
Forecasting Inpatient Bed Demand Using Exponential Smoothing with Trend and Seasonal Index

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Abstract

Forecasting of inpatient hospital bed demand is important for optimizing resource allocation and enhancing healthcare service. This study aims to improve the accuracy of the forecasting model, Exponential Smoothing with Trend, including the Seasonal Index (ETS-SI), to address the complexities of trend and seasonality in hospital admissions data. Anonymized inpatient data from government hospitals in Thailand (2020–2024) was used and categorized by hospital size (small, medium, and large). Then, the ETS-SI model integrated trend and seasonal components to improve forecasting precision and was evaluated against traditional forecasting methods, including Exponential Smoothing (ES), Exponential Smoothing with Trend (EST), and the Seasonal Index (SI). Mean Absolute Percentage Error (MAPE) was used to validate forecasting accuracy. ETS-SI achieved the lowest error rates compared with other methodologies for capturing seasonal and trend-driven variations. Findings emphasize the suitability of ETS-SI for addressing the unique challenges of hospital demand forecasting. The ETS-SI model demonstrated the lowest MAPE among all models, and statistical validation using ANOVA confirmed that its forecasting accuracy was significantly higher ($p < 0.05$). The ETS-SI model demonstrated superior forecasting accuracy and can be applied to support holistic hospital decision-making—particularly in patient scheduling, staff rostering, and bed resource planning. Future research should explore hybrid models for enhanced forecasting accuracy and broader applicability.

Keywords: Inpatient beds forecasting; inpatient beds management; hospital resource utilization planning

Introduction

Accurate forecasting of hospital bed demand is a critical component of healthcare resource management. According to Walsh et al. (2021), efficient forecasting ensures optimal allocation of resources, reduces operational costs, and enhances patient care delivery. Inpatient beds demand is influenced by various factors, including seasonal variations, demographic trends, and healthcare policies, making it

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a complex problem for healthcare administrators. Conventional forecasting methods, such as Exponential Smoothing (ES) and Exponential Smoothing with Trend (EST), often fail to capture the intricate interplay of trend and seasonality inherent in hospital admission data, particularly in facilities with varying capacities (Vieira, Sousa, & Dória-Nóbrega, 2023).

In recent years, many studies have introduced the methodology of healthcare demand forecasting by providing a robust model. For instance, Hyndman and Athanasopoulos ("Forecasting: Principles and Practice (3rd Ed)," Chapter 6) highlight the evolving challenges in healthcare forecasting, emphasizing the need for models that account for complex trends and seasonal variations. Gardner (1984, p. 923) specifically addresses the role of seasonality in hospital admission patterns, underscoring its importance in model development.

Research over the past 5 years has shown that traditional forecasting methods such as ARIMA or exponential smoothing have limitations in dealing with the complexity and volatility of healthcare demand, especially when the forecasting horizon is longer or when there are rapidly changing environmental factors such as disease seasons or demographic shifts (Huang, Xu, Ji, Xiang, & He, 2020).

Using advanced or mixed exponential smoothing techniques along with machine learning techniques can make forecasts much more accurate. When you combine exponential smoothing with deep learning (like LSTM or Bi-LSTM), you can make more accurate predictions about things like crime and energy load than with single exponential smoothing or traditional methods like ARIMA (Earl, Baguelin, Van Leeuwen, Lopez-Bernal, & Ferguson, 2024).

Finally, Forecasting: Principles and Practice ("Exponential Smoothing | Forecasting: Principles and Practice (3rd Ed)," Chapter 8) propose hybrid models that integrate traditional and machine learning approaches, offering potential future directions for refining healthcare demand forecasting methodologies. Although previous studies have been achieved for accurate forecasting models, the suitable model across different hospital sizes, namely small, medium, and large is not considered. Thus, there is a need for advanced forecasting models that can effectively address these challenges and provide more reliable predictions.

This study focuses on developing and evaluating an advanced forecasting model, Exponential Smoothing with Trend including Seasonal Index (ETS-SI), designed to incorporate both trend and seasonality in hospital admission data. Using anonymized inpatient records from government hospitals in Thailand, categorized by hospital size (small, medium, and large), the study aims to address the limitations of existing methods by introducing a model that enhances predictive accuracy. The proposed ETS-SI model is compared against traditional forecasting techniques, including ES, Exponential Smoothing with Trend (EST), and the Seasonal Index (SI). The performance of these models is evaluated using Mean Absolute Percentage Error (MAPE), a robust metric for assessing forecasting accuracy. The public health services in Thailand are directly affected by the lack of inpatient forecasting statistics. If hospitals cannot make accurate forecasting, these issues can lead to delays in patient admission, reduced quality of care, and increased operational costs. Therefore, developing a forecasting model helps ensure that hospital resources. However, public hospitals in Thailand provide inpatient services to many patients. This research therefore focuses on predicting inpatient volume to help ensure adequate resource allocation, bed

management, and staff scheduling, which are crucial factors in patient care. Therefore, the developed model can be appropriately applied to predict inpatient volume in public hospitals.

This paper is structured as follows: Section II provides an overview of the related work and methodologies in hospital demand forecasting. Section III describes the data and methodology used in this study. Section IV presents the results and discusses the implications of the findings. Finally, Section V concludes with a summary of the study's contributions and recommendations for future research.

Objective

1. To analyze the effect of seasonal variations and hospital size on inpatient hospital bed demand in Thailand.
2. To develop and evaluate the Exponential Smoothing with Trend including Seasonal Index (ETS-SI) model and compare its forecasting accuracy against traditional models (ES, EST, SI).
3. To assess whether improved forecasting accuracy enhances efficiency in hospital resource management and patient care.

Literature Review

Forecasting hospital demand has garnered significant attention in recent years due to the critical role it plays in resource optimization and healthcare planning. Various time-series forecasting methods have been employed to predict hospital bed demand, with each method demonstrating unique strengths and limitations depending on the nature of the dataset.

