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TRENDS AND FORECASTS OF OVERWEIGHT PREVALENCE IN TÜRKİYE: A TIME SERIES ANALYSIS USING ARIMA MODELS

TÜRKİYE'DE AŞIRI KİLOLU PREVALANSININ EĞİLİMLERİ VE TAHMİNLERİ: ARIMA MODELLERİNİ KULLANAN BİR ZAMAN SERİSİ ANALİZİ

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ABSTRACT

Objective: This study aimed to fit Autoregressive Integrated Moving Average (ARIMA) models to the prevalence of overweight in Türkiye's overall, female, and male populations and to forecast future trends using the best-performing ARIMA models.

Methods: The dataset comprised annual overweight prevalence values for Türkiye's overall, female, and male populations from 1974 to 2022, obtained from the World Health Organization and World Bank Group databases. The dataset was divided into training and test sets in a chronological sequence with the ratio 80:20, respectively. Training sets were used to fit ARIMA models, while test sets were used to evaluate the predictive performance of the models. Best ARIMA models were chosen based on various evaluation metrics.

Results: The best models were identified as ARIMA (1,3,1) for the overall population, ARIMA (1,3,1) for females, and ARIMA (3,3,1) for males, yielding the lowest error metrics. These models effectively captured the increasing trend in overweight prevalence. Short-term forecasts indicated that the upward trend is likely to continue in the near future.

Conclusion: This study contributes to a foundational understanding of the trajectory of overweight prevalence in Türkiye, providing a basis for evidence-based interventions and long-term health planning.

Keywords: Overweight prevalence, ARIMA models, time series, public health

ÖZ

Amaç: Bu çalışmanın amacı, Türkiye'nin genel, kadın ve erkek nüfusundaki aşırı kilolu prevalansı verilerine Otoregresif Entegre Hareketli Ortalama (ARIMA) modellerini uygulamak ve en iyi performans gösteren ARIMA modellerini kullanarak gelecekteki eğilimleri tahmin etmektir.

Yöntem: Çalışmadaki veri seti, Dünya Sağlık Örgütü ve Dünya Bankası Grubu veri tabanlarından elde edilen 1974-2022 yılları arasında Türkiye'nin genel, kadın ve erkek nüfuslarına ait yıllık aşırı kilolu prevalans değerlerinden oluşmaktadır. Veri seti, kronolojik bir sıra ile 80:20 oranında, sırasıyla eğitim ve test setlerine bölünmüştür. Eğitim setleri ARIMA modellerinin oluşturulması için kullanılırken, test setleri modellerin tahmin performansını değerlendirmek için kullanılmıştır. Çeşitli değerlendirme ölçütlerine göre en iyi ARIMA modelleri seçilmiştir.

Bulgular: En iyi modeller genel nüfus için ARIMA (1,3,1), kadınlar için ARIMA (1,3,1) ve erkekler için ARIMA (3,3,1) olarak belirlenmiş ve en düşük hata metriklerini vermiştir. Bu modeller aşırı kilolu prevalansındaki artış eğilimini etkili bir şekilde yakalamıştır. Kısa vadeli tahminler, artış eğiliminin yakın gelecekte de devam edeceğini göstermektedir.

Sonuç: Bu çalışma, Türkiye'de aşırı kilolu prevalansının gidişatının temelden anlaşılmasına katkıda bulunarak kanıta dayalı müdahaleler ve uzun dönemde sağlık planlaması için bir temel oluşturmaktadır.

