INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN SOCIAL SCIENCE (IJRISS)
ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue I January 2025

Prediction Number of Admissions in the Psychiatric Department of Hospital Universiti Sains Malaysia (HUSM) Using the ARIMA Model

Nur Syuhada Muhammat Pazil, Mariathy Karim*

Mathematical Sciences Studies, College of Computing, Informatics and Mathematics, Universiti Teknologi MARA, Melaa Branch, Jasin Campus

DOI: https://dx.doi.org/10.47772/IJRISS.2025.9010291

Received: 14 January 2025; Accepted: 18 January 2025; Published: 19 February 2025

ABSTRACT

In Malaysia, mental health issues are on the rise. Mental health refers to a person's psychological, emotional, and social well-being, which helps to understand how they deal with stress, make decisions, and connect with others. However, with the current outbreak of COVID-19, which has happened all over the world, including in our country, the trend has been an increase in psychiatric department admissions. Therefore, this study aims to predict the number of patient admissions at the Psychiatrist Department of Hospital Universiti Sains Malaysia (HUSM) using the Auto-Regressive Integrated Moving Average (ARIMA) model. The appropriate model is determined by comparing the measurement errors Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percent Error (MAPE), Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Then, the predicted number of patients was calculated using the best model generated. The finding in this study indicates that ARIMA (1,1,3) was the best-fit model for predicting the number of patients. The prediction model is generally reliable, especially in the middle months of the period studied, where the accuracy is consistently high. This strategy might be applied to data from any hospital department with the same trend pattern for further comparison or future perspective. More time series models could be used to forecast the number of patients for future research.

Keywords: Mental Health, Psychiatric department, ARIMA, patients' admission, prediction

INTRODUCTION

Mental health issues were already on the rise in Malaysia. According to government statistics, approximately half a million Malaysians reported depressive symptoms in the 2019 National Health and Morbidity Survey. However, the world is facing a critical situation caused by COVID-19, which has contributed hugely to increasing levels of depression in the country [1]. COVID-19 and MCO negatively impact many people, such as our frontline, economic sectors, and small business owners. Professionals such as doctors and nurses must do excessive work during the disease outbreak due to a shortage of professionals and an upsurge in workload [2]. The influx of patients and overcrowding in hospital departments is a global issue that has been widely studied over the past decade. This overcrowding occurs due to a mismatch between the hospital's capacity and various factors affecting patient admission, throughput, and discharge, which challenges operational efficiency [3], [4], [5].

Numerous strategies have been proposed in the literature to mitigate these challenges and improve patient flow management. While various techniques exist, there is a predominant focus on quantitative approaches that employ predictive modelling to anticipate patient crowding. A seasonal autoregressive integrated moving average with external regressor models aims to enhance capacity management by analysing patterns and trends in-patient admissions and hospital resource utilization [6], [7]. The issue of patient crowding in hospitals is a significant global concern that can negatively impact patient care. Researchers have developed quantitative models to predict patient crowding to address this, focusing specifically on patient inflow and admissions. Researchers applied the Autoregressive Integrated Moving Average (ARIMA) modelling approach. They determined that the ARIMA (1,0,1) model was the best fit for forecasting patient inflow and admissions based on metrics like AIC and BIC. The model showed high accuracy with minimal errors, indicating its potential to effectively manage patient volume and improve hospital care [8].

Existing research highlights the significance of forecasting in healthcare management, particularly for optimizing resource allocation and improving patient outcomes. Time series modeling has been widely employed to predict healthcare trends, including patient admissions, disease incidence, and resource utilization. Among these models, the Auto-Regressive Integrated Moving Average (ARIMA) model has proven to be a robust and reliable tool for analyzing and predicting trends in various fields, including mental health. Studies have demonstrated ARIMA's efficacy in capturing complex patterns within healthcare data, enabling researchers and policymakers to anticipate future demands accurately[9], [10], [11].

Despite the growing body of literature on time series modeling in healthcare, significant gaps remain, particularly in the context of mental health in Malaysia. Most studies have focused on general healthcare forecasting or specific diseases, with limited attention given to psychiatric admissions [12], [13]. Moreover, while ARIMA has been utilized in international settings to predict mental health trends, its application in Malaysia's healthcare context, specifically at institutions like Hospital Universiti Sains Malaysia (HUSM), remains underexplored. This creates an opportunity to contribute novel insights into the predictive modeling of psychiatric admissions, addressing a critical gap in the existing literature.

