS) in 2016. This increase globally reflects rising usage of antidepressants and antipsychotics, with notable increases in psychostimulant use also noted [4].

Despite the higher prevalence of mental illness in younger age groups, older workers affected by such conditions may find themselves compelled to leave the workforce due to the combined effects of aging and the disabling impacts of their illnesses. In 2010, among the 347,000 Australians aged 45–64 who were out of the labor force due to ill health, depression was attributed to 7.1% (24,000 individuals), while other mental and behavioral disorders were cited by 9.6% (32,000 individuals) as reasons for their exit. By 2007, the annual economic toll resulting from productivity losses due to depression, anxiety, and substance abuse was calculated at AUD 11.8 billion, accompanied by annual reductions in income tax totaling AUD 1.2 billion and welfare expenditures amounting to AUD 12.9 billion [5].

Individuals experienced continuous depressive symptoms from the onset of depression had significantly higher odds of lifetime self-harm, recent self-harm within the past 12 months, multiple instances of self-harm, suicidal ideation, and suicide attempts compared to those who had periods of at least 2 months without symptoms since the initial onset. Both the duration and persistence of depressive symptoms independently contribute to heightened risks of non-suicidal self-injury and suicidal thoughts and behaviors among young individuals [6].

Therefore, in this study, the focus will be on predicting the future prevalence of depression in Australia, the severity of depression in the future, and the number of suicides due to depression. Sampling an ARIMA model to forecast and obtain the final results will help analyze how Australia can better address depression in the future.

2 Research Design

2.1 Data Source

The data sources for this research include:

1. Our World in Data: This website is a reputable data source in academia. The study extracted precise data on depression rates in Australia from 1990 to 2017, as well as total numbers of depression cases and suicides from 2000 to 2019.

2. GitHub repository: This project was completed as a requirement for the Georgia Tech Master's course CSE 6242: Data and Visual Analytics. It involves a BERT

depression detection model using Twitter data for time series analysis to visualize geographic trends in depression scores.

2.2 ADF Unit Root Test

Concept of Unit Root: In time series analysis, the presence of a unit root indicates non-stationarity. This occurs when a process exhibits varying mean and variance over time, suggesting a trend or drift in the data [7].

Steps of ADF Test: The ADF test compares a test statistic against pre-determined critical values to decide whether to reject the null hypothesis.

Construction of ADF Test Statistic. The Augmented Dickey-Fuller test incorporates a regression component, commonly expressed as:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \epsilon_t \tag{1}$$

Where y_t is the time series, Δy_t is the first difference of the time series, t is time trend, ϵ_t is the error term.

Critical Values and Decision Rule. The outcome of the ADF test depends on comparing the test statistic with critical values (see Table 1). If the test statistic is below the critical value, the null hypothesis is typically rejected, indicating stationarity in the time series. Conversely, failing to reject H0 suggests the presence of a unit root, implying the series is non-stationary [8].

Table 1. ADF test results

Asset	p-value
depression percentage (%), yearly	0.99
1st order difference	0.01637
depression score, monthly	0.1653
1st order difference	0.021
2nd order difference	0.01
fitted(numdpress/numsuicide), yearly	0.01

2.3 ARIMA Model

The ARIMA model, a traditional method in time series analysis, forecasts future data trends by integrating autoregressive (AR), differencing (I), and moving average (MA) components. This approach examines historical data patterns and trends, facilitating predictions of future values [9].

ARIMA (p, d, q)(P, D, Q) Model Parameters and Principles p (Autoregressive parameter). p represents the autoregressive (AR) component of the model, which describes how each observation is linearly dependent on its own previous values up to p periods. Mathematically, it is formulated as:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \epsilon_t \quad (2)$$

Here,ϕ_i(for i=1 to p) are the autoregressive coefficients, and at time t, the error term is represented by ϵ_t [10].

q (Moving Average parameter). q represents the moving average (MA) part of the model, which models the relationship between the current observation and a number of lagged forecast errors (previous q periods). Mathematical Formulation:

$$X_t = \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (3)$$

Here, ε_t(for t=1 to q) are the white noise error terms, and θ_j(for j=1 to q) are the coefficients for the moving average component.

d (Order of differencing parameter). The order of differencing required to transform a non-stationary time series into a stationary one is represented by d. Mathematical Formulation:

$$\text{Stationary Series} = X_t - X_{t-1} \quad (4)$$

Differencing involves subtracting the series at the current time period from the series at the previous time period, d times, until the series becomes stationary.

P, D, Q (Seasonal parameters). P, D, Q are similar to p, d, q but refer to the seasonal component of the ARIMA model, which accounts for seasonal variations. Mathematical Formulation:

$$(1 - \sum_{i=1}^{P} \Phi_i L^{S_i})(1 - L)^D (1 - L^S)^D X_t = \left(1 + \sum_{j=1}^{Q} \Theta_j L^{S_j}\right)\varepsilon_t \quad (5)$$

Here, Φ_i and Θ_j are the seasonal autoregressive and moving average coefficients, and L and L^S are lag operators.