Anahtar Kelimeler: Aşırı kilolu prevalansı, ARIMA modelleri, zaman serisi, halk sağlığı

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Introduction

Overweight has become a significant public health challenge globally, affecting populations across all age groups and socioeconomic levels. The World Health Organization (WHO) defines being overweight as a condition characterized by excessive fat deposits, with a body mass index value of 25 or greater. According to WHO reports, 2.5 billion adults over the age of 18 were overweight in 2022. This indicates that 43% of adults over the age of 18 were overweight (43% of men and 44% of women), which is higher than the 25% of people over the age of 18 who were overweight in 1990.[1] This trend has considerable outcomes for public health, as being overweight is associated with various chronic diseases, including cardiovascular disease, type 2 diabetes, certain types of cancer, stroke, dyslipidemia, osteoarthritis, and musculoskeletal disorders.[2-4] Türkiye, like many other countries, is affected by an increase in the number of people categorized as overweight. According to the latest Turkish Health Bulletin published by the Turkish Statistical Institute (TUIK), 47.6% of the population aged 15 and over were overweight in 2008, but this rate increased to 55.8% in 2022.[5] This increase brings serious costs to the healthcare system and reduces the quality of life of individuals.

In the field of epidemiology, utilization of time-series forecasting models, which is constructed upon historical data, are commonly met. These models serve as a valuable tool for making consistent forward-looking predictions, thereby facilitating the identification of disease trends and enabling health authorities to anticipate potential future risks. Unlike the limitations of simple linear models, time series models can control seasonality, trends, and other complexities found in the data.[6,7]

Despite the rising prevalence of overweight in Türkiye, existing studies have primarily focused on cross-sectional analyses, regional variations, and associations with other health factors.[8-10] However, these approaches do not provide insights into future trends, which are essential for proactive public health planning. To our knowledge, no previous studies have specifically applied time-series forecasting models to predict the prevalence of overweight in Türkiye. By addressing this gap, our study provides a data-driven approach to forecasting overweight prevalence. It is crucial to accurately estimate the prevalence of overweight individuals using historical data to develop effective health policies.

This study aims to analyze the trends and forecast the prevalence of overweight in Türkiye using Autoregressive Integrated Moving Average (ARIMA) models. By leveraging historical data on the prevalence of overweight from WHO and The World Health Group health databases, we aim to (i) evaluate the performance of different ARIMA models and identify reliable forecasting models for prevalence of overweight in the overall, female, and male populations of Türkiye, (ii) to make future forecasts on the prevalence values. The results of this study may provide useful information to health professionals in planning and prioritizing interventions to reduce the increasing rates of overweight in Türkiye.

Methods

Dataset

Data used in this study were collected from the open-access databases of WHO and the World Bank.[11,12] The dataset comprises annual data on the prevalence of overweight in the Turkish population aged 18 and over, spanning the period from 1975 to 2022. In addition to the overall prevalence values, the dataset also includes the prevalence values of the female and male populations aged 18 and over.

Autoregressive Integrated Moving Average (ARIMA) Models

Autoregressive Integrated Moving Average (ARIMA) models are statistical models used to predict future values of univariate time-series data proposed by Box and Jenkins.[13] ARIMA is an extension of the Autoregressive Moving Average (ARMA) model that combines the two components: past observations and past error terms of observations. ARMA models are useful for stationary time-series data where the values fluctuate around a constant mean and variance, showing no long-term trends or seasonality. However, real-world data sets frequently exhibit non-stationary structures. ARIMA models can handle such time-series data with trend or seasonality by applying differencing transformations until the time series become stationary.[14] The process of first-order differencing a non-stationary series is expressed in (1)

$$y'_t = y_t - y_{t-1} \quad (1),$$

where y'_t is the first-ordered difference value, y_t and y_{t-1} are the values taken at time t and t-1, respectively. For higher-order differencing (d-th order), it is recursively applied:

$$y_t^{(d)} = \Delta^d y_t = \Delta(\Delta^{d-1} y_t) \quad (2),$$

where $\Delta y_t = y_t - y_{t-1}$.

The ARIMA model consists of three parameters, which are p, d and q. Parameter p is the number of lagged observations, d is the number of times the original series is differenced to make it stationary, and q is the number of lagged errors used in the model. A general formula of ARIMA (p,d,q) is given in (3):

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} - \theta_1 e_{t-1} \theta_2 e_{t-2} - \dots - \theta_q e_{t-q} + e_t \quad (3),$$

where $y_t$is the predicted time series value, c is the constant, ϕ_i autoregressive terms, θ_j moving average terms and e_t is the error term.[15]

This study employed a data partitioning strategy, with an 80:20 ratio, to ensure robust performance evaluation and to avoid the issue of overfitting. The raw data sets were divided into two distinct subsets: the training set, comprising 80% of the data, and the test set, comprising the remaining 20%. This separation was achieved by partitioning the data set into two distinct periods, the earlier as the training set and the latter as the test set, to maintain the chronological sequence.[16,17] The training set comprised the values from 1975 to 2012, while the test set included the values from 2013 to 2022.

