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Time series analysis for forecasting neonatal intensive care unit census and neonatal mortality

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Abstract

Background This study analyzes time series data related to NICU (Neonatal Intensive Care Unit) census numbers, hospitalization days, and mortality rates.

Methods We utilized seven years of retrospective daily NICU census data for model development, covering the period from March 2016 to December 2022, encompassing a total of 7,227 infants. We applied the best-fitting models of ARIMA (Auto Regressive Integrated Moving Average) and SARIMA (Seasonal ARIMA) to forecast census numbers, lengths of hospital stays, and mortality proportions. Additionally, we conducted regression time series analysis to explore the relationships among these variables.

Results The mortality proportion peaked in 2017 at 9.94%. The average duration of hospitalization was 12.42 days, with significant variability observed between deceased and surviving neonates. Multiple regression analysis indicated an inverse relationship between the number of hospitalizations and the duration of hospital stays, with a coefficient of -2.58 days (P-value < 0.001). There was also a notable correlation between longer hospital stays and increased mortality, with a regression coefficient (B) of 0.339 (P-value = 0.018). Time series analysis revealed a decreasing trend in mortality proportion in the NICU, alongside seasonal patterns in census numbers, which peaked during the winter months.

Conclusion Seasonal variations were observed, with the highest admissions occurring in the winter months and the shortest hospital stays during this period. Additionally, longer hospital stays were associated with higher mortality. Forecasting using ARIMA and SARIMA models demonstrated strong predictive capabilities, highlighting the importance of effective resource planning to optimize outcomes in the NICU.

Clinical trial number Not applicable.

Keywords Intensive care units, Neonatal, Time series analysis, Forecasting, Mortality, Hospitalization

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Introduction

The investigation of the situation of medical care, the monitoring of intensive care priorities and related indicators, and the forecasting of situations are significant challenges [1]. Neonatal intensive care units (NICUs) face various demands, such as heavy costs, restricted resources, infection control, ethical problems, and staff exhaustion [2, 3]. Therefore, it is important to monitor, evaluate, and forecast the performance and consequences of NICUs to identify gaps and improve the quality of care.

NICU census is impacted by clinical routines, which can change dynamically over time. Forecasting NICU census and the duration of hospital stay plays a significant role in offering adequate and safe care, supported by appropriate resource planning, and minimizing discrepancies between expected and actual demand for health care resources, e.g., nurse-to-patient ratios and hospital equipment management [4, 5]. Various studies have shown that suboptimal nurse staffing levels are associated with decreased quality of care and neonates' safety due to over- or understaffing (e.g., nosocomial infections) [6–10]. Increasing the number of neonates per nurse in NICUs has been shown to increase the risk of emotional burnout and dissatisfaction [11], and conversely, low nurse-to-patient ratios have been associated with increased adverse patient outcomes, such as increased 30-day mortality and failure to rescue [11].

Neonatal mortality is a major public health problem worldwide. According to the World Health Organization (WHO), an estimated 2.4 million neonatal deaths occurred in 2019, accounting for 47% of all under-five deaths [1].

The pooled proportion of mortality in a systematic review (on 24,995 neonates admitted to NICUs in Iran) was estimated to be 11.40% [12]. In a meta-analysis among very low birth weight (VLBW) newborns (1996–2016) in the Eastern Mediterranean Region (EMR), the pooled prevalence of mortality was obtained as 32.0% (CI 95%: 27.0 to 38.0) [13].

The main causes of neonatal mortality are preterm birth complications, intrapartum-related events (birth asphyxia or trauma), infections, congenital anomalies, and neonatal sepsis [1]. Some studies have reported that survival in neonatal care for very low birth weight or preterm infants is related to the proportion of nurses with neonatal qualifications per shift and the length of hospitalization in NICU [14, 15].

Time series analysis is a statistical technique that examines data collected over time to identify patterns, trends, and make predictions about phenomena. This analysis can be used to forecast NICU census, hospitalization duration, and understand the dynamics of neonatal mortality in NICUs by revealing seasonal and cyclical variations, detecting trends and level changes, and predicting future values. Time series analysis provides valuable information for decision-making and policy-making regarding neonatal healthcare in NICUs.

The aim of this study was to utilize time series analysis to examine the neonatal intensive care unit (NICU) census, length of hospital stay, and mortality, while predicting these factors over the coming months and seasons. Additionally, regression time series analysis was incorporated to explore the relationships between NICU census, length of stay, and mortality. This effort aimed to enhance resource planning, improve the quality of care, and address public health challenges related to neonatal mortality.

Methods and materials

This study was a retrospective cohort study that used data from the electronic NICU medical registry system (ENMRS) of Vali-Asr Hospital (Tehran, Iran) for neonates admitted to the NICU from February 1, 2016, to December 31, 2022.

The NICU at Vali-Asr Hospital has a stable bed capacity of 40 beds, which remained constant throughout the study period, allowing for a focus on census and outcome variations. The multidisciplinary care model includes registered nurses (RNs) with specialized neonatal training, medical doctors (MDs), and trainees. The nurse-to-patient ratio is maintained at 1:3 for critically ill neonates and 1:5 for stable neonates, adhering to international standards. The core team consists of neonatologists, pediatricians, nurses, respiratory therapists, and support staff, all working in clearly defined roles to ensure efficient care delivery. Continuous education and training are emphasized to maintain high standards of care.

The ENMRS contains information on the neonatal and maternal demographic, clinical, and outcome variables. The source population involved all neonates who were hospitalized in the NICU within the study period and had full data on the variables of interest. Neonates who were transferred to other medical centers were excluded from the study. The study was approved by the Institutional Ethical Committee at Tehran University of Medical Sciences (IR.TUMS.IKHC.REC.1402.090).

Time series analysis was used to survey the patterns and forecasting of hospitalization (NICU) census, duration of hospitalization, and neonatal mortality over time (month) at a large tertiary care referral level III NICU. Variables were forecasted for a period of 2.5 years (from January 2023 to September 2025).

Definitions

NICU Census: Refers specifically to the number of hospitalizations in the Neonatal Intensive Care Unit (NICU) within a given time period. Duration of Hospitalization (Length of Stay in the NICU): Defined as the duration of time from the date of admission to the date of either discharge or death. Neonatal Mortality: Defined as the death of an infant during the hospitalization period in the NICU within a given period. Neonatal Mortality Proportion: Calculated as (number of mortalities/number of hospitalizations (NICU census)) × 100 within a given period.

Time series analysis is a statistical technique that analyzes data collected over time to reveal its temporal components, such as trend, seasonality, cycles, and irregularity [16]. Time series analysis can also be used to forecast future values of a variable based on its past behavior [16].