The present study aims to fill this gap by employing the ARIMA model to predict the number of patient admissions to the psychiatric department at HUSM. The research is guided by the hypothesis that a well-fitted ARIMA model can reliably forecast patient admissions, thereby providing valuable insights for healthcare planning and management. By comparing different ARIMA models based on measurement errors such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percent Error (MAPE), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC), the study seeks to identify the most appropriate model for accurate predictions.

This study contributes to the existing body of knowledge by demonstrating the application of ARIMA modeling in a Malaysian healthcare context, specifically for psychiatric admissions. The findings offer practical implications for healthcare administrators, enabling them to make informed decisions regarding resource allocation and patient care. Additionally, the methodology and insights can serve as a reference for future research, potentially extending to other hospital departments or geographical locations with similar trends. Through this work, his study aim to advance the understanding of predictive modelling in mental health and its role in improving healthcare outcomes.

COVID-19 COVID-19 has caused massive damage and has badly impacted many people's physical and emotional health, such as frontliners, small businesses and students facing psychological and mental health consequences due to the COVID-19 pandemic, including vicarious trauma, anxiety, and despair [8]. For all people with mental illnesses to return to a healthy lifestyle, decent care must be offered to those who have struggled. In response, obtaining the assistance of a psychiatrist is an essential part of achieving this goal. As a result, by estimating the number of patients seeking a psychiatrist's assistance, it can see whether there is an impact of the COVID-19 epidemic on mental health or not. Therefore, this research will focus on the trend pattern of patients' admission to Psychiatric Departments before and after the outbreak of COVID-19, as well as predicting the number of patients to manage patient volume and improve hospital care effectively for the year 2024. Secondary data on the number of patients in the Psychiatric Departments of Hospital Universiti Sains Malaysia (HUSM) were collected from 2017 (before predicting the COVID-19 outbreak) to the end of 2023 (roughly three years after the outbreak began), which was then analysed using R-Studio software. The Autoregressive Integrated Moving Average (ARIMA) is used to develop a forecasting model and identify the best-fit model that will be used for the prediction of the number of patients for the future year. The ideal model will be carefully chosen based on the statistical results of different aspects such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percent Error (MAPE), Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). This study can give an overview of whether the trend pattern of psychiatrists seeking help is continuing to rise or sticking the same.

LITERATURE REVIEW

Mental Health Problem and COVID-19 Outbreak

During disease outbreaks, community anxiety tends to spike due to factors like the first death, increased media coverage, and rising case numbers. Mass quarantine can exacerbate this anxiety for several reasons: it signals the severity of the situation, undermines trust in authorities, creates a sense of entrapment, and fuels the spread of rumours. The lack of clear communication can lead people to seek information from unreliable sources, heightening fear [14]. The attempts to stop the outbreak, which includes the act of isolation, make people feel unpleasant and fearful of the change of lifestyle [15].

A study by [16] assessed Malaysian public mental health about two months after the pandemic's start, from May to September 2020. Throughout the research period, there was a rise in depression, anxiety, and stress symptoms, with depression rates increasing the most when there were large percentages of recorded depression (59.2%) and anxiety (55.1%) symptoms compared to stress (30.6%) symptoms. Chui et al. (2021) researched the influence of COVID-19 on nurses' psychological discomfort. According to the findings, more than three-quarters of nurses experienced stress, with nurses working in outpatient departments reporting much greater stress levels than nurses working in inpatient care units.

Auto-Regressive Integrated Moving Average (ARIMA) Method

Auto-Regressive Integrated Moving Average (ARIMA) model is a time-series forecasting technique that predicts the future value of a variable based on its historical values. It employs auto-regression and moving average, as well as a differencing order, to eliminate trend and/or seasonality [4], [6], [7], [17], [18], [19], [20]. The study assesses the accuracy of an ARIMA model in predicting COVID-19 cases. Researchers optimized the model parameters by analysing auto-correlation functions and various accuracy metrics. They then used the best-fit model to forecast confirmed and recovered cases during different phases of Kuwait's preventive measures. The results showed that the actual case numbers largely fell within the model's 95% confidence interval, demonstrating the model's reliability despite the evolving nature of the pandemic and government adjustments [17].

Reference [21] proposed various machine learning models, Auto-Regressive Integrated Moving Average (ARIMA), Random Forest, Support Vector Regression, and Extreme Gradient Boosting, to build predictive models that give accurate influenza-like illness forecasts in sub-tropical areas like Taiwan in which seasonal influenza behaviour is ambiguous. In contrast, the results indicate some time differences in the highest prediction, and the reliability decreased slightly as the forecast time horizons expanded using ARIMA. Apart from that, [17] used the ARIMA model to predict the confirmed and recovered COVID-19 cases. The outcomes showed that the ARIMA model was relatively accurate in its forecast, even with frequent adjustments and modifications to the plan. For all phases except Phase I, the actual values of identified and recovered cases were significantly within the highest and lowest ranges of the prediction.