The training set was employed for model fitting, while the test set was utilized for the evaluation of the predictive performance of the ARIMA models. In the model fitting process, the Augmented Dickey-Fuller (ADF) test was initially applied to evaluate the stationarity of the series.[18] After the series were made stationary by differencing, p and q values, the other parameters of ARIMA models, were determined by using partial autocorrelation (PACF) and autocorrelation (ACF) graphs, respectively. It is recommended that during the process of fitting potential ARIMA models, parsimony models be constructed by selecting small p and q values to avoid the phenomenon of overfitting.[15] In all models, parameter estimations were performed using the maximum likelihood method. In the final stage of the model fitting process, the Box-Ljung test was employed to check whether the residuals (errors) of ARIMA models are uncorrelated, which is a key assumption for the model to be valid.[19]

The predictive performance of the potential ARIMA models was evaluated with Mean Error (ME), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Scaled Error (MASE) using test set values. ME is calculated as the mean of the differences between the observed and predicted values, indicating overall bias in the predictions. MAE is the average of the absolute differences between observed and predicted values, measuring prediction accuracy regardless of direction. RMSE is calculated as the square root of the average of the squared differences between the observed and predicted values. This weighting gives greater importance to larger errors. MAPE is the mean of absolute percentage errors between observed and predicted values, expressed as a percentage to standardize across different scales. Finally, MASE is the mean absolute error scaled relative to the mean absolute error of a naive benchmark model, enabling model comparisons across datasets. MASE value is expected to be less than 1 for a good prediction performance. The smaller the evaluation metrics obtained from the test set, the better the predictive performance.[17] In the final stage, prevalence values of overweight for the years between 2023 and 2032 were forecasted for each population using the best predictive ARIMA models.

All calculations for this study were conducted using R version 4.2.2 and R Studio (version: 2023.09.1+494).[20,21] Model fitting and the evaluation of predictive performance were utilized with the package 'lubridate',[22] package 'forecast',[23] and package 'tseries'.[24] Forecasting graphs were drawn with the package 'ggplot2'.[25]

Results

The stationarity of the time series was examined during the fitting of ARIMA forecast models for the overall, female and male populations using the prevalence of overweight values between 1974 and 2012. The ADF test results for the original time series of the populations indicated that no stationarity was present in the overall (p=0.8501), female (p=0.9363), and male (0.8887) populations. Consequently, differencing procedures were employed to address this issue. Following the application of third-order differencing, stationarity was observed in the prevalence series of the overall (p=0.01), female (p=0.028), and male (p=0.01) populations.

The potential p and q values for the stationary series were determined using PACF and ACF plots, as illustrated in Figure 1. Upon analysis of the plots, it was determined that the values crossing the 5% significance line in the PACF plot for the overall series were at lag 1 and 2, thus chosen for the p parameter. Similarly, the q parameter was chosen as 1 and 2, where the values crossed the significance threshold in the ACF plot. A similar approach was employed to determine the potential p values for the female series, which were found to be 1 and 2, and 1 for q. For the male series, the potential p values were 1, 2, 3, and 4, while the q value was 1. In all series, delays greater than 5 were not evaluated to provide parsimony models.