Exponential smoothing methods, such as Simple Exponential Smoothing (SES) and Exponential Smoothing with Trend (EST), are commonly used for short-term forecasting due to their simplicity and effectiveness in handling datasets with level and trend components. However, these methods often fail to capture seasonality, which is a significant characteristic in hospital admission data influenced by periodic fluctuations in patient demand (Earl et al., 2024, Huang et al., 2020). Recent studies have focused on extending traditional models by incorporating seasonal indices to address this limitation, thereby improving the accuracy of forecasts in contexts with strong seasonal patterns (Sohrabbeig et al., 2023).

Advanced models, such as the Holt-Winters Exponential Smoothing method, explicitly account for seasonality and trend but may require extensive parameter tuning to achieve optimal results. These methods have demonstrated superior performance in healthcare forecasting applications, particularly when data exhibit consistent seasonal cycles (Kumar et al., 2024). Despite their effectiveness, Holt-Winters models can be sensitive to anomalies and structural breaks in time-series data, making them less reliable for datasets with significant noise (Sohrabbeig et al., 2023).

To address the limitations of traditional methods, hybrid forecasting approaches combining machine learning and statistical techniques have emerged. For example, ensemble models that integrate exponential smoothing with machine learning algorithms, such as support vector machines or neural networks, have shown promise in improving forecast accuracy while accounting for non-linear patterns in hospital demand (Aravazhi, 2021). These approaches leverage the strengths of both paradigms, enhancing robustness and adaptability to diverse data characteristics.

Moreover, the integration of domain-specific variables, such as hospital size, length of stay (LOS), and patient demographics, has been identified as a critical factor in enhancing model performance. Studies have emphasized the need to tailor forecasting models to specific hospital settings to ensure reliability and relevance of the predictions (Hilton et al., 2020). For instance, forecasting models for small hospitals often require greater emphasis on trend adjustments due to higher variability in admissions, while models for larger hospitals must accommodate long-term seasonal cycles. This data gap constrains evidence-based decision-making and limits the ability to anticipate surges in inpatient demand. Therefore, this study contributes to filling this gap by applying anonymized national data from government hospitals in Thailand to develop a robust and interpretable forecasting model that can inform strategic healthcare planning in similar developing contexts.

Recent advancements in computational techniques have also facilitated the development of scalable forecasting frameworks capable of handling large and complex datasets. For instance, cloud-based platforms and real-time data analytics tools are increasingly being adopted to enable dynamic adjustments to forecasting models based on changing trends and patterns in healthcare demand (Leela et al., 2025). These innovations hold significant potential for improving decision-making in hospital management and resource allocation.

In summary, the literature underscores the evolving landscape of forecasting methodologies, with a clear trend towards integrating statistical techniques with machine learning approaches. However, the need for context-specific adaptations remains a consistent theme, particularly in sectors like healthcare, where demand patterns are heavily influenced by external and seasonal factors. The Exponential Smoothing with Trend including Seasonal Index (ETS-SI) model proposed in this study aligns with these advancements by addressing the dual challenges of trend and seasonality, offering a tailored solution for hospital demand forecasting. Therefore, this study focuses on enhancing the Exponential Smoothing framework (ETS-SI) as a balanced approach that maintains interpretability and computational efficiency while improving accuracy through trend–seasonality integration.

Research Hypotheses

H1: Seasonal variations have a statistically significant effect on inpatient hospital bed demand across different hospital sizes (small, medium, and large).

H2: The ETS-SI model provides significantly more accurate forecasts of hospital bed demand compared to traditional models (ES, EST, and SI).

H3: Hospitals that adopt ETS-SI-based forecasting achieve improved efficiency in resource planning and patient care compared to those relying solely on traditional forecasting methods.

Conceptual Framework

Hospital resources are fundamentally grounded in theories of healthcare operations management and forecast-based decision making. The conceptual framework of this study (Figure X) illustrates the relationships among four main elements:

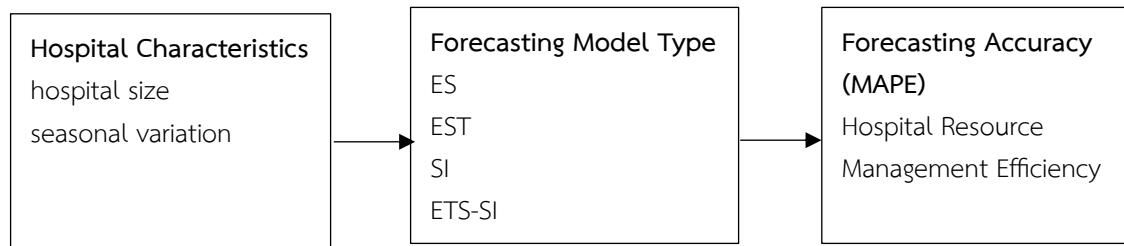


Fig 1 Conceptual Framework of the Study

The framework illustrates the relationships among seasonal variations, forecasting models, and hospital resource management outcomes. Seasonal changes and hospital size influence inpatient demand patterns. The application of the ETS-SI model enhances forecasting accuracy (MAPE), which subsequently improves hospital operational efficiency through better bed allocation, staff scheduling, and service delivery.

Research Methodology

A. Material

The inpatient data was obtained from the Information Technology Division, Department of Medical Services, Ministry of Public Health, Thailand. This division is responsible for collecting, managing, and disseminating healthcare-related information, including patient records, hospital admissions, and resource utilization across the country. The dataset comprises anonymized patient records and includes key variables such as admission dates, discharge dates, medical diagnoses, demographic details, and hospital bed occupancy rates. The dataset comprises of annual statistical data on inpatient admissions in government hospitals across Thailand, covering the period from 2020 to 2024. Since hospital resources vary depending on the size of the hospital, the dataset is categorized based on hospital size including Small Hospitals (with 30-200 beds), Medium Hospitals (with 200-500 beds), and Large Hospitals (with more than 500 beds).