The study conducted by [22] addresses COVID-19 as a global threat and explores the use of various mathematical models for predicting its spread, acknowledging potential biases in these models. The authors propose a simple econometric model, explicitly employing the Auto-Regressive Integrated Moving Average (ARIMA) approach, using epidemiological data from Johns Hopkins to forecast COVID-19 prevalence and incidence trends. They emphasize the importance of maintaining real-time case definitions and data collection for better comparison and future insights. Another study by [23] introduced an integrated web-based healthcare delivery system designed to forecast future hospitalizations, particularly for COVID-19 in Broome County, NY. Recognizing a gap in the literature regarding such systems, the aim was to provide a reference for other healthcare organizations. Three forecasting methods—Simple Exponential Smoothing (SES), non-seasonal and seasonal ARIMA, and Artificial Neural Networks (ANN)—were evaluated, with ARIMA (6, 1, 3) emerging as the best model. This shows forecasting using the ARIMA model gives more accuracy.

Furthermore, [20] addressed the global issue of patient crowding in hospitals by developing a forecasting model to predict patient inflow and admissions, using data from Liaquat University of Medical and Health Sciences (LUMHS) Hospital in Jamshoro. Utilizing MATLAB for analysis, the research applied the Autoregressive Integrated Moving Average (ARIMA) modelling approach. It identified the ARIMA (1,0,1) model as the best fit for inflow and admissions based on criteria like AIC and BIC. The model showed high accuracy with minimal errors, offering valuable insights for hospital management to handle patient volumes better and anticipate future trends in admissions. Meanwhile, [18] also face the same situation. The long waiting times at Puskesmas Curug emphasise the need for effective forecasting to enhance patient care readiness. Using data from 2015 to 2018, the study predicts patient visits, including those from BPJS beneficiaries, employing three techniques: linear regression, single exponential smoothing, and autoregressive integrated moving average (ARIMA). The findings indicate that the ARIMA method achieved the highest accuracy, with a precision rate of 73%. Additionally, the study created a visual representation of the data, which will be shared with the health centre for further evaluation.

METHODOLOGY

Data Description

Secondary data were collected from the Psychiatric Department of Hospital Universiti Sains Malaysia (HUSM) from January 2017 to December 2023. A total of 84 admissions each month were recorded. The data series has been split into estimation and evaluation sections before further work on the model can be performed. It is a standard procedure to divide all available labelled data into estimation and evaluation, with a 75% estimation and a 25% evaluation. The predicted values will be compared to the original values retained in the evaluation section.

Autoregressive Integrated Moving Average (ARIMA)

The ARIMA, a stochastic time series model, is the most conventional and all-encompassing model currently in use. It is frequently used in research on forecasting and other topics. The ARMA model, which uses prior observations and errors to explain the current value of some time series, is generalized by the ARIMA model [24]. ARIMA models investigate the autocorrelations between time series data. The time series must be stationary before developing the forecasting model. The ARIMA model was generated in this study to predict the number of admissions in the psychiatric department of Hospital Universiti Sains Malaysia (HUSM). This model has been identified as one of the most effective methods used to predict time-series data. This method is divided into three phases: identification, estimation and forecasting. The actual data has to be stationary. If the data is not stationary, proceed to the identification stage.

Identification Phase:

Step 1: Plot the time series data to check the trend component

Step 2: Augmented Dickey-Fuller (ADF) test was used to check for seasonality. If the series is not stationary, differentiate the series and re-test for stationary.

Decision Rule: Reject if p-value $\leq$ 0.05

H_0: The data is not stationary.

H_1: The data is stationary

Estimation Phase

The ARIMA model is categorized into three terms, p, d, and q, where p is the order of the autoregressive (AR) term, q is the order of the moving average (MA) term, and d is the number of differencing used to obtain the stationary time series data. These are the mathematical formulas for each term:

Autoregressive (AR), p term,

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t \quad (1)$$

Moving Average (MA), q term,

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

Where ε_t represents white noise.

Number of differencing, d term,

$$\Delta^k y_t = (1 - B)^k y^t \quad (3)$$

Where B is the lag operator.

Therefore, the general formula for the ARIMA model is as follows,

$$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (4)$$

Where y'_t is a differenced series.

