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Research Article

Forecasting Reimbursed Pharmaceutical Expenditures in Türkiye: 2025-2030 Projection

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Abstract: This study uses time series models to examine the trend and seasonality components of the Social Security Institution's prescription count, prescription cost, and total prescription cost data from 2015 to 2024 in Türkiye. Based on the findings, the study also aims to produce a projection for the period from 2025 to 2030. The Prophet forecasting model was used to project the time series data used in the study. Model performance was evaluated using R^2, mean absolute error, and root mean square error metrics. Time series modeling and preliminary analyses were conducted in the Python 3.8 environment. A steady increase in prescription numbers was observed during the 2015–2024 period, alongside seasonal fluctuations, and the forecast showed consistent results. However, the forecast model did not fully predict the decline in prescription numbers during 2020, when the pandemic's effects were at their most severe. Projections indicate that the per-prescription amount and the total number of prescriptions will increase, with the former exceeding 2,000 TRY and the latter exceeding 110 billion TRY by 2030. These findings suggest that the Social Security Institution's drug expenditure burden will increase. This research will provide decision-makers with evidence-based information for future drug reimbursement decisions.

Keywords: Forecasting, Health Policy, Pharmaceutical, Prescription, Reimbursement

1. Introduction

One of the most significant demographic changes affecting healthcare systems is the rapid ageing of the population. The ageing population has been identified as a key factor in the rising prevalence of chronic diseases. Chronic diseases are long-term, slowly progressive conditions that can persist throughout a lifetime. While these diseases may not be entirely curable, effective management strategies exist that can mitigate symptoms and improve patient outcomes. The utilization of pharmaceuticals is a prevalent practice in the management of these conditions. This predicament often results in prolonged illness, necessitating ongoing therapeutic interventions and, consequently, a substantial escalation in pharmaceutical consumption. Indeed, the utilization of pharmaceuticals such as antihypertensives, cholesterol-lowering agents, antidiabetic agents, and antidepressants has increased significantly in OECD countries between 2011 and 2021. Concurrently, pharmaceutical expenditures have risen, accounting for 6% of total health expenditures in OECD countries (OECD, 2023). In Türkiye, pharmaceutical use and expenditures for both chronic and acute diseases increased between 2018 and 2023 (Ministry of Health, 2025). It has been asserted that pharmaceutical expenditures will increase more in importing countries (Bölükbaşı et al., 2021). The increase in pharmaceutical expenditures raises questions about the sustainability of pharmaceutical financing.

In Türkiye, a mixed model is utilized to finance pharmaceuticals. The primary source of financing for pharmaceutical programs is public funds, with out-of-pocket expenditures also being utilized. Furthermore, it has been determined that public funds cover more than two-thirds of pharmaceutical expenditures. The Social Security Institution (SSI) is responsible for covering the expenses incurred by individuals covered by General Health Insurance, provided that specific criteria are met. Since 2013, the SSI has functioned as the sole public purchaser and the primary price setter in the pharmaceutical market (Atasever, 2015). The SSI has the prerogative to specify the pharmaceuticals covered by the scheme and to determine their reimbursement prices. In addition to being the sole public purchaser in

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the pharmaceutical market, it is also the largest purchaser. The total number of prescriptions billed to SSI increased from 15,047,427,391 TRY in 2010 to 330,042,398,859 TRY in 2024. It is estimated that approximately 10% of SSI's total expenditures are accounted for by prescription bill payments (SSI, 2025). Akar (2014) asserts that the SSI's proportion of pharmaceutical expenditures to total health expenditures is approximately 40%. The increase in pharmaceutical use and expenditures, especially during specific periods, pharmaceutical price increases (IQVIA, 2023), and the burden of pharmaceutical expenditures on the social security system raise concerns about sustainability. A nation's sustainability is inextricably linked to that of its social security system. Indeed, social security systems finance healthcare expenditures, which cannot be left to market forces due to their externalities. Future projections must be considered to ensure the financing of pharmaceuticals and the overall sustainability of the SSI.