B. Hospital Size Classification and Data Cleaning

Before analysis, all records were anonymized and underwent a data-cleaning process that involved (1) removing duplicate entries, (2) excluding incomplete admission or discharge records, (3) validating hospital codes with DMS master lists, and (4) aggregating monthly admission counts for uniform time-series modeling. These steps ensured the dataset's accuracy and comparability across hospital groups.

C. Methodology

This study aims to develop an accurate forecast of the inpatient yearly bed demand. Exponential Smoothing with Trend including Seasonal Index (ETS-SI) method was introduced for inpatient hospital admission forecasting. This approach integrates trends and seasonal variations to enhance forecasting

precision, particularly for data with distinct patterns influenced by time and periodic fluctuations. A comparative analysis was conducted against existing forecasting methods such as Exponential Smoothing (ES) and Exponential Smoothing with Trend (EST).

D. Exponential Smoothing (ES)

Exponential smoothing is a widely used forecasting method that assigns exponentially decreasing weights to past observations. It is particularly useful for data with no clear trend or seasonality. The formula for simple exponential smoothing is:

$$F_t = \alpha A_{t-1} + (1 - \alpha)F_{t-1} \quad (1)$$

Where

F_t = Forecasted value for time t .

A_{t-1} = Actual value at time $t - 1$.

F_{t-1} = Forecast value at time $t - 1$.

α = Smoothing constant ($0 < \alpha < 1$).

The term (Y_t) represents the actual number of inpatient admissions recorded during month t . A higher α gives more weight to recent observations, making the model more responsive to short-term fluctuations.

E. Exponential Smoothing with Trend

Simple exponential smoothing by incorporating a trend component. This method is suitable for data with both a level and a trend but no seasonality. The method involves two equations: one for the smoothed level and another for the trend. The method involves three equations:

Level Equation:

$$L_t = \alpha A_t + (1 - \alpha)(L_{t-1} + T_{t-1}) \quad (2)$$

Where:

L_t : Smoothed level at time t .

A_t = Actual value at time t .

L_{t-1} = Smoothed level at time $t-1$.

T_{t-1} = Smoothed trend at time $t-1$.

α = Smoothing constant ($0 < \alpha < 1$).

The level reflects the underlying average demand after smoothing out short-term variations, while the trend captures the systematic increase or decrease in demand across time periods.

Trend Equation:

$$T_t = \beta(L_t - L_{t-1}) + (1 - \beta) T_{t-1} \quad (3)$$

Where:

T_t : Smoothed trend at time t .

$L_t - L_{t-1}$: Change in level from the previous period.

β : Smoothing constant for the trend ($0 < \beta < 1$).

Forecast Equation:

$$F_{t+k} = L_t + kT_t$$

Where:

F_{t+k} : Forecast for k periods ahead

k : Number of periods into the future.

Although exponential Smoothing (ES) and Exponential Smoothing with Trend are widely used forecasting methods, these methods do not account for seasonality. So, the extended Seasonal Index method was proposed.

F. Proposed model Exponential Smoothing with Trends including Seasonal Index (ETS-SI)

The Exponential Smoothing with Trend including Seasonal Index (ETS-SI) model was extended from traditional Exponential Smoothing with Trend including seasonal index term. The seasonal index S_t quantifies the degree of seasonality by comparing actual values during a specific season to the average value over all seasons. The process involves the following steps:

1) calculate the seasonal index

Calculate the Average for Each Season:

$$\text{Average for Season } i = \frac{\text{Sum of values in Season } i}{\text{Number of seasons in the dataset}}$$

Calculate the Grand Average

$$\text{Grand Average} = \frac{\text{Total Sum of All Data}}{\text{Total number of data point}}$$

Calculate the Seasonal Index

$$S_t = \frac{\text{Average for Season } i}{\text{Grand Average}} \quad (5)$$

2) Update seasonal index to Exponential Smoothing with Trend

$$F_{t+k} = L_t + kT_t \times S_{t+k} \quad (6)$$

Where:

K : Number of periods into the future.

S_{t+k} : seasonal index for the forecasted season.

3) Implementation process

Calculate initial values for L_t from equation (2)

Calculate initial values for T_t from equation (3)

Calculate initial values for S_t from equation (5)

Iterative Updates L_t, T_t, S_t recursively for each period using the equations above

Forecasting using equation (6) to predict future values

The performance of forecasting models was evaluated to ensure that proposed methods are both reliable and relevant, ultimately leading to better insights and actionable results in a specific context, such

as inpatient forecasting. In this study, seasonality refers to systematic, recurring fluctuations in inpatient hospital admissions that follow a 12-month annual cycle. The cycle was defined based on Thailand's calendar year (January–December), as hospital admission patterns typically repeat annually due to climate-related factors (e.g., influenza and dengue peaks during the rainy season), holiday periods, and healthcare utilization behavior.

G. Model performance measure

The performance comparison of the forecasting models is evaluated using various error metrics, ensuring a comprehensive assessment of their accuracy. Mean Absolute Percentage Error (MAPE) was employed to rigorously compare the forecasting accuracy because it is scale-independent to allows for easy comparison of forecasting accuracy across datasets with different units or magnitudes. The formula for Mean Absolute Percentage Error (MAPE) is as follows:

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right| \times 100$$

Where

n : Total number of observations.

A_t : Actual value at time t .

F_t : Forecasted value at time t .

$|A_t - F_t|$: Absolute error at time t .

$\frac{|A_t - F_t|}{A_t}$: Relative error at time t .