Forecast Phase:

Check the accuracy of the model to select the best ARIMA model. To verify the accuracy of the model, measuring errors such as RMSE, MAPE, MAE, BIC, and AIC are calculated. Then, the best model is selected to forecast the data.

Model Evaluation

The final evaluation for ARIMA models in this study was based on five measurements: RMSE (Root Mean Square Error), MAPE (Mean Absolute Percentage Error), MAE (Mean Absolute Error), AIC (Akaike Information Criterion), and BIC (Bayesian Information Criterion). These error measurements were formulated as follows:

RMSE= $\sqrt{\frac{\sum e_t^2}{n}}$	(5)
MAPE= $\left(\frac{1}{n}\sum\left\|\frac{e_t}{y_t}\right\|\right)(100)$	(6)
MAE = $\frac{\sum \|e_t\|}{n}$	(7)
AIC = $e^{\frac{2k}{n}} \frac{\sum e_t^2}{n}$	(8)
BIC = $n^{\frac{k}{n}} \frac{\sum e_t^2}{n}$	(9)

Where the forecast error is e_t, and it is calculated by subtracting the forecast value from the series' actual value;

y_t. Here n is the number of practical observations used to match the model. Minimum values of these accuracy measures provide the best-fitting models. All the values were generated using R-studio.

RESULT AND DISCUSSION

Trend the Number of Admission to Psychiatric Department

Figure 1 depicts the number of psychiatric admissions at HUSM from January 2017 to October 2023 and highlights several key trends, particularly related to the impact of COVID-19. Before the pandemic, from 2017 to early 2020, psychiatric admissions followed a relatively stable pattern with regular fluctuations and a slight upward trend. However, the data shows that admissions sharply declined during the beginning of the COVID-19 pandemic in the middle of 2020. This decline is probably the result of pandemic-related factors, such as widespread lockdowns, limitations on access to non-emergency medical services, and anxiety about contracting the virus in medical facilities. Following the initial fall, there was a substantial increase in psychiatric admissions in 2021, which persisted until 2022 and 2023. Based on the visual evidence of an upward trend and seasonal fluctuations, it is likely that the data is non-stationary**.**

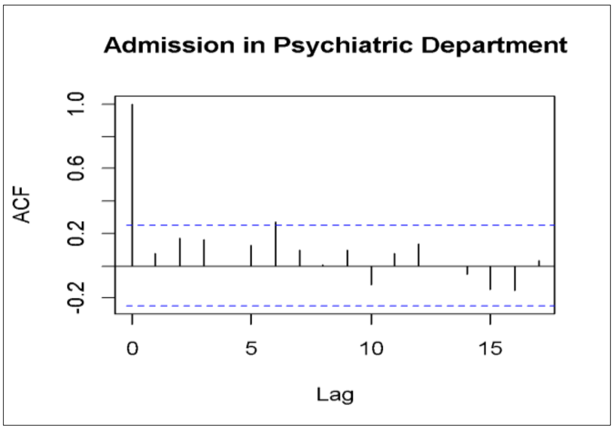

Fig. 1 Monthly Number of Admission to the Psychiatric Department at HUSM

Checking for Stationarity

The data were divided into two parts: estimation (75%) and evaluation (25%). In the estimation part, the data selected are from January 2017 (n=1) to March 2023 (n=63). Data from April 2023 (n=64) to December 2023 (n=84) were used in the evaluation part. One of the critical elements in the ARIMA model is to ensure the time series data are stationary. Different techniques have been deployed to determine and make the dataset stationary. Since the data in Figure 1 shows not stationary, the original data were evaluated using three approaches: the Autocorrelation Function (ACF) plot, the Partial Autocorrelation Function (PACF) plot and the Augmented Dickey-Fuller (ADF) test for the estimation part and evaluation part to check the stationary.