For this study, we used the following steps for time series analysis:

1. Plot observed census numbers, length of stay, and mortality proportion in NICU from March 2016 to December 2022 as time series variables.
2. Transform variables in case of non-stationarity (e.g., linear trend over time).
3. Fit several models to time series variables and estimate model parameters using dependency measures, e.g., Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF).
4. Identify best models using fit criteria, e.g., Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC), sigma, (Moving Average) MA, and Autoregressive (AR) coefficients.
5. Apply diagnostic tools to determine how well the models fit census data, e.g., plot of standardized residuals and their normal Q-Q plot, and forecast n months during 2023 to 2025.
6. Evaluate the accuracy of the forecasts provided by root mean squared error (RMSE) and mean absolute percentage error (MAPE) [17].

The data were analyzed using SPSS-20 software (IBM, Armonk, NY, USA) and STATAMP 14, and a P-value of ≤0.05 was considered significant.

Results

Overview

Between March 1, 2016, and December 31, 2022, 7,227 infants were admitted to the Neonatal Intensive Care Unit (NICU). The number of eligible neonates admitted to the NICU during the study period (March 2016 - December 2022) was 7,216 (Fig. 1).

The patient cohort comprised 3,965 male neonates (54.95%). The mean (SD) gestational age was 35.33 (3.51) weeks, with a range of 22.14 to 41.14 weeks. The mean