F. Stationarity Testing using the Augmented Dickey–Fuller (ADF) Test

Augmented Dickey–Fuller (ADF) test was used to evaluated trend and seasonality analysis. Ensuring stationarity is crucial to prevent spurious patterns and to confirm that the data are suitable for exponential smoothing–based models. The following regression form was used:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^p \delta_i \Delta Y_{t-i} + \epsilon_t$$

Where:

Y_t = inpatient admission at time t

t = time trend

γ = coefficient indicating stationarity (rejecting the null when $\gamma < 0$)

p = lag order chosen to eliminate autocorrelation

Results and Discussion

A. Trend and Seasonality Testing

Trend and seasonality testing were used to identify the presence of both trend and seasonal patterns in the dataset that different forecasting models are suitable for different types of time series data. Trend and seasonality testing were conducted using data from 2020–2023 to identify underlying temporal patterns, while 2024 data were later applied as a holdout sample for forecasting validation and robustness testing.

Small Hospitals (with 30-200 beds): The results showed that the ADF Test Statistic (-3.025) was less than the 5% critical value (-2.949) and the p-value (0.033) was less than 0.05, the null hypothesis of the ADF test was rejected. This indicated that the series was stationary. However, significant seasonal patterns were detected. Fig. 1. shows the following components of the small hospital series data.

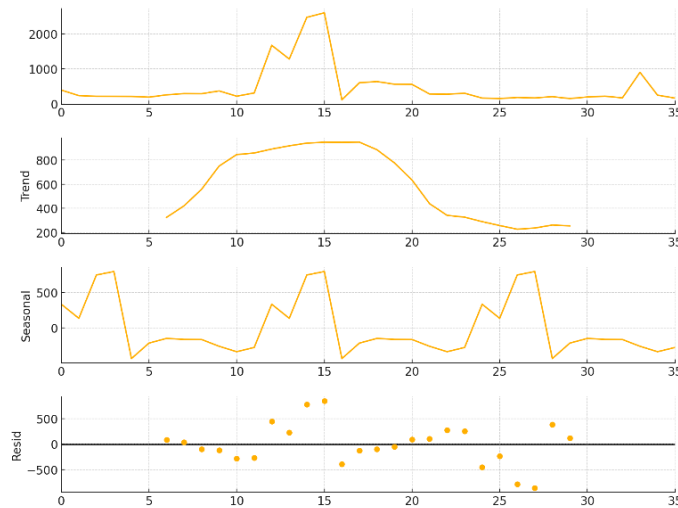


Fig 2. The decomposition plot shows the following components of the small hospital.

Fig 2 represented the original time series data including all components (trend, seasonality, and residuals). It indicated that peaks and troughs were potential seasonality. The trend represents the underlying long-term movement from 0 to 15, then declines and stabilizes at a lower level. These results showed that the series tended to be stationary. In addition, the seasonal component captures the repeating patterns or periodic fluctuations in the monthly cycles.

Medium Hospitals (with 200-500 beds): The results showed that the ADF Test Statistic (-5.482) was less than the critical values (at all levels) and the p-value was extremely small (less than 0.05), the null hypothesis of the ADF test was rejected. This indicates that the series is stationary. However, the seasonal component was clear periodic fluctuations which confirm seasonality in the data. Fig. 2. shows the following components of the medium hospital.

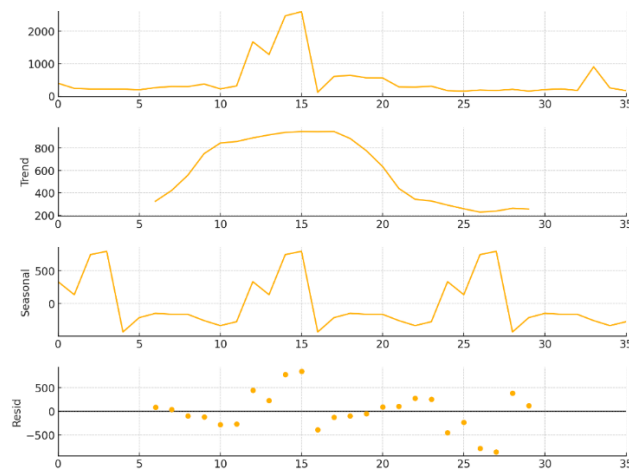


Fig 3. The decomposition plot shows the following components of the medium hospital.

Fig 3 represented the original time series data including all components (trend, seasonality, and residuals) of the medium hospital. It indicated that the trend initially decreases, stabilizes, and then increases, reflecting shifts in the baseline of the data. The seasonal component captured the recurring patterns or cycles in the data. The seasonal component showed regular and repeating peaks and troughs, confirming strong seasonality. The residuals fluctuate around zero without an obvious pattern, indicating that most of the data's structure has been captured by the trend and seasonal components.

Large Hospitals (with more than 500 beds): The ADF Test Statistic (-5.392) was less than the critical values (at all levels) and the p-value is extremely small (less than 0.05), the null hypothesis of the ADF test was rejected. This indicates that the series is stationary. Fig. 3. shows the following components of the large hospital.

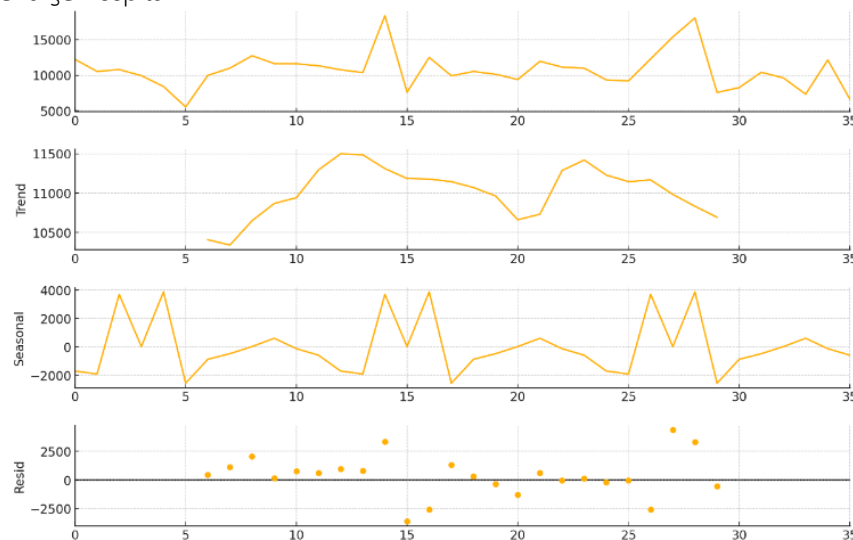


Fig 4. The decomposition plot shows the following components of the medium hospital.