3 Empirical Results and Analysis

3.1 Order Determination and Residual Test

PACF plots can subjectively help determine the p-value, while ACF plots can subjectively help deter-mine the q-value [11]. However, sometimes the values of p and q are not very accurate, which may lead to residuals that do not meet the white noise criterion, which implies the need to adjust the values of p and q. After combining the AIC criterion with ACF plot and PACF plot provided by figure 1, 2 and 3, the following models were determined: ARIMA (2,1,2) for myts (depression percentage), ARIMA (2,2,2)

(0,0,2) [12] for mytx (depression score), and ARIMA (2,0,2) for m1(fitted (num-dpress/numsuicide)).

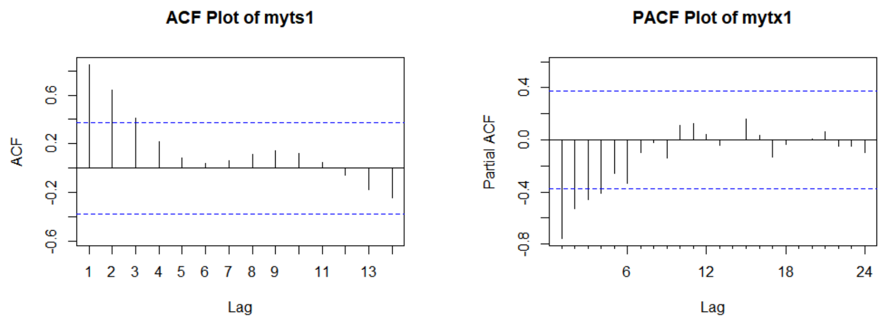

Fig. 1. myts1(1st) (Photo credit: Original)

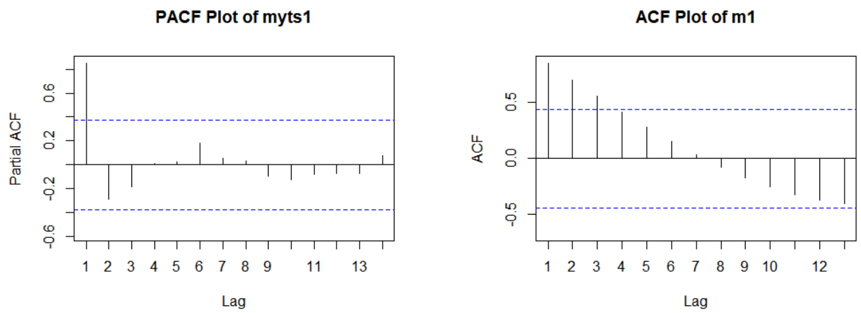

Fig. 2. mytx1(2nd) (Photo credit: Original)

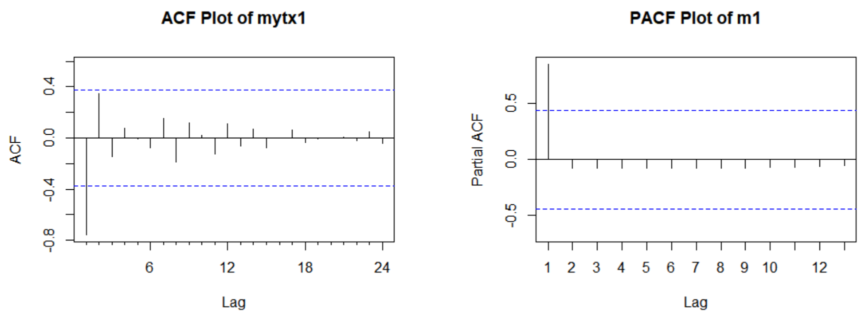

Fig. 3. m1 (Photo credit: Original)

By examining the residuals, it was found that all three models mentioned above conform well to white noise, indicating minimal model selection errors. From table 2, it is clearly that the ARIMA models are fitted for them because all p-values are bigger than 0.05.

Table 2. Residual test

Asset		p-value
depression (%), yealy		
myts		0.1563
depression score, monthly		
mytx		0.2869
fitted(numdpress/numsuicide), yearly		
m1		0.5082

3.2 Forecast Results and Interpretation

From table 3, it can be seen that the total proportion of depressed people in Australia remains relatively stable at around 4.5% to 4.6% over the next few years. Although the proportion of the total depressed population is relatively stable, the increasing trend in Australia's overall population means that the number of people suffering from depression will continue to rise, significantly impacting the emotional well-being of Australian society.

Table 3. forecast for depression percentage

Year	Point Forecast	Lo 95	Hi 95
2018	4.591588	4.579853	4.603324
2019	4.565456	4.531640	4.599271
2020	4.546030	4.478287	4.613774
2021	4.533040	4.422096	4.643984
2022	4.525679	4.365387	4.685972
2023	4.522859	4.310071	4.735648
2024	4.523401	4.257511	4.789290
2025	4.526179	4.208529	4.843828
2026	4.530212	4.163476	4.896948

From table 4, it can be seen that the degree of depression among Australians has a significant relationship with seasonality, with higher depression generally occurring in winter and spring. The overall picture shows significant fluctuations in Australia's general level of depression.