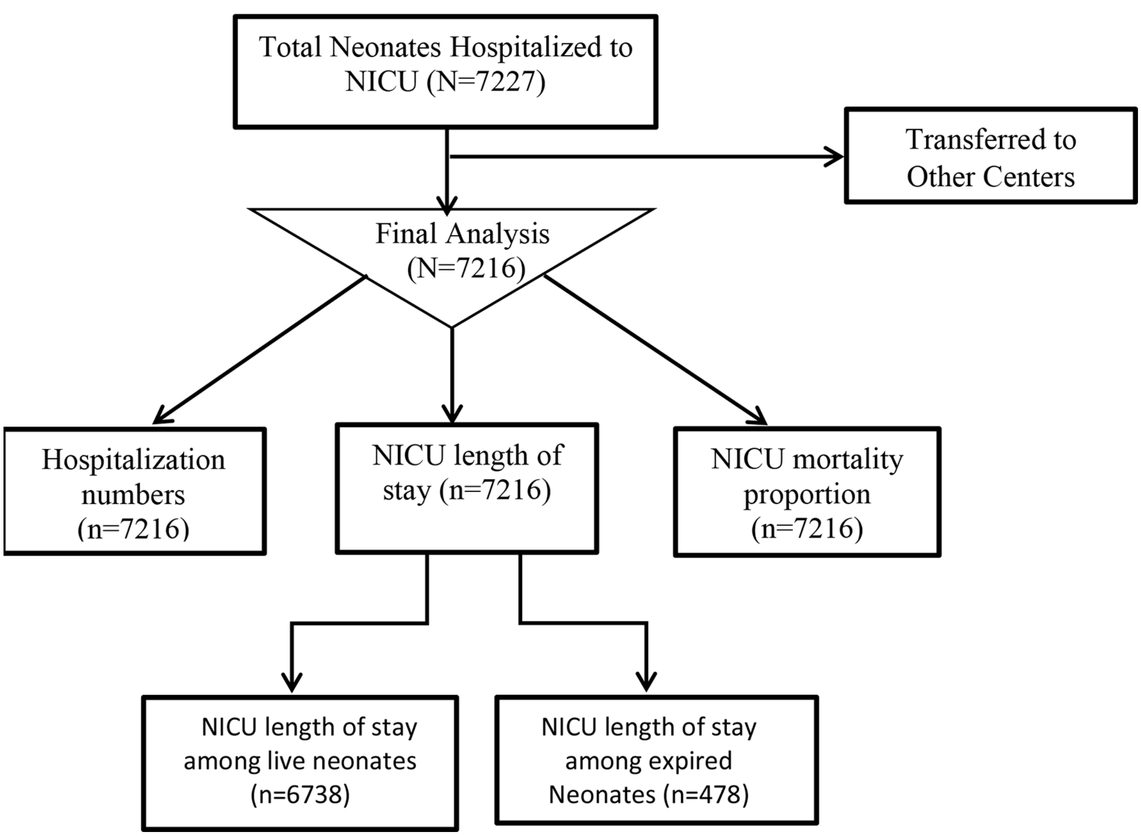

Fig. 1 Flowchart of Neonates Hospitalized in the NICU from 2016 to 2022

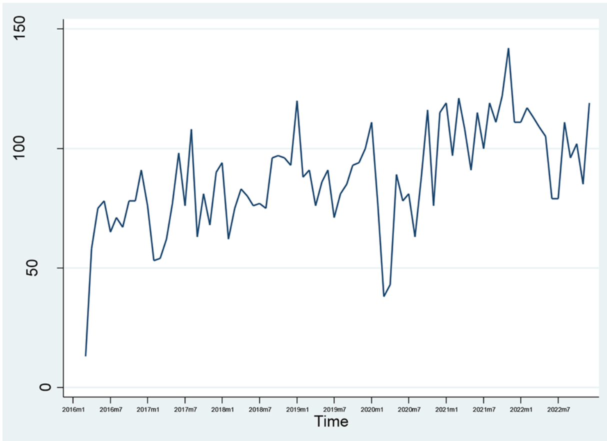

Fig. 2 Time series of NICU census numbers from 2016 to 2022

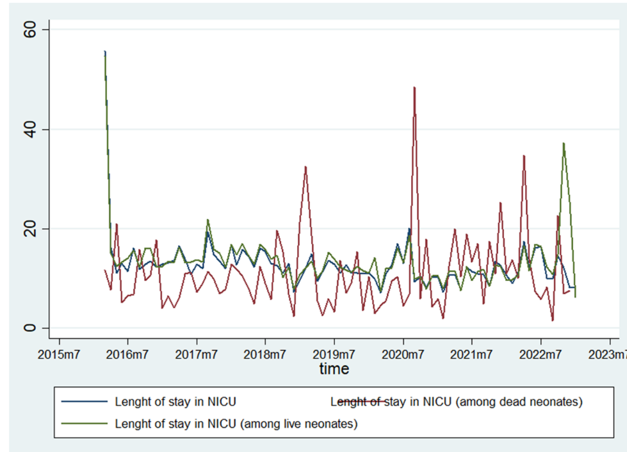

Fig. 3 Time series of hospitalization days from 2016 to 2022

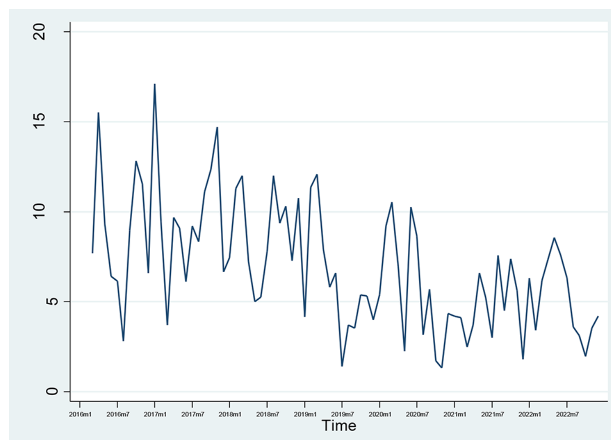

Fig. 4 Time series of mortality proportion from 2016 to 2022

(SD) birth weight was 2,506 (863.27) grams, with a range of 400 to 6,000 g. Additionally, 12.63% of the neonates ($n = 911$) had congenital anomalies. The mean (SD) Apgar score at 1 min was 6.85 (2.31), and at 5 min was 8.58 (1.89). Furthermore, 85.49% of the neonates ($n = 6{,}169$) were delivered via cesarean section. The most common primary diagnoses included prematurity (60.27%), neonatal sepsis (12.42%) and respiratory distress syndrome (7.62). Overall, 93.4% of the neonates ($n = 6{,}738$) were discharged home, while 6.62% ($n = 478$) unfortunately passed away.

Based on Table 1, the highest proportion of mortality occurred in January 2017: 13/76 (17.11%), April 2016: 9/58 (15.52%), and November 2017: 10/68 (14.71%). Based on aggregated data without considering specific years, the highest proportion of mortality was observed in April with 42 deaths out of 539 admissions (7.79%). Conversely, the lowest proportion of mortality was recorded in December with 38 deaths out of 719 admissions (5.29%). The Chi-Square test was performed to determine if there was a significant association between observed mortality proportions and the months of the year. The Chi-Square test results indicate a significant association for the month of December in comparison to other months, with a χ^2 value of 4.23 and a p-value of 0.04.

Based on aggregated data for the years 2016 to 2022, the highest proportions of neonatal mortality were observed in 2017 with 88 deaths out of 914 admissions (9.63%), and in 2018 with 88 deaths out of 1,004 admissions (8.76%). Conversely, the lowest proportions of neonatal mortality were recorded in 2021 with 64 deaths out of 1,356 admissions (4.72%), and in 2022 with 63 deaths out of 1,213 admissions (5.18%). The Chi-Square test was conducted to determine if there was a significant association between observed mortality proportions and the years. The results indicate a significant relationship between the years and mortality, as evidenced by the combined Chi-Square test values across the years (Table 1).

Figures 2 and 3, and 4 illustrate the time series data for NICU census numbers, length of stay in the NICU, and mortality proportions from 2016 to 2022. The horizontal axis represents the days spanning from March 1, 2016, to December 31, 2022, while the vertical axis shows the daily census in Fig. 2, the length of hospital stay in Fig. 3, and the mortality proportion in Fig. 4.

NICU census

The NICU census time series reveals fluctuating patterns, with several peaks highlighted throughout the years (Fig. 2). Notably, December recorded the highest number of hospitalizations, with a total of 719 censuses, followed closely by October, which had 689 censuses. These two months were identified as peak periods for neonatal admissions. In contrast, February and March displayed the lowest census numbers, with February having the lowest at 493 admissions and March slightly higher at 505 admissions (Table 1) (Fig. 2).

Table 1 Monthly frequency of census and mortality proportion (%) on admitted neonates to NICU from 2016 to 2022

	Death/census (mortality proportion)							mortality proportion	Chi2(*p*-value)
Month	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**Total**	
Jan	-	13/76 (17.11%)	7/94 (7.45%)	5/120 (4.17%)	6/111 (5.41%)	5/119 (4.20%)	7/111 (6.31%)	43/631 (6.82%)	1.07 (0.36)
Feb	-	5/53 (9.43%)	7/62 (11.29%)	10/88 (11.36%)	7/76 (9.21%)	4/97 (4.12%)	4/117 (3.42%)	37/493 (7.51%)	2.17 (0.14)
Mar	1/13 (7.69%)	2/54 (3.70%)	9/75 (12.00%)	11/91 (12.09%)	4/38 (10.53%)	3/121 (2.48%)	7/113 (6.19%)	37/505 (7.33%)	0.97 (0.33)
Apr	9/58 (15.52%)	6/62 (9.68%)	6/83 (7.23%)	6/76 (7.89%)	3/43 (6.98%)	4/108 (3.70%)	8/109 (7.34%)	42/539 (7.79%)	1.35 (0.25)
May	7/75 (9.33%)	7/77 (9.09%)	4/80 (5.00%)	5/86 (5.81%)	2/89 (2.25%)	6/91 (6.59%)	9/105 (8.57%)	40/603 (6.63%)	1.95 (0.16)
Jun	5/78 (6.41%)	6/98 (6.12%)	4/76 (5.26%)	6/91 (6.59%)	8/78 (10.26%)	6/115 (5.22%)	6/79 (7.59%)	41/615 (6.67%)	1.29 (0.26)
Jul	4/65 (6.15%)	7/76 (9.21%)	6/77 (7.79%)	1/71 (1.41%)	7/81 (8.64%)	3/100 (3.00%)	5/79 (6.33%)	33/549 (6.01%)	2.23 (0.13)
Aug	2/71 (2.82%)	9/108 (8.33%)	9/75 (12.00%)	3/81 (3.70%)	2/63 (3.17%)	9/119 (7.56%)	4/111 (3.60%)	38/628 (6.05%)	3.17 (0.07)
Sep	6/67 (8.96%)	7/63 (11.11%)	9/96 (9.38%)	3/85 (3.53%)	5/88 (5.68%)	5/111 (4.50%)	3/96 (3.13%)	38/606 (6.27%)	1.65 (0.20)
Oct	10/78 (12.82%)	10/81 (12.35%)	10/97 (10.31%)	5/93 (5.38%)	2/116 (1.72%)	9/122 (7.38%)	2/102 (1.96%)	48/689 (6.98%)	1.04 (0.37)
Nov	9/78 (11.54%)	10/68 (14.71%)	7/96 (7.29%)	5/94 (5.32%)	1/76 (1.32%)	8/142 (5.63%)	3/85 (3.53%)	43/639 (6.73%)	1.29 (0.26)
Dec	6/91 (6.59%)	6/90 (6.67%)	10/93 (10.75%)	4/100 (4.00%)	5/115 (4.35%)	2/111 (1.80%)	5/119 (4.20%)	38/719 (5.29%)	4.23 (0.04)
Total	59/674 (8.75%)	88/914(9.63%)	88/1004 (8.76%)	64/1076 (5.95%)	52/974 (5.33%)	64/1356 (4.72%)	63/1216(5.18%)	478/7216 (6.24%)	
Chi2(p-value)	5.73 (0.017)	12.31 (< 0.001)	6.03 (0.014)	3.94 (0.047)	4.15 (0.042)	9.82 (0.002)	6.90 (0.009)	29.48 (< 0.0001)	

Length of hospitalization in the NICU

The length of hospitalization for neonates in the NICU was analyzed across three categories: all neonates, those who passed away, and those who survived.