Following the fitting of potential ARIMA models for all series, the Box-Ljung test was used to assess whether the errors of the models exhibit autocorrelation. The models fitted for the overall series, namely ARIMA (1,3,1) (p=0.860), ARIMA (2,3,1) (p=0.866), ARIMA (1,3,2) (p=0.867) and ARIMA (2,3,2) (p=0.870), were found to exhibit no autocorrelation. Similarly, no autocorrelation was identified in the models fitted for the female series, ARIMA (1,3,1) (p=0.950) and ARIMA (2,3,1) (p=0.996), and in the models fitted for the male series, which are ARIMA (1,3,1) (p=0.403), ARIMA (2,3,1) (p=0.809), ARIMA (3,3,1) (p=0.965) and ARIMA (4,3,1) (p=0.997).

Predictive performance metrics of the fitted potential ARIMA models are given in Table 1. Upon the assessment of four different ARIMA models fitted for the overall population, it was observed that the MASE values were consistently below one across all models. Although the lowest MASE value was observed in the ARIMA (1,3,2) model, the remaining metrics, which are ME, MAE, RMSE, and MAPE, provided the lowest values and indicated that the ARIMA (1,3,1) model should be employed. In the context of a comparative analysis of two different ARIMA models for the female population, it was observed that all evaluation metrics belonging to ARIMA (1,3,1) presented the lowest values, thus indicating that ARIMA (1,3,1) was the optimal model. Finally, an examination of the ARIMA models fitted for the male population revealed that the ARIMA (4,3,1) model was not a suitable fit, as evidenced by its high ME, MAE, RMSE, MAPE and MASE values. It was determined that ARIMA (3,3,1), which exhibited the lowest evaluation metrics among the other models, was the most appropriate fit (Table 1).

Once the best ARIMA models had been identified for each population, prevalence forecasts were calculated using these models for the years 2023 to 2032. The resulting forecasts are presented as points with associated 95% confidence intervals for each year in Table 2.