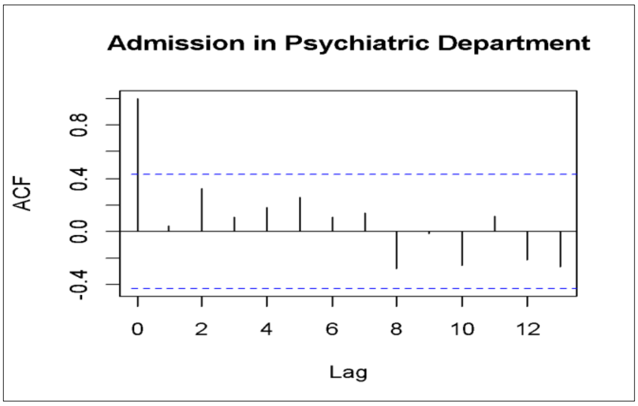

Fig. 2 ACF plot for estimation part

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue I January 2025

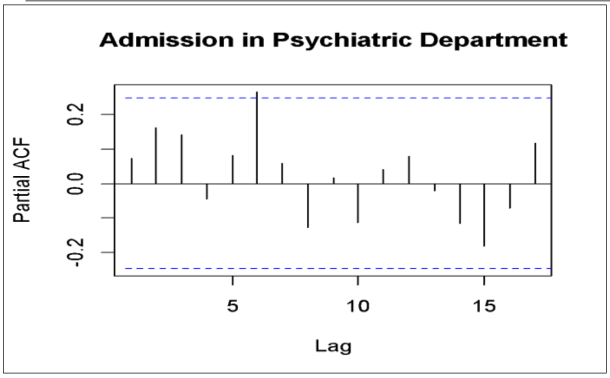

Fig. 3 ACF plot for evaluation part

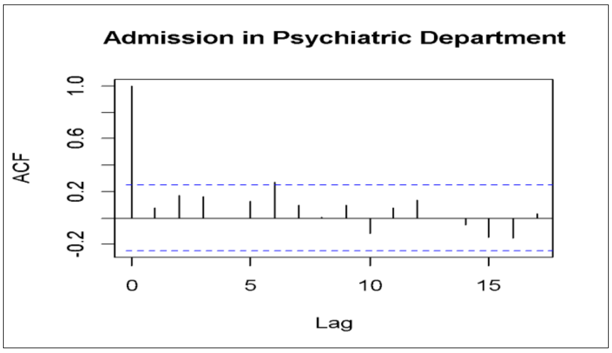

Fig. 4 PACF plot for estimation part

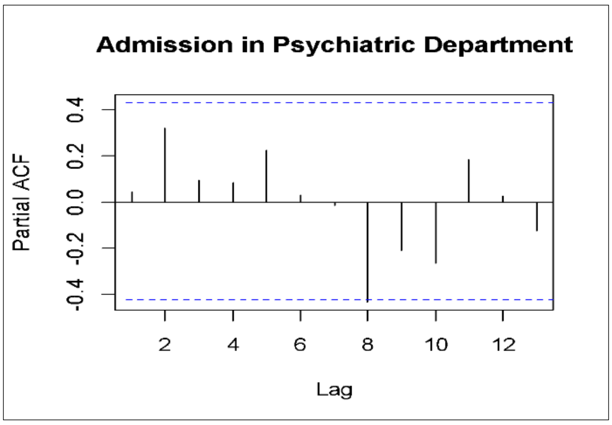

Fig. 5 PACF plot for evaluation part

The decay pattern is shown in the ACF plot in Figure 2 and Figure 3. Figure 4 and Figure 5 show the PACF plot of the estimation and evaluation parts, respectively, with a large spike. Therefore, the data is not stationary. Thus, the ADF test was generated using the R-studio software to determine the stationarity of the data set for the estimation and evaluation parts. The result was tested at a 5% level of significance. For both the estimation and evaluation parts, the decision rule was to reject the null hypothesis, H_0: The data is not stationary if the *p*-value was less than 0.05.

Table I Output of ADF Test for Estimation and Evaluation Part

	Estimation Part	Evaluation Part
Null Hypothesis	The data is not stationary	
Alternative Hypothesis	The data is stationary	

Decision Rule	Reject H_0 if p-value < 0.05	
P-value	0.8224	0.1139
Decision at a 5% significant level	Do not Reject H_0	Do not Reject H_0
Conclusion	The data is not stationary	The data is not stationary

Since all the alternatives show that the data of the estimation and evaluation parts are not stationary, the first differencing should be done by checking the KPSS test.

Table II Output of KPSS Test for Estimation Part

Statistics	**Model**
Decision Rule: Reject H_0 if p-value < 0.05.	H_0: The data is stationary. H_1: The data is not stationary.
P-value	0.1
Decision (5% significant level)	Do not Reject H_0
Conclusion	The data is stationary.

The results of the KPSS test for the estimation part of the psychiatric admissions data are summarized in Table 2, which shows that the data is stationary around a deterministic trend. After verification of the stationary on the first differencing, several models were tested to identify the most suitable one. Five ARIMA models with tentatively selected p, d, and q values were estimated [25]. Hence, the measurement errors of the five ARIMA models, RMSE, MAPE, MAE, AIC and BIC were computed using R-studio.