This study aims to analyze the trend and seasonality components of SSI's prescription count, prescription cost, and total prescription cost data for the 2015–2024 period using time series models and to produce future projections for the 2025–2030 period based on the findings. This projection will provide evidence-based information on how many resources the SSI should allocate for pharmaceuticals over the next five years. The research findings underscore the study's significance, as they provide guidance for plans to sustain public financing in the Turkish pharmaceutical sector. A review of the literature reveals a range of pharmaceuticals in the health field (Çeliker et al., 2024; Sarı & Gül, 2022; İmece & Beyza, 2022) and serum sets (Yiğit, 2016), in addition to surgical gauze (Uçakkuş & Koçyiğit, 2019), syringes (Özüdoğru & Görener, 2015), gloves, sterile sponges, glucose strips, ECG electrodes, cannulas, kidney trays, and venous valves (Torun & Deste, 2021). In the course of these studies, past consumption data were utilised to determine future demand for the relevant pharmaceuticals and supplies. Furthermore, the emergency department (Barut & Patır, 2024; Çiftçi & Batur Sir, 2023; Esen & Kaya, 2021; Sarıyer, 2018), the mental health and disorders outpatient clinic (Şahin, 2019), the oral and dental health centres (Oruç & Başağağlu, 2024), the paediatric intensive care units (Karakaş, 2019), the various surgical units (Dedeoğlu & Çetin, 2021), and the hospitals (Irmak et al., 2012) have been identified as the primary healthcare providers. In these studies, future patient demand was also predicted from past patient visits. Beştaş's (2023) study analyzed pharmacy sales data to forecast future trends. Akar (2014) compared prediction methods by comparing the predicted values with SSI data from 2009-2013. In contrast to the extant literature, this study offers a more comprehensive analysis by estimating the levels to which the number of prescriptions and the total and mean invoice amounts for SSI will reach over the next five years (2025–2030). The absence of a study of this scope in the literature clearly demonstrates the originality and necessity of this research.

2. Methods

This study produced projections with 95% confidence intervals for the number of prescriptions, the amount per prescription, and the total prescription amount to determine SSI pharmaceutical expenditures for the 2025-2030 period. The pharmaceutical expenditure and prescription count data covered by the SSI for the 2015–2024 period were analyzed using time series models to examine trend and seasonal components. The prescription count, mean prescription cost, and total prescription expenditure data used in the study were obtained from the SSI data application. These data are publicly available in the SSI data application (SSI, 2025). There are no missing values or observations in the dataset. All data were collected monthly ($t = 1, ..., 120$) at the national level in Türkiye from January 2015 to December 2024.

The Prophet forecasting model was used to project the time series data used in the study. This powerful yet flexible model can capture nonlinear trends, seasonality, holiday effects, and crises (Hyndman & Athanasopoulos, 2018; Taylor & Letham, 2018). The data analyzed consisted of the annual number of prescriptions and the monthly invoice amount per prescription. In this study, the variables 'Number of

Prescriptions' and 'Invoice Amount per Prescription' were trained independently to forecast the total prescription amount. The trained prediction models then generated monthly projections for 2025–2030 at the monthly frequency. These projections were then multiplied to obtain the total prescription expenditure projection. To accurately reflect the model's predicted uncertainties and risks, the analysis provided 95% confidence intervals. These intervals were calculated for the forecasts of both components and visualized in the graphs. Confidence intervals are important for decision-makers because they show the probability that actual values will be within the predicted range (Armstrong & Collopy, 2001).

In the pre-analysis stage, statistical and visual analyses were performed on the series used. Initially, trends and seasonal structures were examined using three-month moving means and monthly percentage change graphs for the series of prescription numbers, invoice amounts per prescription, and total prescription amounts. The Augmented Dickey-Fuller (ADF) test was then applied to examine the data's stationarity properties. The p-value exceeding 0.05 in both series supported the presence of trends and seasonal structures. Additionally, autocorrelation (ACF) analyses revealed repeating patterns every 12 months in the prescription count series, indicating a distinct seasonal pattern. A comparative analysis was also conducted between the 2015–2019 and 2020–2024 periods to determine the statistical significance of the observed structural differences in the time series. In this context, independent samples t-tests were applied to three key variables: prescription count, prescription-specific invoice amount, and total prescription amount. These tests assessed whether structural changes during and after the pandemic were statistically significant. The Prophet model's ability to model trends and seasonal structures separately made it suitable for this dataset. The Prophet model was suitable for the data structure used in this study because it can address trend and seasonality elements separately.