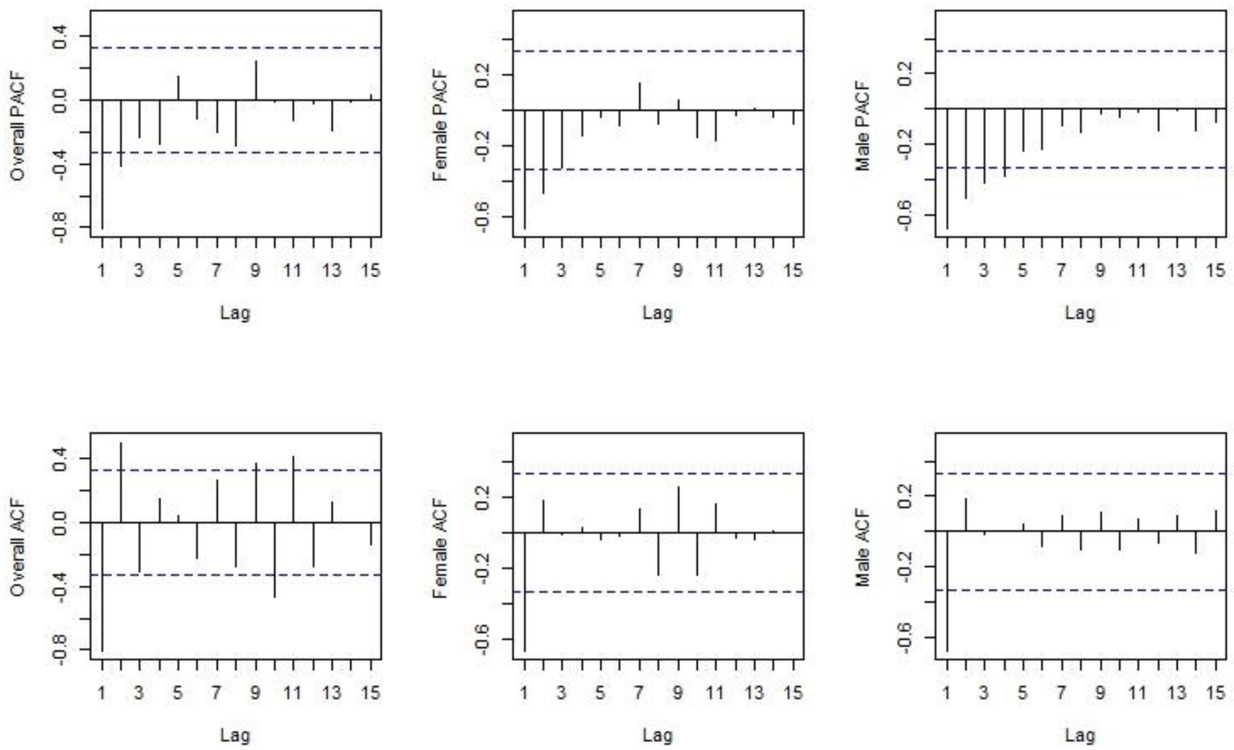

Figure 1. Partial autocorrelation (PACF) and autocorrelation (ACF) plots of third-order difference series of overweight prevalence in the overall, female, and male populations

Tablo 1. The test set-based prediction performance metrics of the potential ARIMA models

Population	Models	ME	MAE	RMSE	MAPE	MASE
Overall	ARIMA (1,3,1)*	0.4483	0.4723	0.6478	0.6965	0.5964
	ARIMA (2,3,1)	0.4543	0.4772	0.6546	0.7038	0.6026
	ARIMA (1,3,2)	0.4551	0.4779	0.6555	0.7047	0.3034
	ARIMA (2,3,2)	0.4586	0.4807	0.6595	0.7090	0.6071
Female	ARIMA (1,3,1)*	0.5002	0.5150	0.7254	0.7294	0.6781
	ARIMA (2,3,1)	0.5431	0.5525	0.7718	0.7827	0.7274
Male	ARIMA (1,3,1)	-0.1942	0.1942	0.2237	0.3005	0.2326
	ARIMA (2,3,1)	-0.1828	0.1828	0.2124	0.2827	0.2189
	ARIMA (3,3,1)*	-0.1419	0.1419	0.1609	0.2198	0.1699
	ARIMA (4,3,1)	-1.0874	1.0874	1.1627	1.6882	1.3020

*ARIMA: Autoregressive Integrated Moving Average, ME: Mean Error, MAE: Mean Absolute Error, RMSE: Root Mean Squared Error, MAPE: Mean Absolute Percentage Error, MASE: Mean Absolute Scaled Error, *;best predictive model in each population*

Tablo 2. Point and 95% confidence level forecasts for the prevalence of overweight in overall, female, and male populations using the best fit ARIMA models (%)

Year	Overall[1]			Female[2]			Male[3]		
	Point	LCL	UCL	Point	LCL	UCL	Point	LCL	UCL
2023	67.769	62.863	72.675	70.600	65.738	75.463	66.684	59.933	73.436
2024	68.000	62.188	73.812	70.933	65.391	76.476	67.131	59.458	74.804
2025	68.209	61.401	75.017	71.255	64.998	77.513	67.571	58.926	76.216
2026	68.396	60.499	76.294	71.566	64.558	78.574	68.004	58.337	77.671
2027	68.562	59.480	77.643	71.865	64.071	79.659	68.430	57.691	79.169
2028	68.706	58.342	79.069	72.153	63.538	80.767	68.849	56.989	80.709
2029	68.828	57.082	80.574	72.429	62.960	81.899	69.261	56.229	82.292
2030	68.928	55.697	82.159	72.695	62.336	83.053	69.666	55.414	83.918
2031	69.007	54.186	83.828	72.949	61.667	84.231	70.064	54.541	85.586
2032	69.064	52.545	85.582	73.191	60.952	85.430	70.454	53.612	87.296

LCL: Lower confidence limit, UCL: Upper confidence limit, [1]: ARIMA (1,3,1) model for overall population prevalence, [2]: ARIMA (1,3,1) model for female population prevalence, [3]: ARIMA (3,3,1) model for male population prevalence