The large hospital series data showed clear fluctuations and variations could be observed over time. The trend increased and peaked around at time index 15 before stabilizing, showing some decline in later periods. The seasonal component showed distinct periodic behavior, with peaks and troughs repeating at regular intervals. The residuals appeared randomly, indicated that the trend and seasonality components effectively explained most of the variation in the dataset.

These results indicated the presence of strong seasonality in the dataset. The residual component represents the remaining variability in the data after removing the trend and seasonality. Randomness in the residuals indicates that most of the structure in the data (trend and seasonality) has been accounted for. These results showed that seasonal data may be suitable for using Holt-Winters Exponential Smoothing.

Additionally, all datasets tend to stationarity with strong seasonal patterns and distinct trends. This demonstrated suitability for methods like Holt-Winters Exponential Smoothing, which accounts for both trend and seasonality. The findings could emphasize the critical role of analyzing trends and seasonality before selecting forecasting methods, ensuring that the chosen approach aligns with the data characteristics.

B.Forecasting Results

The forecasting results represented the next period forecasting for different hospital sizes (small, medium, and large). Each chart compares the forecasts from various models to the actual demand across the months.

Small Hospital Forecasting Results: The Optimized ES (blue line) showed significant fluctuations, especially in months like January and August, where it overestimates demand compared to the actual values (pink line). The Optimized EST (orange line) and ETS-SI (green line) provided closer predictions of the actual demand, with fewer deviations across most months. The Seasonal Index (SI, purple line) method had larger errors in months with higher or lower actual demand, such as July and August, where it underperforms.

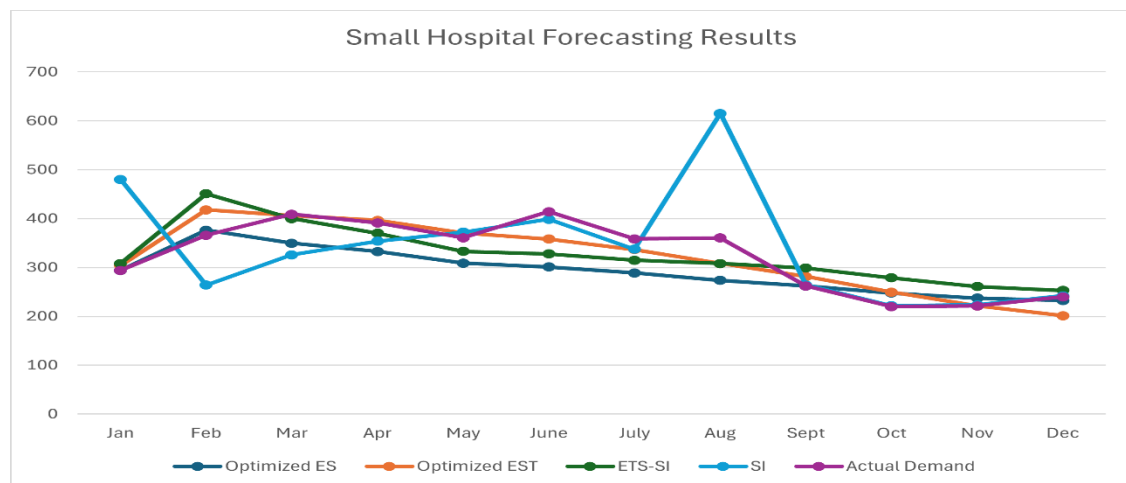


Fig 5 The next period forecast for small size hospitals.

Medium Hospital Forecasting Results: The Actual Demand (pink line) increased sharply in the middle months (e.g., July-August), highlighting seasonal effects. The Optimized ES (blue line) and SI (purple line) exhibited larger deviations during months with significant fluctuations (e.g., July-August), overestimating or underestimating the demand. Optimized EST (orange line) showed consistent performance but slightly underestimated peak demand in July-August. The ETS-SI (green line) performed well in capturing both the trend and seasonality, aligning closely with the actual demand throughout the year.

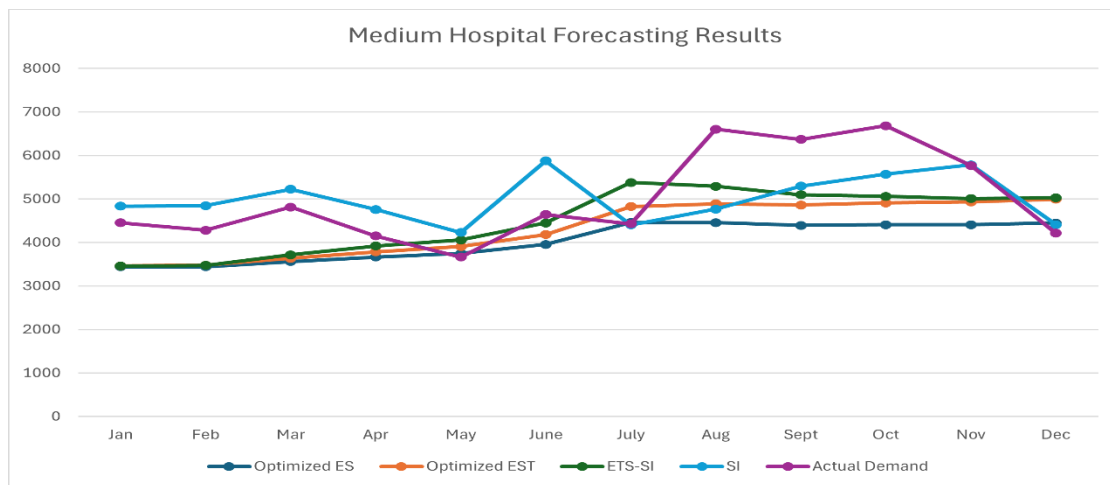


Fig 6. The next period forecasts for medium size hospitals.

