ATATÜRK ÜNİVERSİTESİ YAYINLARI
ATATURK UNIVERSITY PUBLICATIONS

Research Article *Araştırma Makalesi* DOI: 10.5152/TBE.2023.220091

# A Prediction for Medical Supplies Consumptions During Coronavirus Disease 2019

## COVID-19 Döneminde Koruyucu Sarf Malzemelerin Tüketiminin Tahmin Edilmesi

İlkay SARAÇOĞLU[1]
Ramazan YAMAN[2]
Çağrı Serdar ELGÖRMÜŞ[3]

[1]Department of Industrial Engineering, Haliç University, İstanbul, Turkey
[2]Department of Industrial Engineering, İstanbul Atlas University, İstanbul, Turkey
[3]İstanbul Atlas University, Faculty of Medicine, İstanbul, Turkey

### ABSTRACT

Extraordinary periods experienced since the beginning of human history have caused the formation of specific patterns. The current coronavirus disease 2019 pandemic we are experiencing has provided critical viewpoint on the use and supply of preventive consumable materials like masks, gowns, and disinfectant. These are used as hygienic items to protect against infectious diseases and are assumed not to be very significant and easily managed in hospitals during normal periods. This study first assessed the supply, stock, and consumption processes for these protective and preventive items considering data from 2019, considered a normal period in hospital operation. In the second part of the study, the differences in supply and use of these items were modeled based on data during the development of the pandemic. To estimate the use of consumption of the protective equipment, number of doctors, healthcare workers, administrative personnel, patients, and surgeries were chosen as independent variables. Multivariate linear regression analysis was applied to examine the changes in the independent variables on protective consumables. It has been observed that different variables are effective in estimating the consumption of each protective consumable. N95 mask, tie band surgical mask, and medical face mask consumptions were explained by the number of coronavirus disease patients and healthcare workers. Hand disinfectant and examination glove consumption were predicted with the number of doctor and coronavirus disease patients. Surgical glove prediction was estimated by using the number of surgeries. In this study, multivariate regression models are proposed to help predict the consumption of protective consumables in hospitals.

**JEL Codes:** C13, C39, C53

**Keywords:** COVID-19, healthcare providers, medical supplies, multiple linear regression, prediction, protection items

### ÖZ

İnsanlık tarihinin başlangıcından bu yana yaşanan olağandışı dönemler kendine özgü düzenlerin oluşmasına neden olmuştur. Hastanelerde olağan dönemlerde çok önemli olmadığı öngörülen ve kolay yönetilebildiği varsayılan, maske, önlük ve dezenfektan gibi koruyucu sarf malzemelerinin kullanımı ve tedariği, 2019 koronavirüs hastalığı (COVID-19) pandemi dönemi ile birlikte kritik bir bakış açısı kazanmasına neden olmuştur. Bu çalışmada, öncelikle, bir hastane işleyişinde olağan durum sayılan 2019 yılı verileri dikkate alınarak bu koruyucu ve önleyici malzemelerin tedarik, stok ve tüketim süreçleri değerlendirilmiştir. Çalışmanın ikinci kısmında ise pandemi döneminin gelişmesi esnasında oluşan veriler dikkate alınarak, bu koruyucu ve önleyici sarf malzemelerin tedarik ve kullanımlarında oluşan farklılaşmalar modellenmiştir. Koruyucu sarf malzemelerinin kullanımlarının tahminini modellemek için doktor, hemşire, idari personel, hasta sayısı ve ameliyat sayısı bağımsız değişkenler olarak seçilmiştir. Bağımsız değişkenlerdeki değişimin koruyucu sarf malzemeler üzerindeki değişimlerini incelemek amacıyla çok değişkenli doğrusal regresyon analizi uygulanmıştır. N95 ve bağcıklı cerrahi maske ve lastikli maskenin tüketimi, COVID hasta sayısı ve sağlık çalışanı sayısı ile açıklanmıştır. El dezenfektan ve muayene eldiveni tüketimi doktor sayısı ve COVID hasta sayısı ile tahmin edilmiştir. Cerrahi eldiven tahmini, ameliyat sayısına bağlı olarak tahmin edilmiştir. Bu çalışmada, hastanelerde koruyucu sarf malzemelerinin tüketimlerinin tahmin edilmesine yardımcı olacak çok değişkenli modeller önerilmiştir.

**JEL Kodları:** C13, C39, C53

**Anahtar Kelimeler:** COVID-19, sağlık hizmeti sağlayıcıları, tıbbi sarf malzemeler, çoklu doğrusal regresyon, tahmin, koruyucu malzemeler

Geliş Tarihi/Received: 05.09.2022
Kabul Tarihi/Accepted: 07.02.2023
Yayın Tarihi/Publication Date: 28.03.2023

Sorumlu Yazar/Corresponding Author: İlkay SARAÇOĞLU
E-mail: ilkays@sbbdanismanlik.com

Cite this article as: Saraçoğlu İ, Yaman R, Elgörmüş Ç. S. (2023). A prediction for medical supplies consumptions during coronavirus disease 2019. *Trends in Business and Economics*, 37(2), 120-136.