All neonates in the NICU The length of hospitalization varied from 7.08(April 2016) to 55.73 (March 2016) days, with a mean of 12.42 days (SD = 1.15) (Fig. 3).

Neonates who passed away For neonates who passed away, the length of hospitalization also varied. The highest mean length was observed in April 2022 at 34.78 days, and the lowest was in December 2018 at 2.4 days. The overall mean length of hospitalization for this group was 9.55 days (SD = 6.02) (Fig. 3).

Neonates who survived In the case of neonates who survived, hospitalization durations ranged widely. The highest mean was noted in March 2016 at 54.75 days, while the lowest was in March 2017 at 4.17 days. The overall mean length of hospitalization for this group was 15.82 days (SD = 2.04) (Fig. 3).

Mortality proportion

The highest mortality proportion recorded during the period from 2016 to 2022 was 7.79% in April (see Table 1). This figure excludes the incomplete data for January and February 2016. From 2017 to 2022, the months of February and January had the highest mortality proportions, at 7.51% and 6.82%, respectively. The time series of mortality proportions is illustrated in Fig. 4.

Preparing time series variables for modeling

Data smoothing and transformation

Before developing the ARIMA model, we applied smoothing techniques to the variables—census numbers, hospitalization days (length of hospitalization), and mortality proportion—to enhance the accuracy of our predictions. Smoothing reduces noise and highlights underlying trends in the data, making it easier to identify patterns. We achieved this by calculating a uniformly weighted moving average with a window size of 4, which averaged each data point with the previous three data points.

To further stabilize the variance of the time series data, we took the natural logarithm (LN) of each variable. This transformation helps address heteroscedasticity, which occurs when the variability of a variable is unequal across its range of values.

Stationarity testing

Stationarity is a crucial assumption in time series analysis. A stationary time series exhibits constant statistical properties, such as mean, variance, and autocorrelation, over time. To evaluate the stationarity of our time series data, we employed the MacKinnon approximate test. The results indicated a high probability of stationarity for the census and mortality proportion time series (P-value < 0.001). This finding suggests that these series maintain consistent statistical properties over time. In contrast, the hospitalization days for all neonates in the NICU demonstrated a low probability of stationarity, with a P-value of 0.193, signaling potential non-stationarity.

All three variables—census, length of stay for all neonates in the NICU, and mortality proportion—exhibited a linear trend (P-value < 0.001), which is indicative of a non-stationary series. Non-stationary time series can yield unreliable and spurious results when directly used in forecasting models.

Data transformation

To address non-stationarity and eliminate trends, we applied differencing to the time series data. Differencing involves subtracting the previous observation from the current observation, helping to stabilize the mean and remove trends. This transformation is essential for the accurate development of ARIMA models, ensuring that the data satisfy the stationarity assumption required for reliable forecasting.

By implementing these preprocessing steps, we prepared the time series data for ARIMA modeling, enhancing the accuracy and reliability of our forecasts regarding NICU census numbers, length of hospital stay for all neonates, and neonatal mortality proportions.

Length of hospitalization for dead and live neonates We analyzed the hospitalization days for deceased and surviving neonates separately to understand the different patterns and trends in their NICU stays. The MacKinnon approximate test indicated high stationarity (P-value < 0.01) for these hospitalization days. However, a linear trend was observed. To address these trends, we applied smoothing using a uniformly weighted moving average with a window size of 4 and computed the natural logarithm (LN) of the variables to stabilize the variance.

Time series modeling

We developed ARIMA and SARIMA models to forecast future NICU census numbers, hospitalization durations, and mortality proportions (%). The ARIMA (p, d, q) model consists of autoregressive (AR) and moving average (MA) components, represented by p and q, as well as an ordinary differencing component, d. The SARIMA (P, D, Q) model incorporates seasonal autoregressive and moving average components (P and Q), a seasonal differencing component (D), and the order of seasonal lag (s).

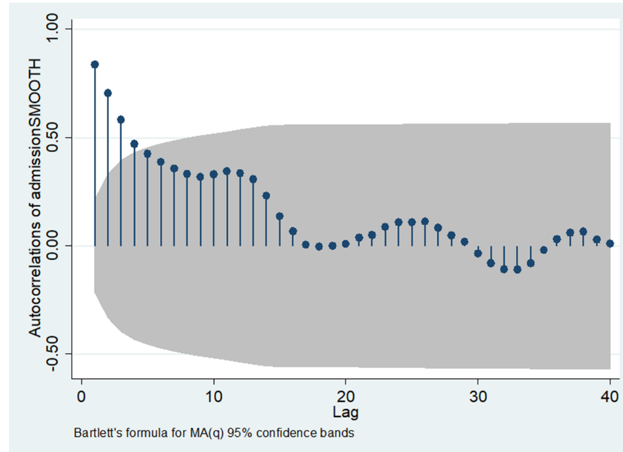

Fig. 5 Autocorrelation function of NICU census variable

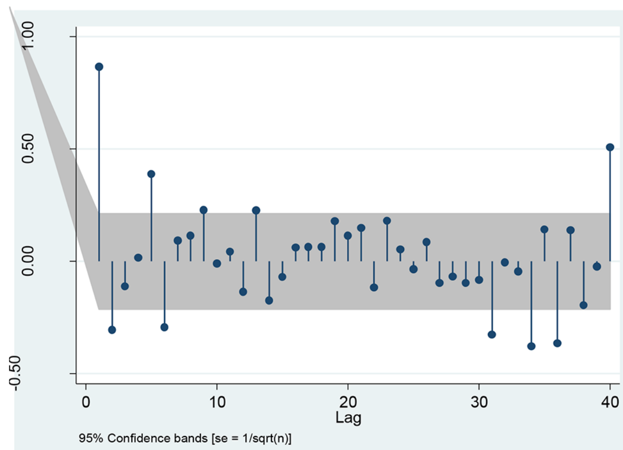

Fig. 6 Partial autocorrelation function of NICU census variable

Autocorrelation and partial autocorrelation analysis

Autocorrelation (ACF) and Partial Autocorrelation (PACF) analyses are essential for identifying patterns, seasonal effects, and the appropriate order of AR and MA components in time series data. These analyses help ensure stationarity and accuracy for ARIMA and SARIMA models by selecting the right lagged terms.