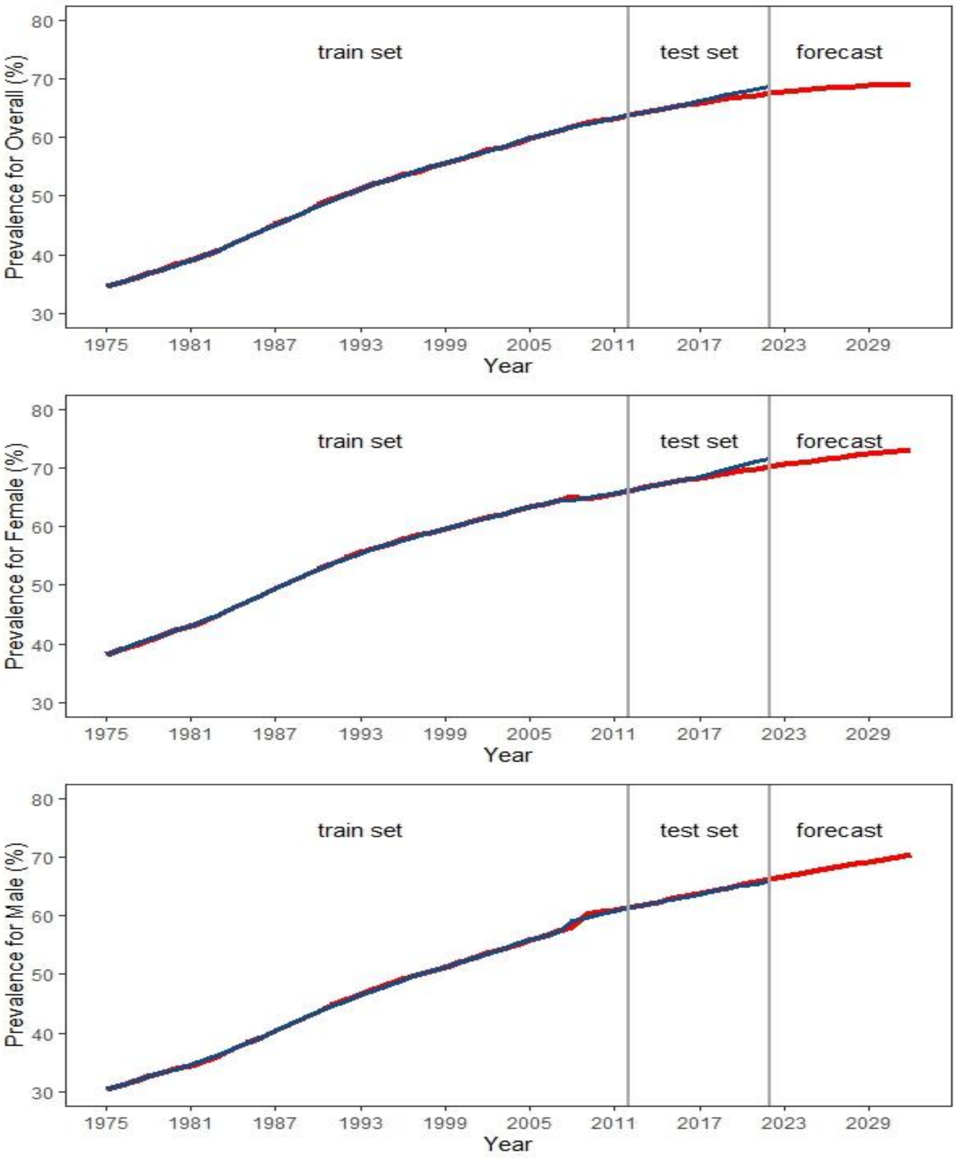

Figure 2. Best ARIMA models' forecast plots for the overweight prevalence of overall, female, and male populations

Figure 2 presents the original series and forecasted prevalence values based on the best-fitted ARIMA models of each population. In the plots where the periods of model fitting (train set), evaluation (test set), and future forecasts (forecast) are shown in detail, blue lines indicate the original series, while red lines show the point forecasted prevalence values. It was observed that the model fitted for the male population was superior in terms of compliance with the test set in comparison to other models. Upon examination of the forecasted data, it was evident that the increasing trend in prevalence values will persist in the following years.