Selection of the Best Model

The measurement errors for the five distinct ARIMA models, including ARIMA (1,1,1), ARIMA (1,1,2), ARIMA (1,1,3), ARIMA (2,1,1), and ARIMA (2,1,2) are shown in Table 3. These models were evaluated based on the following measurement errors: RMSE (Root Mean Square Error), MAPE (Mean Absolute Percentage Error), MAE (Mean Absolute Error), AIC (Akaike Information Criterion), and BIC (Bayesian Information Criterion).

Table III Measurement Errors of the Five ARIMA Models

Measurement Errors	ARIMA (1,1,1)	ARIMA (1,1,2)	ARIMA (1,1,3)	ARIMA (2,1,1)	ARIMA (2,1,2)
RMSE	110.5962	110.6065	103.1822	110.6066	110.5714
MAPE	8.3335	8.3242	7.7229	8.3293	8.3274
MAE	91.3500	91.3256	84.2978	91.3359	91.3526
AIC	253.02	255	255.48	255.01	256.99
BIC	256	258.98	260.46	258.99	261.97

Many important error measures show that ARIMA (1,1,3) performs the best out of the five models. Its average error in squared deviations is the least, as indicated by its lowest RMSE (103.1822). In addition, it records the lowest MAE (84.2978) and MAPE (7.7229), demonstrating that it offers the most accurate forecast in terms of both percentage and absolute errors. Regarding model selection criteria, AIC and BIC are often used to penalize model complexity. Although ARIMA (1,1,1) has slightly better AIC and BIC values compared to ARIMA (1,1,3), the overall performance of ARIMA (1,1,3) in terms of error metrics (RMSE, MAPE, and MAE) makes it a preferable choice for forecasting the admissions data. Hence, the ARIMA (1,1,3) model has been selected as the most suitable model for forecasting the number of patients admitted to the psychiatric department.

Prediction of the Number of Admission to Psychiatric Department

The predicted number of patient admissions was computed using the best ARIMA (1,1,3) model, as shown in Table 4. The table illustrates that the predictions are highly accurate between February and June, with accuracy of around 95% and above, showing that the model is well-tuned for most months. In January, the prediction was lower than the actual attendance, with an accuracy of 85.13%, indicating that while close, 14.87% of the attendance was unaccounted for. February's prediction was more accurate, with 96.41% accuracy and a slight deviation of 3.59%. Similarly, March showed 96.25% accuracy, with only a 3.75% deviation. April had excellent accuracy at 99.32%, with less than a 1% error, while May maintained high accuracy with a slight overprediction, deviating by 4.02%. June's accuracy of 98.01% demonstrated strong performance, with a 2% deviation. However, July's prediction was significantly lower than actual attendance, with an accuracy of 85.81%, suggesting that a factor affecting attendance in July may have been missed, leading to a 14.19% error.

Table IV Predicted Number of Admissions to the Psychiatric Department of Hospital Universiti Sains Malaysia (HUSM) in January – July 2024

Month	**Predicted Number**	**Actual Number**	**Accuracy (%)**
January	1145	1345	85.13
February	1182	1141	96.41
March	1163	1121	96.25
April	1179	1187	99.32
May	1165	1120	95.98
June	1177	1154	98.01
July	1167	1360	85.81

Figure 6 shows the predicted and actual number of admissions in the psychiatric department of Hospital Universiti Sains Malaysia (HUSM).

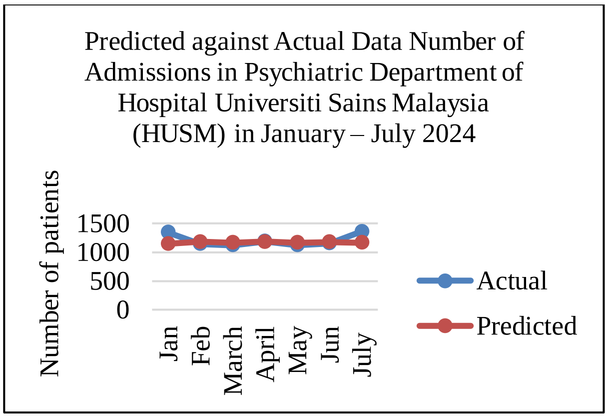

Fig. 6 Predicted and Actual Number of Admission to the Psychiatric Department at HUSM

Overall, the graph indicates that the predictions follow the actual data closely, with the predicted values generally lying close to the exact values. Thus, the ARIMA (1,1,3) model fits the actual data well.