In this study, the NICU census variable exhibited a slowly decaying ACF with a trend and statistically significant autocorrelation up to lag 40 (Fig. 5). The PACF suggested possible non-stationary behavior (Fig. 6). The hospitalization day's variable showed persistent and decaying autocorrelation with significant lags in both

ACF and PACF, along with noticeable seasonality (Figs. 7 and 8). (ARIMA models with lags 1–3 for ACF and 1–2 for PACF, along with SARIMA models with lags 1 and 4 for hospitalization days of live neonates, and ARIMA with lags 1–3 for ACF and 1–2 for PACF, as well as SARIMA with lags 1 and 4. For the hospitalization days of deceased neonates (Figs. 1s, 2s, 3s and 4s). The mortality proportion displayed a decaying autocorrelation structure with significant correlations in both ACF and PACF (Figs. 9 and 10).

Model selection and evaluation

Based on the ACF and PACF graphs, we identified the most suitable models:

- **NICU census**: The best-fitting model was ARIMA(1, 2, 1) with SARIMA(1, 0, 1, 4). We evaluated this model using metrics such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), sigma coefficient, and log-likelihood (Table 2). Diagnostic tools like the normal Q-Q plot, eigenvalue stability, and the Portmanteau test (P-Value = 0.58) were utilized to assess the goodness of fit (Figs. 5s and 6s).
- **Hospitalization days**: For hospitalization days, we identified ARIMA with lags 1–3 for ACF and lags 1–2 for PACF, as well as one differencing. SARIMA with lags 1 and 4 was also considered. Ultimately, SARIMA(4, 0, 1, 4) was chosen as the best model based on goodness of fit metrics (Table 3). The Portmanteau test (P-Value = 0.46) further confirmed the fit (Figs. 7s and 8s). (Suitable models for the hospitalization days of deceased neonates: ARIMA (1,0,1) SARIMA(4,0,3,4), and for hospitalization days of live neonates smooth long stay ARIMA (1,0,1) SARIMA(1,0,1,4) (Table 1s, Table 2s).
- **Mortality proportion**: For the mortality proportion, ARIMA(1, 1, 4) was found suitable based on ACF and PACF graphs (Figs. 9 and 10) and evaluation metrics (Table 4). The Portmanteau test (P-Value = 0.69) was applied to assess model fit (Figs. 9s and 10s).

Forecasting of time series variables

- **NICU census forecast**: The estimated monthly forecast for the NICU census from January 2023 to September 2025 ranges from 93 to 105 cases (Table 5). This forecast indicates a decreasing trend during this period, with a trend coefficient of -0.222 and a P-value of 0.002, as shown in Fig. 11. When examining the longer trend from 2016 to 2023, a slight increase in census numbers is evident, although statistically insignificant, with a trend coefficient of 0.36 and a P-value of 0.163.
- **Hospitalization duration forecast**: The forecasted length of hospitalizations in the NICU for the same

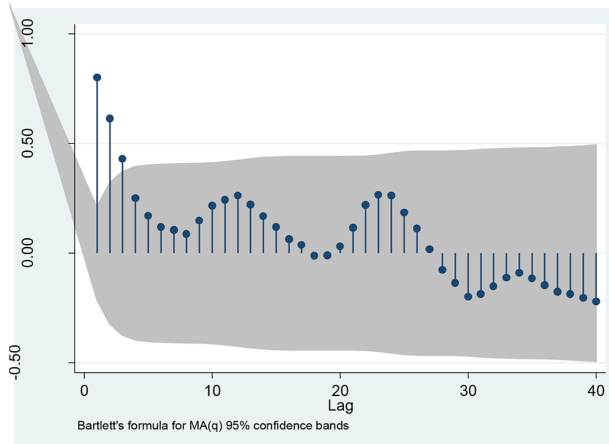

Fig. 7 Autocorrelation function of hospitalization days

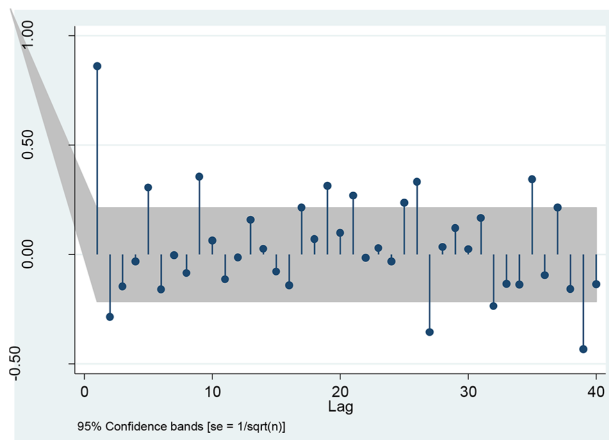

Fig. 8 Partial Autocorrelation function of hospitalization days

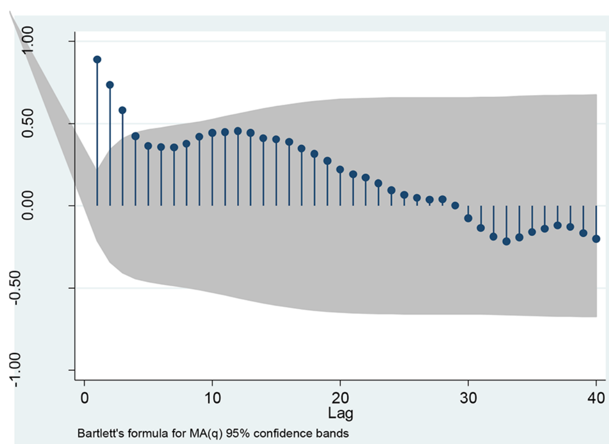

Fig. 9 Autocorrelation function of mortality proportion

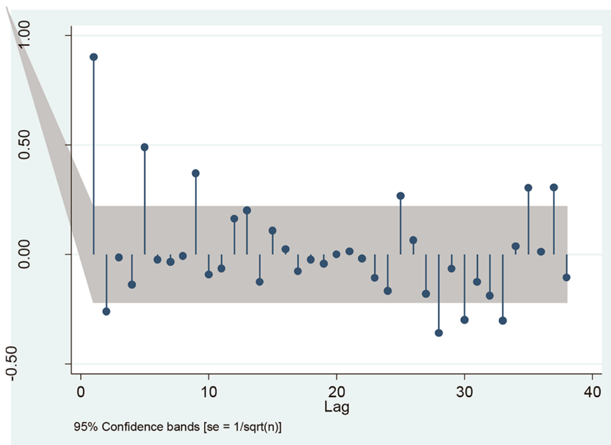

Fig. 10 Partial autocorrelation function of mortality proportion

period ranges from 11 to 13 days (6 to 11 days for deceased neonates and 20 to 36 days for live neonates) (Fig. 12) (Table 5).