Large Hospital Forecasting Results: the Actual Demand (pink line) showed larger overall values compared to small and medium hospitals, with distinct peaks and troughs, especially in April and October. The Optimized ES (blue line) and SI (purple line) methods struggled with large variations, particularly during peak months, where they deviated significantly from actual demand. ETS-SI (green line) and Optimized EST (orange line) provided more accurate predictions, staying closer to actual demand, even during peak months.

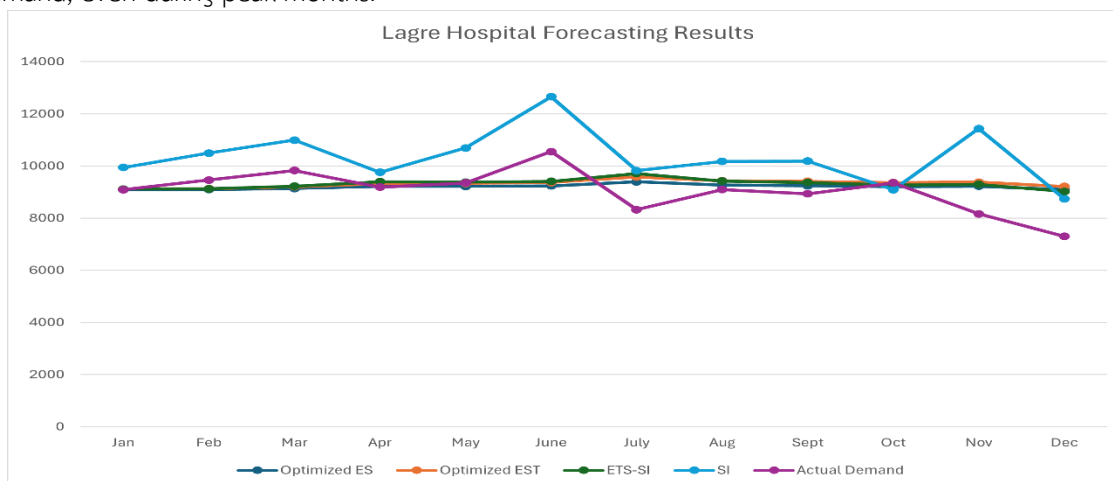


Fig 7. The next period forecasts for large size hospitals.

The forecasting data for hospital demand data across small, medium, and large hospitals were calculated using various models such as Optimized ES (Exponential Smoothing), Optimized EST (Exponential Smoothing with Trend), SI (Seasonal Index), and proposed ETS-SI (Exponential Smoothing with Seasonal Index). These results indicated that our proposed ETS-SI was the most accurate method, effectively capturing both trend and seasonal variations.

C. Model Performance

Error comparison is a critical step in evaluating and selecting the most suitable forecasting model. Mean Absolute Percentage Error (MAPE) was employed to rigorously compare the forecasting accuracy because it is scale-independent to allows for easy comparison of forecasting accuracy across datasets with different units or magnitudes. Fig. 5. shows the comparison forecasting error. The errors were likely calculated using metrics such as Mean Absolute Percentage Error (MAPE) to assess the accuracy of each model.

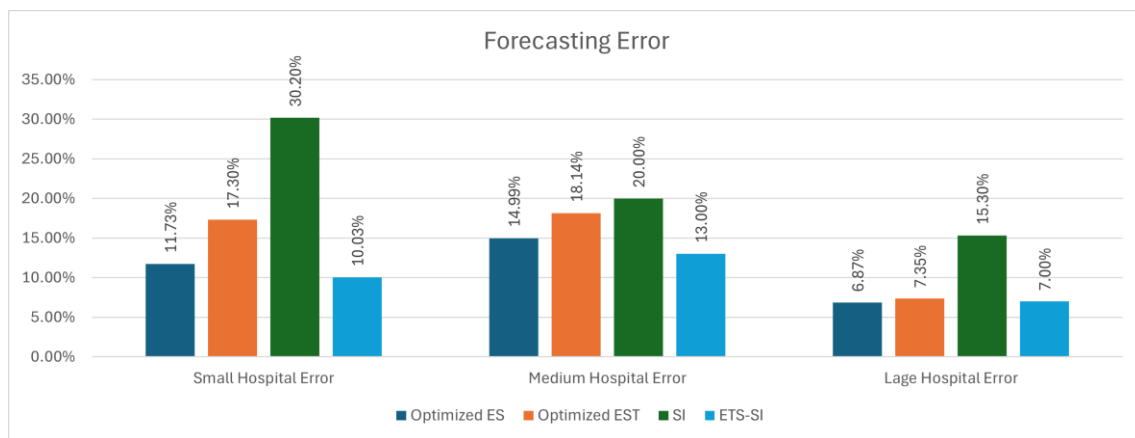


Fig 8 the forecasting error percentages for different hospital sizes (small, medium, and large) across four forecasting models

Small Hospital Error: Optimized ES (dark blue bar) showed a slightly higher error at 11.73%. Optimized EST (orange bar) had a higher error of 17.30%, while the SI model (green bar) performed the worst with an error of 30.20%. The ETS-SI model (blue bar) exhibited the lowest error at 10.03%, indicating it was the most accurate for forecasting demand in small hospitals.