CONCLUSION

This study was conducted to find the best model of ARIMA to predict the number of admissions of psychiatric patients in Hospital Universiti Sains Malaysia (HUSM) from January 2024 until July 2024. The study's models with the lowest measurement errors determined the best model. The approach used for the research should generate prediction results that correspond to the actual behaviour of the time series data. This study was therefore analysed using ARIMA (1,1,3) since the model was chosen as the best model for assessing the actual number of admissions psychiatric patients' data from January 2017 to December 2023.

The analysis shows the model is precise for most months, as evidenced by the highly accurate predictions, which have 95% and above accuracy. Furthermore, the model performs reasonably well for most of the months, maintaining consistent accuracy with the lines for the predicted and actual values running parallel and close to each other. This visual representation supports the earlier conclusion that the ARIMA (1,1,3) model is effective, though it may benefit from further adjustments to improve its predictive accuracy during periods of higher variability. Other hospitals can also use this model with a similar number of attendance trend patterns of any department to predict the subsequent monthly attendance. Hospital workers and government officials will benefit from the study's findings. It will provide the hospital employees with the data they need to plan enough treatments and therapists. Apart from that, this research will notify the government about the trend number of individuals who have a mental illness, allowing them to raise awareness and prepare to assist. Once the trend pattern of people seeking psychiatric help is discovered, the number of patients in the psychiatric department for upcoming months and years can be forecast. The researchers suggest that to predict the number of admissions of psychiatric patients accurately, more time series methods should be used in future research.

ACKNOWLEDGEMENT

This research was not funded by any grant. Special thanks to the reviewers for their useful suggestions. The corresponding author can be contacted at mariathy@uitm.edu.my.

REFERENCES

1. J. H. Hashim, M. A. Adman, Z. Hashim, M. F. Mohd Radi, and S. C. Kwan, "COVID-19 epidemic in Malaysia: Epidemic progression, challenges, and response," Front. Public Heal., vol. 9, no. May, pp. 1–19, 2021, doi: 10.3389/fpubh.2021.560592.
2. G. Joshi and G. Sharma, "Burnout: A risk factor amongst mental health professionals during COVID-19," Asian J. Psychiatr., vol. 54, no. July, pp. 8–10, 2020, doi: 10.1016/j.ajp.2020.102300.
3. T. M. Abuhay, S. Robinson, A. Mamuye, and S. V. Kovalchuk, "Machine learning integrated patient flow simulation: why and how?," J. Simul., vol. 17, no. 5, pp. 580–593, 2023, doi: 10.1080/17477778.2023.2217334.
4. S. S. Jones, A. Thomas, R. S. Evans, S. J. Welch, P. J. Haug, and G. L. Snow, "Forecasting daily patient volumes in the emergency department," Acad. Emerg. Med., vol. 15, no. 2, pp. 159–170, 2008, doi: 10.1111/j.1553-2712.2007.00032.x.
5. J. P. Ansah et al., Modeling Emergency Department crowding: Restoring the balance between demand for and supply of emergency medicine, vol. 16, no. 1 January 2021. 2021. doi: 10.1371/journal.pone.0244097.
6. M. Ba-Aoum, N. Hosseinichimeh, K. P. Triantis, K. Pasupathy, M. Sir, and D. Nestler, "Statistical analysis of factors influencing patient length of stay in emergency departments," Int. J. Ind. Eng. Oper. Manag., vol. 5, no. 3, pp. 220–239, 2023, doi: 10.1108/ijieom-10-2022-0056.
7. A. Choudhury and E. Urena, "Forecasting hourly emergency department arrival using time series analysis," Br. J. Healthc. Manag., vol. 26, no. 1, pp. 34–43, Jan. 2020, doi: 10.12968/bjhc.2019.0067.
8. N. M. Noor, R. C. Yusof, and M. A. Yacob, "Anxiety in frontline and non-frontline healthcare providers in kelantan, malaysia," Int. J. Environ. Res. Public Health, vol. 18, no. 3, pp. 1–10, 2021, doi: 10.3390/ijerph18030861.