- **Mortality proportion forecast**: The forecasted monthly mortality proportion is expected to range from 1.72 to 4.15 cases, with a mean (SD) of 2.79 (0.72) (Fig. 13). For the period from 2016 to September 2025, the forecast indicates an expected decrease of -0.027 per month with a P-value of less than 0.001, suggesting a statistically significant downward trend (Table 5).

Validation of forecasting

To evaluate the accuracy of our forecasts, we used two metrics: the mean absolute percentage error (MAPE) and the root mean square error (RMSE). According to Muge Capan's literature [5], a MAPE value of less than 10% indicates highly accurate forecasting. The Table 6 provides the MAPE and RMSE values for all of the variables that were forecasted.

Regression analysis on time series variables

- Relationship between Hospitalizations and Length of Stay: The regression time series analysis revealed a significant inverse linear relationship between the number of hospitalizations per month and the

Table 2 Comparison of log-likelihood, AIC, BIC, autocorrelation, moving average, and Sigma coefficients of different models for selecting the best-fitted model in forecasting census numbers

	Log likelihood	AR (SE)	MA (SE)	Seasonal		Sigma (SE)	AIC	BIC
				AR (SE)	MA (SE)			
D2.ln. smooth census number = ARIMA (1,2,1) SARIMA (1,0,1,4)	**69.65**	**0.939 (0.172)**	**-0.829 (0.229)**	**0.116 (0.149)**	**-0.799 (0.195)**	**0.101 (0.006)**	**-140.49**	**-93.54**
D2.ln.smooth census number = ARIMA(4,2,1) SARIMA(1,0,1,4)	65.25	-0.885 (0.142)	0.999 (0.109)	-0.921 (0.129)	0.771 (0 0.233	0.096 (0.931)	-105.54	- 95.33824
D2.ln.smooth census number = ARIMA(1,2,1) SARIMA(4,0,1,4)	60.19	0.908 (0.205)	-0.032 (0.0693)	0.099 (0.007)	0.498 (0 0.663)	0.108 (0.693)	-107.38	-95.83
D2.ln.smooth census number ARIMA(1,2,4) SARIMA(1,0,1,4)	67.25	−0.489 (0.565)	-0.756 (0.289)	-0.917 (0 0.149)	0.779 (0 0.301)	0.099 (0.025)	-118.35	-99.50

*Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC)

Table 3 Comparison of log-likelihood, AIC, BIC, autocorrelation, moving average, and Sigma coefficients of different models for selecting the best-fitted model in forecasting of hospitalization days

	Log likelihood	AR(SE)	MA(SE)	Sigma(SE)	AIC	BIC
LN. smooth length of stay SARIMA (1,0,4,4)	51.17	0.563 (0.173)	0.487(0.58)	0.119 (0.530)	-88.342	-71.33
LN. smooth length of stay SARIMA (4,0,1,4)	**48.91**	**0.563 (0.173)**	**−0.426 (0.99)**	**0.0.113 (0.530)**	**-92.19**	**-76.19**
LN. smooth length of stay SARIMA (1,0,1,4)	45.88	-0.153 (0.454)	0.462 (0.376)	0.139 (0.013)	-83.77	-74.04
LN. smooth length of stay SARIMA (4,1,4,4)	54.09	−0.519 (0.225)	0.179 (0.523)	0.0958 (0.029)	-83.82	-73.14
LN. smooth length of stay SARIMA (4,1,1,4)	49.26	-0.294 (0.163)	-1.000009 3121.368	0.118 (0.592)	-84.501	-67.839
LN. smooth length of stay SARIMA (1,1,1,4)	45.44	0.125 (0.127)	-1	0.128 (0.011)	-84.88	-77.74
LN. smooth length of stay SARIMA (1,1,4,4)	51.17	-0.789 (0.258)	-0.426 (0.1)	0.119 (0.530)	-86.29	-71.99

*Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC)

Table 4 Comparison of log-likelihood, AIC, BIC, autocorrelation, moving average, and Sigma coefficients of different models for selecting the best-fitted model in forecasting mortality proportion

models	Log likelihood	AR (SE)	MA (SE)	Sigma (SE)	AIC	BIC
D1.ln. smooth mortality ARIMA (1,1,1)	64.54	0.889 (0.039)	− 0.0078 (0.094)	0.111 (0.005)	-129.09	-114.37
D1.ln. smooth mortality ARIMA (1,1,4)	**72.03**	**0.886 (0.1)**	**-0.416 (0.269)**	**0.0995 (0.912)**	**-133.27**	**-118.05**
D1.ln. smooth mortality ARIMA (4,1,1)	72.07	0.743 (0.139)	0.99 (NC)*	0.099 (0.006)	-132.14	-117.56
D1.ln. smooth mortality ARIMA (4,1,4)	73.03	0.795 (0.255)	-0.411 (NC)*	0.097 (0.69)	-128.07	-106.19

*Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), NC = no calculated

Table 5 The forecasted number of census, hospitalization days, and mortality proportion using ARIMA (1,2,1) SARIMA (1,0,1,4), SARIMA (4,0,1,4), and ARIMA (1,1,4), respectively

Time	Predicted value				
	census number; ARIMA(1,2,1)SARIMA(1,0,1,4)	Hospitalization days			mortality proportion; ARIMA(1,1,4)
		All neonates SARIMA (4,0,1,4)	Live neonates ARIMA(1,0,1)	Dead neonates ARIMA (2,0,1) SARIMA(1,0,1,4)	
2023m1	94.86	12.48	20.35	6.49	3.19
2023m2	104.75	12.24	24.26	11.62	3.15
2023m3	101.67	11.62	28.13	9.54	3.79
2023m4	105.20	11.92	27.35	9.24	4.10
2023m5	101.20	11.92	27.57	8.59	4.15
2023m6	102.64	12.19	27.96	6.90	4.06
2023m7	102.84	12.85	28.46	6.54	3.70
2023m8	102.66	13.14	30.50	6.85	3.37
2023m9	102.67	12.68	32.10	6.51	3.16
2023m10	102.32	12.54	33.51	7.52	3.01
2023m11	102.48	12.47	34.72	8.16	2.98
2023m12	102.07	12.17	35.16	8.19	3.00
2024m1	101.88	11.98	35.60	8.73	2.99
2024m2	101.48	12.11	35.92	9.15	2.97
2024m3	101.28	12.24	36.12	7.90	2.89
2024m4	100.84	12.04	36.40	8.05	2.77
2024m5	100.84	12.14	36.48	7.80	2.65
2024m6	100.48	12.24	36.41	7.08	2.53
2024m7	100.02	12.44	36.20	8.03	2.44
2024m8	99.63	12.52	35.80	8.16	2.37
2024m9	99.13	12.40	35.31	8.78	2.31
2024m10	98.65	12.36	34.74	9.85	2.26
2024m11	98.11	12.35	34.09	8.99	2.2
2024m12	98.11	12.27	33.39	8.98	2.13
2025m1	96.42	12.21	32.64	8.97	2.058
2025m2	95.80	12.24	31.85	7.94	1.98
2025m3	95.17	12.27	31.02	8.45	1.91
2025m4	94.51	12.20	30.18	8.55	1.84
2025m5	93.83	12.23	29.32	8.85	1.78
2025m6	93.12	12.27	20.35	6.49	1.72