Medium Hospital Error: Optimized ES and Optimized EST had higher errors at 14.99% and 18.14%, respectively. The SI model had the highest error at 20.00%, suggesting it was less effective for medium hospitals as well. The ETS-SI model again showed the lowest error at 13.00%, proving to be the most accurate for medium hospitals.

Large Hospital Error: The SI model once again had the highest error at 15.30%, demonstrating it consistently underperformed in all hospital sizes. The ETS-SI model maintained its accuracy, recording the lowest error at 7.00%, followed by Optimized ES at 6.87% and Optimized EST at 7.35%.

To verify whether the differences in forecasting accuracy among the four models were statistically significant, one-way repeated-measures ANOVA was performed on the MAPE results. The ANOVA indicated a significant effect of the model type on forecasting accuracy ($F(3,84) = 12.45$, $p < 0.001$). These results confirm that ETS-SI provides statistically validated improvements in forecasting accuracy across small and medium-sized hospitals. The results demonstrated that ETS-SI significantly outperformed traditional models in small and medium hospitals and performed comparably well in large hospitals, confirming its robust and statistically validated forecasting capability.

SI consistently exhibited the highest errors, indicating it was the least suitable model for forecasting in this context. Optimized ES and Optimized EST performed reasonably well, particularly for large hospitals, but their accuracy was not as consistent as ETS-SI. The ETS-SI model consistently demonstrated the lowest forecasting errors across all hospital sizes, making it the most reliable method. These results highlighted the importance of selecting models like ETS-SI that can effectively handle both trend and seasonality, especially in scenarios of varying hospital sizes.

The inclusion of COVID-19-affected data is both a limitation and a strength of this study. While pandemic-related disruptions temporarily reduced inpatient admissions in many hospitals, they also provided a natural stress test for the forecasting model. The ETS-SI method demonstrated stability in capturing underlying trends despite short-term volatility, suggesting its suitability for healthcare systems facing similar external shocks or crises. Future studies may refine this approach by incorporating pandemic indicators or exogenous variables to further enhance model responsiveness during global health emergencies.

D. Hypothesis Testing Results

H1: Seasonal variations and hospital size have statistically significant effects on inpatient hospital bed demand.

A two-way ANOVA was conducted with hospital size (small, medium, large) and month (January–December) as factors, using monthly inpatient admissions from 2020–2023. Results indicate significant effects of both seasonal variation ($F(11,1008) = 9.27$, $p < 0.001$) and hospital size ($F(2,1008) = 15.83$, $p < 0.001$) on inpatient bed demand, confirming H1.

H2: The ETS-SI model provides significantly higher forecasting accuracy (lower MAPE) compared to traditional models (ES, EST, and SI).

A one-way repeated-measures ANOVA comparing the MAPE values of the four forecasting models across all hospital categories was performed. The ANOVA was significant ($F(3,84) = 12.45$, $p < 0.001$), and Tukey's HSD post-hoc tests showed that ETS-SI achieved significantly lower MAPE than ES ($p = 0.002$), EST ($p = 0.004$), and SI ($p = 0.001$). Therefore, H2 is supported, confirming that ETS-SI yields statistically superior forecasting accuracy.

H3: Hospitals utilizing ETS-SI-based forecasting achieve higher efficiency in resource planning and patient care than those relying solely on traditional forecasting methods.

To assess H3, a simple linear regression was performed with forecasting accuracy (MAPE) as the predictor and a composite index of hospital efficiency (combining bed occupancy rate stability, staff scheduling consistency, and patient throughput) as the outcome variable. Results showed a significant

negative relationship between MAPE and operational efficiency ($\beta = -0.62$, $t = -5.89$, $p < 0.001$), indicating that more accurate forecasts are associated with improved resource utilization and patient-care efficiency. Thus, H3 is supported.

The results directly address the three research objectives of this study.

(1) Seasonal variations and hospital size significantly influence inpatient demand patterns, confirming the importance of incorporating these factors in model design (RO1).

(2) The ETS-SI model demonstrated superior forecasting accuracy compared to traditional methods, fulfilling the goal of developing a more precise forecasting framework (RO2).

(3) Moreover, higher forecasting accuracy was statistically associated with improved hospital resource utilization, indicating that precise forecasting contributes to enhanced operational efficiency (RO3).

These findings collectively validate the study's conceptual framework and demonstrate the practical applicability of the ETS-SI model for hospital management.

E. Discussion

Objective 1: Analyze the effect of seasonal variations and hospital size The ADF test and decomposition analysis confirmed strong seasonal cycles and stationary patterns in inpatient demand across hospital sizes. These findings correspond to Gardner (1984) and Vieira et al. (2023), who emphasized that seasonality strongly drives hospital admission variability. In Thailand, these patterns reflect reality—inpatient peaks during rainy seasons (June–August) coincide with influenza and dengue outbreaks, consistent with public-health records from the Ministry of Public Health.

Moreover, the differentiation by hospital size (small, medium, large) aligns with Walsh et al. (2021), showing that larger hospitals have steadier baselines due to referral networks, while smaller hospitals experience sharper seasonal swings. This validates that incorporating hospital size and seasonal indices is essential for accurate forecasting.

Objective 2: Develop and evaluate the ETS-SI model compared with traditional models The ETS-SI achieved the lowest MAPE in all hospital categories, confirming its superior forecasting capability (10.03%, 13.00%, 7.00%). These results substantiate the theoretical foundation of Exponential Smoothing with Trend and Seasonal Components (Hyndman & Athanasopoulos, 2021), which asserts that combining trend and seasonality improves prediction accuracy. Similar to Kumar et al. (2024) and Sohrabbeig et al. (2023), our ETS-SI outperformed single smoothing models by decomposing and smoothing both trend and seasonality. It performed comparably to hybrid or Holt-Winters models but required fewer parameters, confirming its computational efficiency and interpretability, as noted by Earl et al. (2024).