9. N. Gerard, “Healthcare management and the humanities: An invitation to dialogue,” Int. J. Environ. Res. Public Health, 2021, doi: 10.3390/ijerph18136771.
10. R. L. da Costa, L. Pereira, R. Gonçalves, Á. Dias, C. H. Jerónimo, and N. Teixeira, “Healthcare management and leadership roles,” Int. J. Electron. Healthc., 2022, doi: 10.1504/IJEH.2022.122135.
11. E. L. Linnander, J. M. Mantopoulos, N. Allen, I. M. Nembhard, and E. H. Bradley, “Professionalizing healthcare management: A descriptive case study,” Int. J. Heal. Policy Manag., 2017, doi: 10.15171/ijhpm.2017.40.
12. F. Piccialli, F. Giampaolo, E. Prezioso, D. Camacho, and G. Acampora, “Artificial intelligence and healthcare: Forecasting of medical bookings through multi-source time-series fusion,” Inf. Fusion, 2021, doi: 10.1016/j.inffus.2021.03.004.
13. M. Niaz and U. Nwagwu, “Managing Healthcare Product Demand Effectively in The Post-Covid-19 Environment: Navigating Demand Variability and Forecasting Complexities,” Am. J. Econ. Manag. Bus., 2023, doi: 10.58631/ajemb.v2i8.55.
14. G. J. Rubin and S. Wessely, “The psychological effects of quarantining a city,” BMJ, vol. 368, no. January, pp. 1–2, 2020, doi: 10.1136/bmj.m313.
15. S. Y. Ren, R. D. Gao, and Y. L. Chen, “Fear can be more harmful than the severe acute respiratory syndrome coronavirus 2 in controlling the corona virus disease 2019 epidemic,” World J. Clin. Cases, vol. 8, no. 4, pp. 652–657, 2020, doi: 10.12998/wjcc.v8.i4.652.
16. L. P. Wong et al., “Escalating progression of mental health disorders during the COVID-19 pandemic: Evidence from a nationwide survey,” PLoS One, vol. 16, no. 3 March, pp. 1–14, 2021, doi: 10.1371/journal.pone.0248916.
17. H. Alabdulrazzaq, M. N. Alenezi, Y. Rawajfih, B. A. Alghannam, A. A. Al-Hassan, and F. S. Al-Anzi, “On the accuracy of ARIMA based prediction of COVID-19 spread,” Results Phys., vol. 27, p. 104509, 2021, doi: 10.1016/j.rinp.2021.104509.
18. M. Aprilia and W. Wella, “Visualization and prediction the number of patients visit in Curug Health Center,” G-Tech J. Teknol. Terap., vol. 8, no. 3, pp. 1379–1385, Jul. 2024, doi: 10.33379/gtech.v8i3.4245.
19. H. J. Kam, J. O. Sung, and R. W. Park, “Prediction of daily patient numbers for a regional emergency medical center using time series analysis,” Healthc. Inform. Res., vol. 16, no. 3, pp. 158–165, 2010, doi: 10.4258/hir.2010.16.3.158.
20. Sakina Kamboh, Mir Ghulam Hyder Talpur, Nawab Khan Chand, Liaquat Ali Zardari, Abdul Wasim Shaikh, and Shakeel Ahmed Kamboh, “Time series modeling and forecasting of the patients’ inflow and admission in the hospitals: A cases study of LUMHS Hospital Jamshoro Pakistan,” VFAST Trans. Math., vol. 12, no. 1, pp. 311–322, Jun. 2024, doi: 10.21015/vtm.v12i1.1840.
21. H. Y. Cheng et al., “Applying machine learning models with an ensemble approach for accurate real-time influenza forecasting in Taiwan: Development and validation study,” J. Med. Internet Res., vol. 22, no. 8, pp. 1–14, 2020, doi: 10.2196/15394.
22. D. Benvenuto, M. Giovanetti, L. Vassallo, S. Angeletti, and M. Ciccozzi, “Application of the ARIMA model on the COVID-2019 epidemic dataset,” Data Br., vol. 29, p. 105340, 2020, doi: 10.1016/j.dib.2020.105340.
23. A. Kasasbeh, E. Issa, N. Khan, M. Yildirim, A. Booth, and H. Sayama, “Web-Based healthcare delivery integrated system to forecast COVID-19 hospitalizations in a marginalized patient population: A case study in Broome County, New York,” Adv. Public Heal., vol. 2024, pp. 1–15, 2024, doi: 10.1155/2024/6644557.
24. K.-R. Kim, J.-E. Park, and I.-T. Jang, “Outpatient forecasting model in spine hospital using ARIMA and SARIMA methods,” J. Hosp. Manag. Heal. Policy, pp. 1–8, 2020, doi: 10.21037/jhmhp-20-29.
25. N. S. M. Pazil, N. Mahmud, S. H. Jamaluddin, and N. A. Ali, “Forecasting dengue outbreak data using ARIMA model,” Int. J. Acad. Res. Bus. Soc. Sci., vol. 11, no. 6, pp. 1746–1755, 2021, doi: 10.6007/ijarbss/v11-i6/10106.