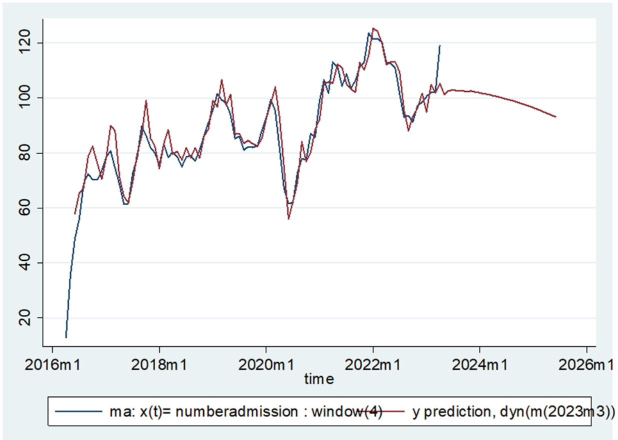

Fig. 11 Forecasted values of census number for 2023 to 2026

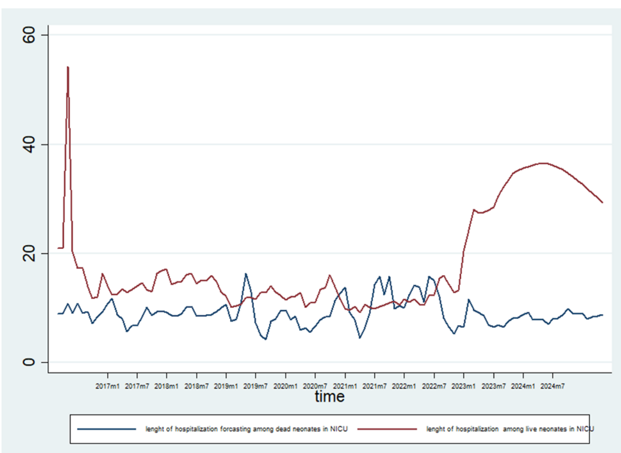

Fig. 12 Forecasted values of hospitalization days among live and dead neonates for 2023 to 2026

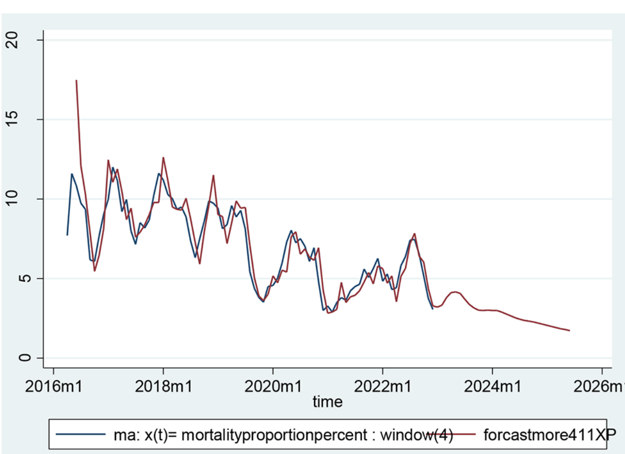

Fig. 13 forecasted values of mortality proportion for 2023 to 2026

Table 6 Accuracy of forecasts by mean absolute percentage error (MAPE) and the root mean square error (RMSE)

Models	MAPE	RMSE
census number; ARIMA(1,2,1)SARIMA(1,0,1,4)	4.73	0.869
hospitalization days; SARIMA (4,0,1,4)	4.35	0.89
mortality proportion; ARIMA(1,1,4)	2.03	0.021

duration of hospital stays. Specifically, for each additional monthly hospitalization, the duration of hospital stays decreased by an estimated coefficient of -2.58 days (P-value < 0.001). This suggests that increased census number is associated with shorter individual hospital stays, likely due to the efficiency of resource utilization in the NICU.

- Impact of Length of Stay on Mortality Proportion: Additionally, the analysis identified that for each additional day a neonate spends in the NICU, the proportion of mortality increases by 0.339, adjusted for the number of hospitalizations (B (SE) = 0.339 (0.139), P-value = 0.018). This indicates that extended stays are correlated with a higher mortality rate, highlighting the critical need for timely and effective interventions to reduce prolonged NICU stays and improve neonatal outcomes.

Discussion

A comprehensive analysis of NICU census data, hospitalization durations, and neonatal mortality proportion provides valuable insights into the dynamics of neonatal care and outcomes. The findings reveal distinct patterns and relationships that can inform evidence-based strategies to optimize NICU management and enhance neonatal health outcomes.

In this study, NICU census data showed notable seasonal variations, with the highest census numbers recorded during the winter months. Interestingly, the average length of hospitalization decreased during this same period. Regression time series analysis indicated an inverse relationship between census numbers and hospitalization duration (P-Value < 0.01). Similar findings regarding the importance of seasonal resource planning in NICU settings have been reported in previous studies, such as Capan et al. (2016) [5].

One plausible explanation for this inverse relationship is that higher admission rates demand efficient resource utilization, leading to quicker patient turnover and shorter hospital stays. Healthcare providers often implement discharge optimization strategies during peak admission periods to maintain care quality.

The highest mortality proportion recorded between 2017 and 2022 occurred in February and January, at 7.51% and 6.82%, respectively. These findings suggest that certain months are associated with increased mortality risk. Identifying and addressing the underlying causes of these variations may help improve neonatal survival rates. Previous studies have also highlighted specific months with higher neonatal mortality [18].

In the regression time series analysis, a positive correlation was found between neonatal mortality and length of hospital stay (B = 0.339). Fu (2023) identified critical risk factors affecting prolonged NICU stays, including birth weight, gestational age, sepsis, necrotizing enterocolitis (NEC), bronchopulmonary dysplasia (BPD), and retinopathy of prematurity (ROP) [15]. Additionally, longer hospital stays increase the risk of nosocomial infections and mortality. This correlation underscores the importance of timely and effective interventions to reduce prolonged NICU stays and improve neonatal outcomes.