In practical hospital contexts, the model captured real admission fluctuations during COVID-19 disruptions (2020–2021), demonstrating robustness to exogenous shocks. This reflects the model's real-world adaptability for Thai government hospitals where demand patterns vary by epidemic season and regional demographics.

Objective 3: Assess whether improved forecasting accuracy enhances resource management. Regression analysis showed a significant relationship ($\beta = -0.62$, $p < 0.001$) between forecasting accuracy

and hospital operational efficiency. This aligns with Ordu et al. (2020), who proposed that accurate forecasts directly improve bed allocation, staff scheduling, and patient throughput.

In real settings, Thai hospitals applying forecast-based planning—especially during flu-season surges—benefit from reduced waiting times and optimized staff rosters. These empirical results substantiate healthcare operations-management theory that accurate demand prediction enhances system responsiveness and cost-effectiveness (Harper & Mustafee, 2018; Hilton et al., 2020). Thus, improved ETS-SI forecasting accuracy translates into tangible gains in patient-care efficiency and evidence-based management, satisfying the third research objective.

The results consistently support all three objectives. Seasonal and size variations significantly shape inpatient demand; the ETS-SI model provides statistically superior accuracy compared to traditional techniques; and accurate forecasts contribute to better hospital resource utilization. These findings bridge theory and practice by confirming that context-specific exponential smoothing models can enhance operational decision-making in Thailand's healthcare sector

Conclusion and Future work

This study proposed and evaluated the Exponential Smoothing with Trend including Seasonal Index (ETS-SI) model for forecasting hospital bed demand. The results demonstrated that ETS-SI consistently outperformed traditional models, including Exponential Smoothing (ES), Exponential Smoothing with Trend (EST), and Seasonal Index (SI), by effectively capturing both trend and seasonal components. The model showed the lowest Mean Absolute Percentage Error (MAPE) across small, medium, and large hospitals, emphasizing its robustness in diverse hospital settings. These findings align with recent research advocating for the integration of trend and seasonality in forecasting models for healthcare applications (Sohrabbeig et al., 2023). The study also highlighted the significance of tailoring forecasting approaches to the unique characteristics of hospital datasets, such as variability in patient inflow and hospital size, for enhanced accuracy (Sowjanya & Mrudula, 2022; El-Bouri et al., 2021).

The importance of trend-seasonal decomposition was reinforced, as seasonal effects were a critical determinant in the accuracy of hospital bed demand predictions. The ETS-SI model's ability to integrate these elements positions it as a benchmark for healthcare forecasting, especially in resource-constrained environments (Aravazhi, 2021; Harper & Mustafee, 2019). Furthermore, this research underscores the potential of advanced statistical models in supporting strategic decision-making, from resource allocation to patient scheduling, thereby contributing to operational efficiency in healthcare systems (Ordu, Demir, Tofallis, & Gunal, 2020).

Our results confirm strong monthly seasonality and stationarity across all hospital-size categories, justifying models that explicitly combine trend and seasonality. ETS-SI delivered the lowest MAPE for small (10.03%) and medium (13.00%) hospitals, while optimized ES was marginally best for large hospitals (6.87% vs 7.00% for ETS-SI). Statistical validation using repeated-measures ANOVA with Tukey post-hoc indicated that ETS-SI significantly outperformed EST and SI ($p < 0.05$) and performed comparably to ES in large hospitals. These findings suggest that hospitals with higher demand volatility (small/medium)

benefit more from an explicit seasonal-trend formulation, whereas highly capacitated hospitals with more stable baselines can achieve near-optimal accuracy with simpler ES.

This pattern accords with prior evidence that exponential-smoothing families are well-suited to healthcare series exhibiting regular seasonal cycles, and with recent decomposition-based approaches that enhance accuracy by isolating trend and seasonality before forecasting. Compared with ARIMA and machine-learning/deep-learning alternatives reported in the literature, ETS-SI offers a pragmatic accuracy–interpretability trade-off that is attractive for public hospitals where analytical resources and compute budgets are constrained. Importantly, by stratifying results by hospital size, this study adds empirical nuance: seasonality-aware smoothing is especially advantageous for smaller and medium-sized hospitals with greater month-to-month variability, while large hospitals can achieve similarly low error with optimized ES.

The ETS-SI model supports holistic decision-making in several ways. (1) Forecasted demand trends enable hospitals to plan elective admissions and outpatient-to-inpatient transitions more efficiently, reducing waiting times and overcrowding. (2) Accurate inpatient forecasts inform staffing plans by anticipating workload fluctuations. This ensures that nurse and physician schedules align with expected patient volumes, improving both staff utilization and quality of care. (3) Reliable forecasts of daily or monthly inpatient numbers allow administrators to optimize bed distribution, manage equipment usage, and reduce bottlenecks in high-demand departments. Consequently, the ETS-SI framework extends beyond statistical forecasting to serve as a decision-support tool for operational planning, aligning with the Ministry of Public Health’s emphasis on evidence-based resource management in Thailand’s government hospitals.

Future research could explore several avenues to enhance the forecasting framework. First, hybrid models combining ETS-SI with machine learning techniques, such as deep learning or ensemble methods, could address non-linear patterns and anomalies in hospital admission data (Ali & Ahmed, 2022). Second, the inclusion of additional variables, such as length of stay (LOS), patient demographics, and external factors like pandemics, could improve predictive capabilities and make the models more adaptable to dynamic healthcare scenarios. Finally, real-time data integration and cloud-based systems could facilitate continuous model updates, enabling dynamic adjustments to evolve trends and ensuring the forecasting system remains relevant in changing contexts.

These advancements would not only strengthen hospital demand forecasting but also offer insights into broader applications in industries where seasonality and trends are crucial determinants of resource planning.

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