Discussion

This study was conducted with the objective of fitting ARIMA models for the future prevalence of overweight in overall, female, and male populations of Türkiye, and making forecasts for a short-term future using the best-fitted ARIMA models. The models were fitted using annual prevalence data from 1974 to 2022, sourced from the WHO and World Health Group databases. The data sets were divided chronologically for use as the training and test sets, respectively, in the model fitting and model evaluation stages. In contrast to many time series studies that employ ARIMA, a more rigorous approach was taken in selecting the best ARIMA model, whereby model performance was evaluated with observations not included in the model fitting process.[16,17]

The prevalence of overweight in the Turkish population, both in children and adults, has been the subject of several studies. The studies are predominantly cross-sectional in design and aim to ascertain the prevalence of overweight and the risk factors associated with it.[26-29] It is consistently highlighted in the literature that the prevalence of overweight and obesity is on the rise across Türkiye, with a higher prevalence observed in the female population compared to the male population. It has been established that the rise in childhood obesity is associated with maternal overweight and the level of parental education.[26] Additionally, it has been irrefutably demonstrated that there is a relationship between hypertension and overweight in adults.[27] To the best of our knowledge, no studies have specifically focused on forecasting the prevalence of overweight in Türkiye using time series models.

This study highlights the utility of time series models in forecasting the prevalence of overweight, offering a data-driven approach for anticipating trends in Türkiye. As Table 1 and Figure 2 are examined, it becomes evident that the models exhibiting the lowest prediction error are those pertaining to the male population. It can be thought that the slightly higher error rate in the overall and female populations is due to the low amount of overfitting that occurs during the model-fitting process. Nevertheless, the fact that the MASE values for the best ARIMA models of the populations are below one indicates that these models are effective in forecasting the prevalence of overweight.

Our results indicate that ARIMA models capture the underlying trends in the data effectively, offering credible forecasts for the future burden of overweight. These forecasts reveal a potential continued increase in the prevalence of overweight, aligning with global trends observed in similar demographic and socioeconomic settings.[30] From a public health perspective, forecasts indicating an upward trend, as highlighted in previous studies, suggest an increasing burden on healthcare resources and underscore the need for comprehensive prevention and management strategies.[31] These results underscore the importance of preemptive action to address the prevalence of overweight in Türkiye.

The selected ARIMA models demonstrated good fits, as indicated by evaluation metrics, suggesting its reliability in short-term forecasting. However, one limitation of the model lies in its reliance on historical data, which may not fully account for future changes in lifestyle, policy interventions, or health promotion efforts that could influence overweight trends. Incorporating exogenous variables, such as income level, urbanization rate, or healthcare access, could potentially enhance the model's predictive accuracy, especially for long-term forecasts. Another limitation of this study is the lack of data from the years preceding 1974. The incorporation of additional data into the training set has the potential to enhance the model and substantiate a more robust trend. It is recommended that future research concentrate on enhancing the model's applicability by integrating socioeconomic and behavioral variables, as well as expanding the dataset to capture longer historical trends. Moreover, further studies could focus on translating these forecasts into actionable public health strategies to mitigate the rising burden of overweight. Finally, this study did not compare ARIMA models with alternative forecasting methods, such as machine learning-based approaches or other time series models (e.g., exponential smoothing or state-space models). Exploration of these methods in future research could provide insights into whether alternative models offer enhanced predictive capabilities in estimating overweight prevalence trends.

This study employed the ARIMA models to model the prevalence of overweight in the overall, female, and male populations of Türkiye, as well as to forecast short-term future prevalence. The increasing trend in the prevalence of overweight in Türkiye was emphasized. The results of this study can inform policymakers in the development of realistic, evidence-based interventions for reducing overweight prevalence and guiding resource allocation to high-risk demographics.

Compliance with Ethical Standards

Ethical approval was not required

Conflict of Interest

No conflict of interest was declared by the authors.

Author Contribution
HÖ, DÖ: Concept; HÖ: Data collection and/or processing; HÖ, DÖ: Analysis and/or interpretation; HÖ: Literature review; HÖ, DÖ: Writing article.

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