During the analysis phase, the seasonal and trend components were optimized to improve the model's predictive performance. The seasonal prior variance was increased to avoid limiting the model's response to seasonality, enabling the deterministic seasonal structure to be learned more flexibly. Conversely, to accurately capture structural changes in the trend component, the penalty term for change points was reduced to increase the model's sensitivity to breakpoints. This approach avoids overfitting while allowing for potential structural transformations in the series (Bai & Perron, 2003; Box & Jenkins, 2015). The models' performance was evaluated using R^2, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). Time series modeling and preliminary analyses were performed in a Python 3.8 environment.

3. Findings

To examine the temporal trend of prescription-based healthcare expenditure in Türkiye in a multidimensional manner, the number of prescriptions, mean invoice amount per prescription, and total prescription amount were analyzed in terms of absolute values (actual value and three-month moving mean) and proportional changes. Figure 1 shows the development of the number of prescriptions over time. From 2015 to 2025, it exhibited regular fluctuations with seasonal patterns. These were characterized by recurring increases in February–March and October–November, and decreases in June–July and December–January. Filtering for this seasonality with a 3-month moving mean revealed a more apparent trend. While prescription numbers sharply declined in 2020, they steadily increased between 2022 and 2024. Examining the percentage change curve revealed that the number of prescriptions can increase or decrease rapidly and sharply from one month to the next.

Figure 1

Development of The Number of Prescriptions Over Time

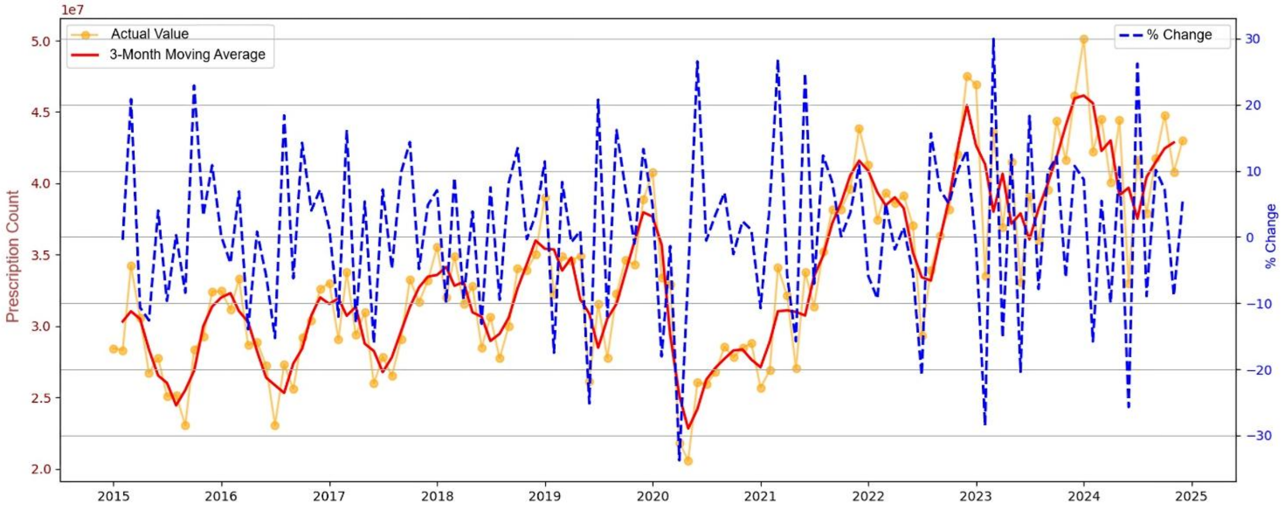


Figure 2 shows the development of the invoice amount per prescription (TRY) over time. While the invoice amount per prescription remained relatively flat between 2015 and 2020, it has increased since 2021. Notably, the sharp increase in absolute values and moving means after 2023 suggests that prescription-based costs are rising rapidly. The percentage change curve reveals that, although it occasionally dips into negative territory, it has stabilized mainly in positive territory since 2023. This situation suggests that costs per prescription are continuously increasing.