The ARIMA and SARIMA models developed for forecasting NICU census numbers, hospitalization durations, and mortality rates demonstrated strong predictive capabilities. The use of ARIMA and SARIMA models in NICU settings is supported by various studies [19]. The best-fitting models were selected based on diagnostic tools and goodness-of-fit metrics, including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and the Portmanteau test.

Forecasted findings from January 2023 to September 2025 indicate a relative decrease in census numbers (R = -0.222, P-value = 0.002). However, no significant overall trend was observed from March 2016 to September 2025 ($p > 0.05$).

There has been a significant decrease in the incidence of neonatal mortality in the NICU. However, the generalizability of these findings may be limited. This study primarily focused on variations in census numbers and mortality without accounting for additional influencing factors such as age, gender, socioeconomic status, environment, and political conditions. Nevertheless, the methodologies and analyses presented offer valuable insights that can enhance decision-making and optimize health resource allocation, ultimately contributing to a reduction in NICU mortality rates.

Beyond methodological constraints, operational challenges within the NICU further influence forecasting accuracy. These factors must be considered alongside predictive modeling to ensure effective neonatal care planning.

Accurate predictions of NICU census numbers, hospitalization durations, and mortality proportions are essential for maintaining high-quality neonatal care and ensuring efficient resource utilization. However, it is important to recognize that this forecasting approach is uniquely tailored to a single institution and relies on historical trends over a specific time period. Its accuracy depends on a relatively stable and homogeneous institutional environment, making predictions highly specific to the operational dynamics of Vali-Asr Hospital.

Institutional risk factors, including seasonal nursing shortages and fluctuations in patient acuity, may introduce bias across different time periods, impacting forecasting accuracy. One notable trend observed in this study is the decline in the nurse-to-bed ratio during early spring, particularly around Nowruz (Persian New Year), which may result in increased workload per nurse and affect patient care efficiency. Additionally, during high NICU census congestion, neonates may be transferred or discharged earlier than planned to accommodate the admission of critically ill infants requiring intensive care. These operational shifts may alter hospitalization duration trends and introduce variability into forecasting models. These institutional constraints emphasize the need for proactive staffing adjustments and dynamic resource allocation strategies, ensuring neonatal care remains adaptive to fluctuating demands.

Conclusion

This comprehensive analysis provides valuable insights into the dynamics of NICU care, revealing distinct seasonal variations in census data and an inverse relationship between census and hospitalization duration. The study highlights the need for timely interventions to reduce prolonged stays and improve neonatal outcomes, especially given the observed positive correlation between length of stay and mortality risk. Accurate forecasting using ARIMA and SARIMA models supports effective resource planning, helping to maintain high-quality care and reduce neonatal mortality in NICUs.

Supplementary Information

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Supplementary Material 1

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Author contributions

H.D and L.S designed the study. L.S and M.Sh collected data L.S modeled and analyzed data. L.S and H.D wrote the initial draft of the manuscript which was subsequently modified by M.Sh. All authors read and edited the manuscript for important intellectual content. All authors have seen and approved the final version of the manuscript.

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
The study was approved by the Research Ethics Committee of Tehran University of Medical Sciences (IR.TUMS.IKHC.REC. REC.1402.090), Tehran, Iran. All methods were performed in accordance with the relevant guidelines and regulations by including a statement in ethical approval contract and in accordance with the declarations of Helsinki. The information documented by the hospital registry system was used for the study and waived the need for informed consent by ethics committee of biomedical research, Imam Khomeini hospital complex, Tehran University of medical sciences.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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References
1. Silva ABD, et al. Auto-Regressive integrated moving average model (ARIMA): conceptual and methodological aspects and applicability in infant mortality. Revista Brasileira De Saúde Materno Infantil. 2021;21:647–56.
2. Gudayu T, Zeleke E, Molla A. Time to death and its predictors among neonates admitted in the intensive care unit of the university of Gondar comprehensive specialized hospital, Northwest Ethiopia. Res Rep Neonatol. 2020;10:1–10.
3. Wesenu M, Kulkarni S, Tilahun T. Modeling determinants of Time-To-Death in premature infants admitted to neonatal intensive care unit in Jimma university specialized hospital. Annals Data Sci. 2017; 4.
4. Murray LL, et al. Forecasting ICU census by combining time series and survival models. Crit Care Explor. 2023;5(5):e0912.
5. Capan M, et al. Time series analysis for forecasting hospital census: application to the neonatal intensive care unit. Appl Clin Inf. 2016;7(2):275–89.
6. Sankar MJ, et al. When do newborns die? A systematic review of timing of overall and cause-specific neonatal deaths in developing countries. J Perinatol. 2016;36(Suppl 1):S1–11.
7. Jehan I, et al. Neonatal mortality, risk factors and causes: a prospective population-based cohort study in urban Pakistan. Bull World Health Organ. 2009;87(2):130–8.
8. Rogowski JA, et al. Nurse staffing and NICU infection rates. JAMA Pediatr. 2013;167(5):444–50.
9. Jakuskiene R, et al. Neonatal outcomes of very preterm infants admitted to a tertiary center in Lithuania between the years 2003 and 2005. Eur J Pediatr. 2011;170(10):1293–303.
10. Penoyer DA. Nurse staffing and patient outcomes in critical care: a concise review. Crit Care Med, 2010. 38(7): pp. 1521-8; quiz 1529.
11. Sheward L, et al. The relationship between UK hospital nurse staffing and emotional exhaustion and job dissatisfaction. J Nurs Manag. 2005;13(1):51–60.
12. Karimi P, et al. Mortality in neonatal intensive care units in Iran: A systematic review and Meta-Analysis. Iran J Neonatology. 2019;10(3):70–80.
13. Nayeri F, et al. Mortality and morbidity patterns of very low birth weight newborns in Eastern mediterranean region: A Meta-Analysis study. J Pediatr Rev. 2019;7(2):67–76.
14. Tarnow-Mordi WO, et al. Hospital mortality in relation to staff workload: a 4-year study in an adult intensive-care unit. Lancet. 2000;356(9225):185–9.
15. Fu M et al. Risk factors for length of NICU stay of newborns: A systematic review. Front Pead. 2023; 11.
16. Sheikhtaheri A, et al. Prediction of neonatal deaths in NICUs: development and validation of machine learning models. BMC Med Inf Decis Mak. 2021;21(1):131.
17. Bekele T. et al. Predictors of mortality among neonates hospitalized with neonatal sepsis: a case control study from Southern Ethiopia. BMC Pediatr. 2022; 22.
18. Nyári TA, McNally R. Seasonal variation in childhood mortality. J Matern Fetal Neonatal Med. 2020;33(24):4055–61.
19. Szostek K, et al. Analysis of the effectiveness of ARIMA, SARIMA, and SVR models in time series forecasting: A case study of wind farm energy production. Energies. 2024;17:4803.

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