Table 4. Forecasts for depression score

Month	Point Forecast	Lo 95	Hi 95
Jul 2022	0.232906	0.1430572	0.322756
Aug 2022	0.209090	0.1180106	0.300170
Sep 2022	0.187952	0.0966308	0.279273

Oct 2022	0.224661	0.1329693	0.316353
Nov 2022	0.229532	0.1372809	0.321784
Dec 2022	0.202172	0.1091681	0.295176
Jan 2023	0.249944	0.1563868	0.343501
Feb 2023	0.223329	0.1284740	0.318185
Mar 2023	0.220094	0.1236466	0.316541
Apr 2023	0.184800	0.0864500	0.283151
May 2023	0.231334	0.1307546	0.331914
Jun 2023	0.195852	0.0927072	0.298997
Jul 2023	0.243514	0.1341657	0.352862
Aug 2023	0.245745	0.1327686	0.358722

Table 5 displays a fitted data model. The correlation analysis between the total number of individuals diagnosed with depression (numdepression) and the total number of suicides (numsuicide) indicates a robust correlation coefficient of 0. 8836146.The ratio(numsuicide/numdepression) serves as an approximate coefficient t, where a higher t indicates a greater likelihood of suicide among individuals with depression. To address the small t value and instability observed in the ADF test, steps were taken initially to stabilize the data. Subsequently, a linear function was applied to fit the data, followed by the natural logarithm (ln) transformation of the resulting values to achieve greater stability in t. It is evident from the increasing trend in t that the impact of depression on life in Australia is becoming more severe.

Table 5. Forecasts for fitted (numsuicide/numdepression)

Year	Point Forecast	Lo 95	Hi 95
2021	0.09158974	0.09158968	0.09158980
2022	0.09225785	0.09225761	0.09225809
2023	0.09292550	0.09292497	0.09292602
2024	0.09359267	0.09359180	0.09359354
2025	0.09425937	0.09425811	0.09426064
2026	0.09492561	0.09492390	0.09492732
2027	0.09559137	0.09558917	0.09559356
2028	0.09625665	0.09625393	0.09625937
2029	0.09692146	0.09691817	0.09692474

Overall, based on the forecasted results, Australia's depression situation is expected to worsen over the next decade, particularly considering the significant impact of the COVID-19 pandemic from 2020 to 2023. With economic instability and rising unemployment rates, this could lead to more adverse outcomes for depression in Australia. Australia also ranks among the countries with the highest levels of depression globally. According to data from the Australian Department of Health, there has been in-creasing economic investment and improvements in medical care for depression, which may mitigate the worsening societal impacts to some extent. How-ever, overall, the outlook for depression levels in Australia over the next decade remains quite pessimistic.

4 Discussion

One unique aspect of this study is the use of t-values to approximate the probability of suicide among de-pression patients, followed by linear regression to reduce errors.

According to recent data on depression in Australia, the situation is expected to worsen. How-ever, many experts have also noted a high rate of misdiagnosis of depression, often confusing it with symptoms of bipolar disorder. This misdiagnosis can lead not only to incorrect treatment decisions for those without depression but also exacerbate the condition for those who are misdiagnosed.

In recent years, with the rise of artificial intelligence (AI), there has been an increasing application of AI in medical diagnosis. For instance, Professor Fei-Fei Li's team at Stanford University has ap-plied machine learning to depression diagnosis with an accuracy rate as high as 80% [12]. Despite its promising advancements, AI is still in its nascent stages, suggesting that a combined approach of AI and human diagnosis may be more cost-effective and reliable.

AI has also been integrated into therapeutic ap-plications. For example, new AI software developed at Flinders University shows promise in preventing relapses of severe mental illnesses [13], significantly aiding patient recovery.

5 Conclusion

Through this study, it becomes evident that Australia's current state regarding depression is increasingly concerning, showing a clear trend towards deterioration. This conclusion is underscored by recent news reports from the past two years, suggesting that the actual situation may be more severe than previously anticipated.

Australia, known for its high level of development and competitiveness, imposes significant stress and anxiety on individuals due to its fast-paced lifestyle. Furthermore, the nation's lenient regulation of drugs, including certain prescription medications and substances, complicates the landscape of mental health issues. While diagnosis and treatment play crucial roles in alleviating symptoms, they do not address the root causes of these problems.

While diagnosis and treatment are essential for alleviating symptoms, they do not cure the underlying problems. Hence, it is imperative for the Australian government to allocate greater resources towards ad-dressing the psychological well-being and needs of its population.

The Australian government could invest more in funding mental health research, supporting the development and application of new treatment methods and interventions. This includes collaborating with universities and research institutions to conduct large-scale mental health research projects.

For specific high-risk groups, such as youth, the elderly, Indigenous Australians, and residents of rural areas, the government provides specialized mental health services and support programs. These programs aim to meet the unique needs of different populations, ensuring they receive appropriate mental health support.

This strategic investment is essential for combating the pervasive issue of depression in Australian society effectively. Only through a comprehensive approach to these challenges can Australia hope to mitigate the alarming prevalence of depression and its associated impacts on public health and well-being.

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