Figure 2

Development of the Invoice Amount Per Prescription (TRY) Over Time

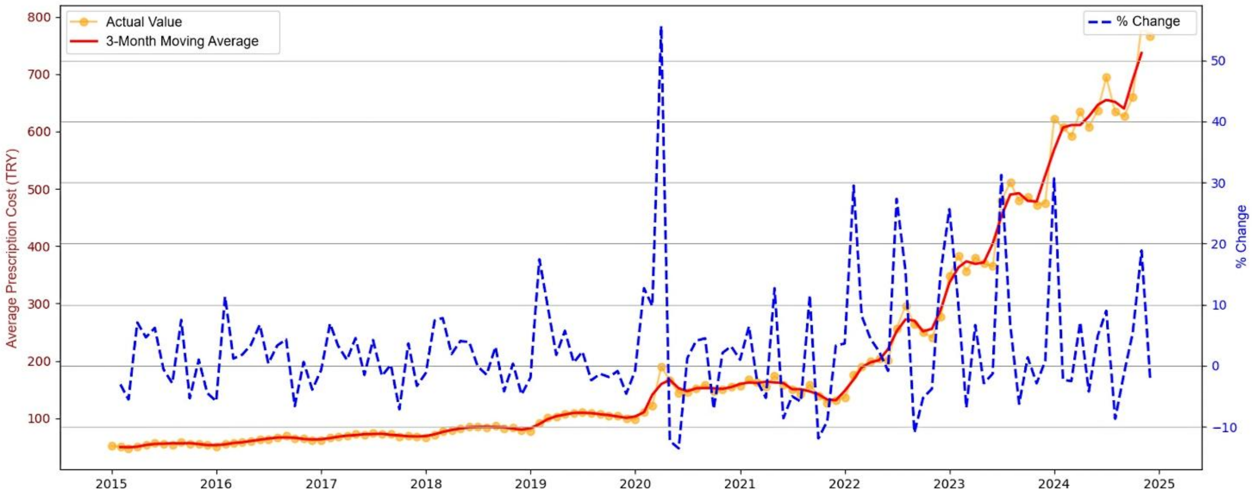
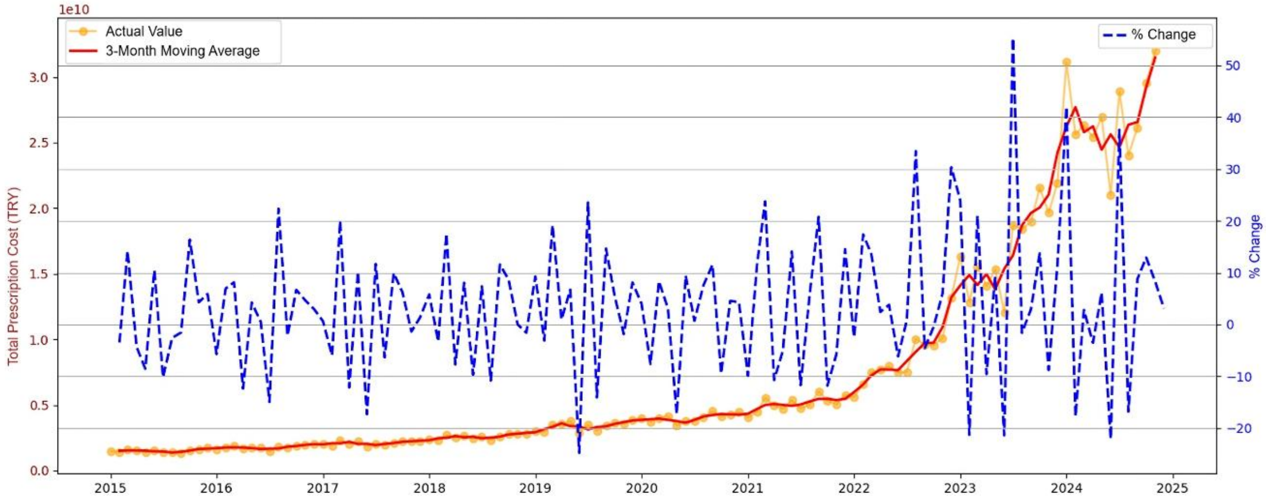


Figure 3 shows the temporal development of the total prescription amount. The figure reflects the combined effect of the number of prescriptions and the invoice amount per prescription. The total invoice amount has steadily increased since 2015, accelerating further since 2020, and exhibiting exponential growth since 2023. This situation indicates that the recovery in the number of prescriptions and the increase in unit costs have combined to affect total expenditure. Examining the percentage change curve reveals significant variability. The continuity of positive values after 2023 confirms the structural trend of increasing expenditure. In other words, both the number of prescriptions and the amount per prescription have increased.

Figure 3

Temporal Development of the Total Amount of Prescriptions



T-test analysis revealed statistically significant differences in the mean number of prescriptions, invoice amount per prescription, and total prescription amount between the 2015–2019 and 2020–2024 periods (Table 1). In other words, the means for the pre- and post-pandemic periods demonstrate systematic differences rather than random fluctuations in the number of prescriptions, the amount per prescription, and total expenditure.

Table 1

Mean Difference Analysis of Prescription Data Between the 2015–2019 and 2020–2024 Periods

Implemented model policies	**t**	**p**
Prescription Count	-5.95	<0.001
Mean Prescription Cost	-9.42	<0.001
Total Prescription Cost	-8.58	<0.001

Figure 4 shows the estimated values and 95% confidence intervals for the number of prescriptions between 2015 and 2030. The model's projections of the number of prescriptions match the actual data for 2015–2024. The model accurately represented the trend and seasonality components derived from past observations, intra-year cyclical patterns, and the general increase in prescription volume over time. Notably, the model-predicted values and the actual number of prescriptions after 2016 are close to the 3-month moving mean. This suggests that the model correctly captures the underlying trends and regular variations. However, the model could not fully capture the sudden decline in 2020 due to the pandemic. During the projection period beginning in 2025, the model continued the observed trend and predicted an acceleration in the increase of prescription numbers. The predicted increase persisted with seasonal fluctuations throughout the year, indicating that the model retained its seasonality. However, the 95% confidence interval widens as the projection moves further into the future. This suggests that long-term predictions are more uncertain. When evaluated using monthly prescription count forecast performance metrics, the forecasts essentially captured the overall trend and seasonality. The model explains approximately 72% of the total variance in the actual data (R^2 = 0.72). The mean absolute error (MAE) is 2.35 million prescriptions, while the root mean square error (RMSE) is 3.19 million. These values indicate deviations of 5–10% from the mean monthly prescription volume, suggesting that the model is reasonably accurate.

However, the relatively high difference between the RMSE and MAE indicates that the model is not very sensitive to sudden shocks and unusual fluctuations (e.g., the collapse during the 2020 pandemic).

Figure 4

Estimated Values for the Number of Prescriptions for the Period 2015–2030

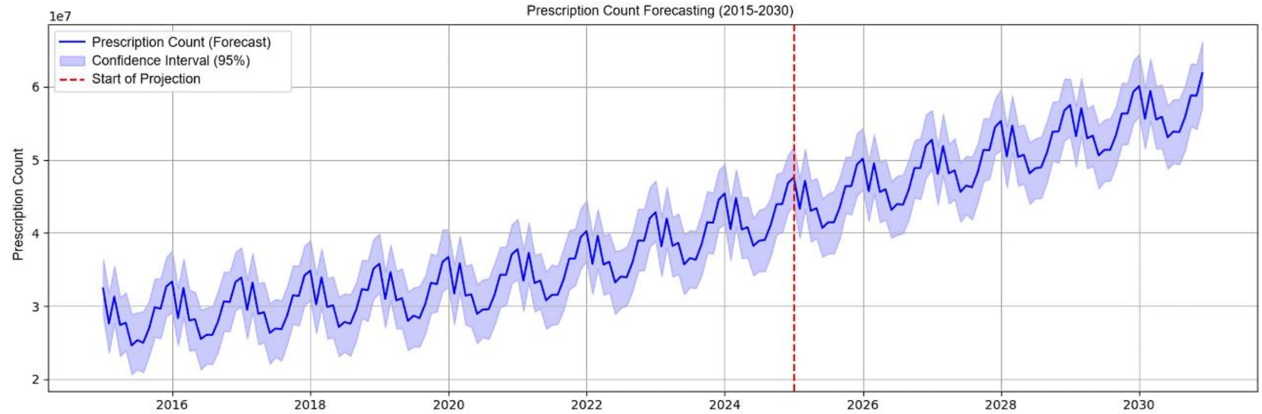
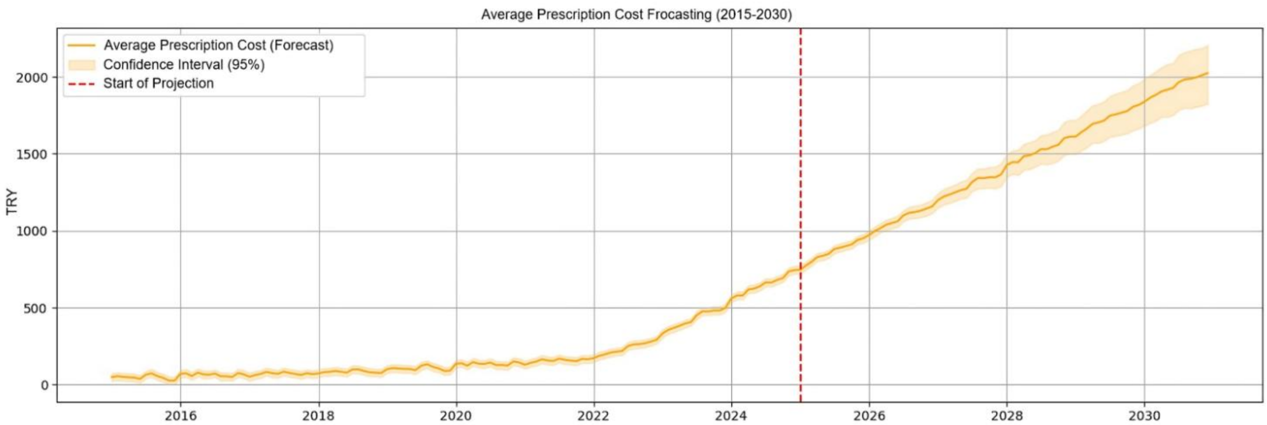


Figure 5 presents the estimated prescription amounts for the 2015–2030 period and the 95% confidence intervals for these estimates. The model's predicted values are consistent with the observed data, particularly from 2015 to 2024. The per-prescription amount shows a gradual upward trend starting in 2015, which the model has accurately captured. The momentum of the increase observed in the 2019–2020 period, as well as the significant cost increases after 2022, have been accurately reflected in the model's prediction curve. In this regard, the model is consistent with historical data in terms of both trend direction and magnitude. The upward trend in the per-prescription amount is expected to continue during the projection period, but the confidence intervals are widening, too. The model predicts that the per-prescription amount could exceed 2,000 TRY by 2030. The model's prescription amount estimate shows firm consistency in performance metrics. An R^2 value of 0.96 indicates that the model explains 96% of the total variance in the dataset, meaning the forecast line successfully captures almost all fluctuations and trend components throughout the period. Considering the mean absolute error (MAE = 14.99 TRY) and root mean square error (RMSE = 19.68 TRY) in the context of the mean monthly prescription amount (ranging from 70 to 750 TRY between 2015 and 2024), the deviation range is 3–10%. This proves the model's high accuracy. The relatively higher RMSE indicates that the model produces larger-than-expected deviations in rare periods (e.g., sudden price spikes), which points to the impact of external shock components (e.g., policy changes and price regulations) on the model.

Figure 5

Prescription-Based Amount Forecast Values for the 2015–2030 Period

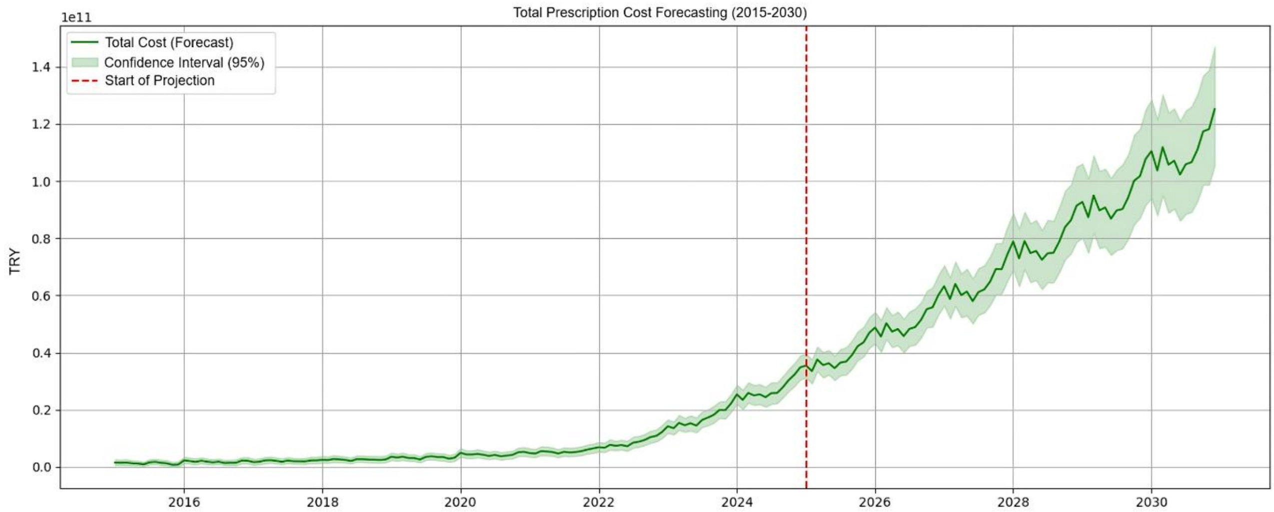


Note: R^2 (Prescription Amount): 0.97, MAE (Prescription Amount): 14.99, RMSE (Prescription Amount): 19.68

The estimated total prescription expenditure values for the 2015–2030 period, along with the 95% confidence intervals for these estimates, are presented in Figure 6. The model captured the low-level increase trend in the 2015–2020 period. However, the sudden decline during the pandemic period was captured by the model's seasonality trend. The accelerated increase between 2021 and 2024 was highly consistent with the forecast curve both direction and magnitude, as well as in the trend and seasonality components. When examining the 2025–2030 projections, the model carries forward past growth momentum and seasonal fluctuations, predicting that the total prescription amount will reach approximately 110 billion TRY in January 2030; at the same time, it shows that long-term uncertainty will increase as the confidence interval widens.

Figure 6

Estimated Total Prescription Value for the 2015–2030 Period



4. Discussion

This study examined how SSI financed pharmaceutical expenditures have developed. According to the findings, the number of prescriptions fluctuated regularly between 2015 and 2025, with seasonal patterns evident. These fluctuations are characterized by recurring increases in February–March and October–November, and recurring decreases in June–July and December–January. A sharp decline in prescriptions was observed in 2020, which is thought to have been driven by pandemic-related restrictions on access to healthcare. Over-the-counter pharmaceuticals was made available during this period to prevent access limitations and reduce the risk of infection. In this context, patients with pharmaceutical usage reports due to chronic illnesses could obtain prescription-free pharmaceuticals by extending their report periods without applying to a healthcare institution (SSI, 2024). This largely explains the decline in prescriptions. However, there was also a significant decline in physician visits in Türkiye during this period (from 812,903,622 in 2019 to 600,261,131 in 2020). The volume of pharmaceutical sales also decreased in 2020 compared to the previous year (151.7 million boxes), (Ministry of Health, 2025). The decrease in the use of healthcare services for non-urgent acute conditions during the pandemic explains the fall in doctor visits and the subsequent decline in pharmaceutical sales. Between 2022 and 2024, when the effects of the pandemic had diminished and the state of emergency had ended, prescriptions steadily increased. The 2025–2030 prescription count forecast model produced results consistent with the data for the 2015–2024 period. However, it did not fully capture the sudden decline in 2020 due to the pandemic. Until the pandemic, there had been no similar outbreak with such a global impact for many years. As prediction models are based on historical data, it was not expected that the model would be able to anticipate such an impact, given that the pandemic's effects were an extraordinary shock not present in historical datasets.

Notably, prescription numbers fluctuate regularly, with seasonal patterns. Curves showing percentage change have revealed that prescription numbers can increase or decrease rapidly from one month to the next. These sudden fluctuations are generally attributed to external factors, such as epidemics, seasonal flu, or changes in health policies. In other words, prescription numbers are susceptible to such external influences. Studies emphasize the impact of seasons on pharmaceutical use. Seasonal disease patterns influence pharmaceutical use. For example, it is commonly found that antibiotic use is particularly high during the winter (Ahmed, 2020; Beckstrøm et al., 2021; Suda et al., 2014; Winders et al., 2020). Zhang and colleagues (2012) demonstrated significant geographical differences in antibiotic prescribing practices and seasonal differences across regions, thereby highlighting the complex sociocultural dynamics that influence pharmaceutical use. Beyond antibiotics, other pharmaceutical classes also exhibit seasonal variability (Wilkes et al., 2009). Projections for 2025–2030 also anticipate the impact of seasonal fluctuations in prescription numbers.

The development of the invoice amount per prescription remained relatively stable between 2015 and 2020, but then began to rise in 2021. The sharp increase observed after 2023 shows that prescription-based costs are rising rapidly. The total prescription amount has steadily increased since 2015, accelerating further after 2020 and doubling by 2023. This indicates that the recovery in the number of prescriptions and the increase in unit costs have combined to affect total expenditure. Changes in pharmaceutical price regulations, exchange rate fluctuations, increased production costs, and structural changes to healthcare provision could be reasons for this. After 2021, the rapid rise in general economic inflation and the delayed impact of exchange rate increases on the pharmaceutical sector significantly increased the mean cost per prescription. In Türkiye, pharmaceutical prices are determined based on the euro exchange rate. Although a fixed exchange rate system is in place (Official Gazette, 2024), exchange rate fluctuations affect the fixed rate, increasing production costs and leading to higher pharmaceutical expenditures.

In Türkiye, SSI covers pharmaceuticals within the scope of reimbursement based on the public price (i.e., the price of pharmaceuticals after the public institution discount is applied to the retail price or the warehouse sales price, including VAT for pharmaceuticals without a retail price) (Official Gazette, 2022). However, not all pharmaceuticals are covered by reimbursement, and those are subject to change. The list of reimbursable pharmaceuticals is updated periodically. This may also result in changes to the total prescription amount. Moreover, the high rate of health inflation compared to general inflation (TurkStat, 2025) explains the high cost per prescription and the high total invoice amount. Khan and colleagues (2016) emphasize that health systems that do not incentivize generic and branded pharmaceuticals equally exacerbate price volatility and contribute to overall prescription costs. Pricing strategies implemented by pharmaceutical manufacturers can also contribute significantly to accelerated cost increases, particularly in specialty pharmaceuticals. These pharmaceuticals are often launched at higher prices, which has driven up the overall price of branded pharmaceuticals (Hayford, 2024). Regulatory and legal aspects also play an important role in pharmaceutical pricing.

The cost per prescription gradually increased between 2015 and 2024, a trend the model correctly predicted. It predicts that this upward trend will continue, potentially exceeding 2,000 TRY by 2030. The forecast of a gradual increase in total prescription expenditure over the 2015–2020 period, followed by a sharp decline during the pandemic and a subsequent rapid increase over the 2021–2024 period, along with seasonal fluctuations, was consistent with the actual values. The 2025–2030 projections, on the other hand, suggest that the increase will continue with seasonal fluctuations, reaching approximately 110 billion TRY by 2030. This finding is supported by the growing use of pharmaceuticals, driven by population ageing and rising disease burden. Economic development is expected to increase pharmaceutical expenditures as more types and quantities of pharmaceuticals becomes available for public services. Conversely, the exponential annual increase in pharmaceutical expenditure puts pressure on country administrations (Şenol et al., 2022).

The pharmaceutical expenditures of importing countries are predicted to increase significantly (Bölükbaşı et al., 2021). Although Türkiye has increased its efforts to meet its pharmaceutical needs through localization and domestic production, it still relies on foreign pharmaceuticals (Tıraş, 2020). This dependency is particularly evident in the areas of raw materials (active ingredients) and high-tech pharmaceuticals. It is suggested that pharmaceutical pricing and reimbursement policies are putting pressure on the national sector (İlaç Endüstrisi İşverenler Sendikası, 2024). Both actual and forecast data show that pharmaceutical expenditure will increase. The creation of up-to-date models to strengthen the national sector is considered beneficial to ensure the sustainable financing of pharmaceutical expenditures and avoid problems accessing pharmaceuticals.

5. Conclusion and Recommendations

This study produced projections for the number and amount of prescriptions covered by the SSI within the scope of reimbursement in Türkiye for 2025–2030. Accordingly, a balanced increase in the number of prescriptions was observed during the 2015–2024 period, with seasonal fluctuations, and the forecast produced consistent results. However, the forecasting model failed to fully predict the decline in prescriptions in 2020, when the pandemic's effects were at their most severe. Based on monthly data for the 2015–2024 period, the 2025–2030 projection predicts an increase with seasonal fluctuations. Projections for the amount per prescription and the total amount of prescriptions indicate that these amounts will increase, with the amount per prescription exceeding TRY 2,000 and the total amount of prescriptions exceeding approximately TRY 110 billion in 2030. The projections indicate that the burden of SSI's pharmaceutical expenditure will increase. The study provides evidence-based information on the resources the SSI will require to sustain its future pharmaceutical expenditure. This information is believed to be useful to decision-makers when determining and updating pharmaceutical reimbursement lists. This study used SSI prescription statistics. Future studies that analyze the SSI's expenditure statistics and estimate the proportion of total expenditure accounted for by pharmaceuticals are recommended.

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