## Introduction

The outcomes of epidemic diseases are different from other disasters due to two special features: these are caused by long-term irregularities and have increasing spread. The inability to control this type of disaster causes severe disruptions to supply chains and societies, and as a result, irreparable losses occur (Mena et al., 2022; van der Laan et al., 2016). Additionally, with the declaration of a pandemic for the whole world by the World Health Organization (Johnson, 2020) in January 2020, large changes occurred in supply chains. The ability to manage this process with very rapid and accurate decisions carries great importance. During this COVID-19 pandemic period, especially the health and logistics sector was among the most affected sectors. As a result, the demand for the items of medical supplies used in the health sector to provide hygiene and protection has grown unusually (Cohen & Rodgers, 2020; Rhee, 2020). Additionally, the inability to find suppliers or inadequate stocks caused increases in their prices. During this coronavirus disease 2019 (COVID-19) pandemic, increases of nearly 3.8 times the monetary value spending on consumables were observed from the related hospital database compared to the period before the pandemic. Roshan et al. (2020) observed a sudden increase in the demand of hand sanitizers during the COVID-19 pandemic. They presented that there has been four times increase in the consumption of hand sanitizers in March and April 2020. The aim of this study was to estimate the increasing demands for items in progressing and developing periods with the COVID-19 pandemic and additionally to create a model that can be used as an example for similar situations.

Researchers have started to conduct modeling and prediction studies about epidemics and all connected scientific problems as a result of the advent of unknown infectious diseases. Planning for medical needs and public health services will continue to benefit from these modeling and prediction research in the future. Numerous prediction techniques have started to be applied in the subject of epidemics, particularly with the growth of data science. To date, many studies have been performed about topics like scientific predictions, medical supply, demand prediction, selection of suppliers, and design of supply chains in the medical field.

During the COVID-19 pandemic, Ekingen and Demir (2021) looked at the rates of change for the personal protective equipment utilized in hospitals. They compared the usage of the protective equipment in the COVID-19 period with the non-COVID-19 period. They showed that the amount of usage of this equipment has increased, but there was no significant increase in the number of staff and patients. The multiple linear regression technique is used to predict varied applications, for example, energy consumption (Aranda et al., 2012; Catalina et al., 2013), evaluation and measurement of education system (Olsen et al., 2020; Uyanık & Güler, 2013), predicting the price of the apartment (Čeh et al., 2018), and distribution of food demand (Crivellari et al., 2022). We focus on the multiple linear regression technique that has been applied during this time of epidemic diseases. According to the review of the literature in the epidemic disease period, there are lots of studies about the prediction of the COVID-19 patients. The descriptions of a few of the studies that were presented are provided here. Rath et al. (2020) developed a model for prediction of the COVID-19 to visualize the trend of the affected cases by using the linear and multiple linear regression analysis (LRA) techniques for the India region. Cihan (2022) applied different machine learning regression methods to predict the total number of intensive care patients, total intubated patients, and the number of daily death caused by COVID-19. Chaurasia and Pal (2020) analyzed and forecasted changes in the transmission of the COVID-19 infection, and two artificial intelligence (AI) models—auto regressive integrated moving average (ARIMA) and regression models—were used in their study. Demirkol (2022) developed a mathematical model to minimize the cost associated with the distribution and collection process supply chain network design problem that emerged during the pandemic process of a factory producing hygiene products. Furman et al. (2021) proposed an approach based on queueing theory to predict demand for personal protective equipment (PPE) such as surgical masks, gloves, and gowns required over a specified time horizon, which has increased significantly since the onset of the COVID-19 pandemic. The WHO (2020) summarizes the rational use of PPE in healthcare and community settings as well as during the handling of cargo; in this context, PPE includes gloves, medical masks, goggles or face shields, gowns, and, for specific procedures, respirators (i.e., N95 or FFP2 standard or equivalent) and aprons.

In the second section, accessible references related to the topic will be assessed. In the third section, materials and methods used in the study are presented. The fourth section creates a multiple linear regression model based on a hospital sample and the final section discusses the results.

## Methods

### Materials

This study obtained data about the consumption of consumable items providing hygiene and protection from a private hospital located in one of the regions with the densest population in the metropolitan city of Istanbul. The first COVID-19 case was seen in Turkey on March 11, 2020. From March 20, 2020, all hospitals were declared pandemic hospitals. In this period, most COVID-19 cases were in April 2020. There were fewer coronavirus cases in May and June 2020 as a consequence of the country's implementation of general restrictions. However, with the removal of restrictions in June, numbers began to rise again in July 2020. The hospital where data were obtained functioned as a pandemic hospital from March to September 2020. In September and October, hospitals ceased being pandemic hospitals. With the increase in the pandemic around the world and in Turkey in the autumn, all hospitals were declared pandemic hospitals again in November. Within this scope, after interviews with the hospital management, the study noted consumable items without a high degree of importance (noted as C group items in the ABC analysis) beforehand but with differing supply management affected by the COVID-19 pandemic, including tie band surgical mask and medical face mask (MRUBSUR), N95 mask (MN95), hand disinfectant (HDSF), examination glove (EXGLV), and surgical glove (TTSURGLV) (World Health Organization (WHO), 2020). Data were collected about the numbers of doctors (NDOC), healthcare workers (NNUR), administrative personnel (NEMP), patient examinations (NPAT), COVID-19 patients (NCOV), and surgery (NSUR) considered to affect the consumption of medical supplies. As a result of shortages and supply chain challenges, hospital administration decided to design their own surgical/isolation gown, which is not taken into account in this study. All data within the scope of the study used consumption figures from the period of the COVID-19 pandemic (March 2020–March 2022) and from a similar period of the previous year (January 2019–February 2020). Additionally, the management stated there were no changes in elements related to capacity like number of beds or doctors. All variables and definitions used in the study are given in Table 1 that shows the statistical descriptive data according to the pandemic period. In this research, the time frame with COVID-19 was referred to as COVID, and the time frame without COVID-19 was referred to as N-COVID. Data are all given as numbers, with HDSF given in liters.

The variation in amounts consumed from January 2019 to March 2022 is shown in Figure 1. According to Figure 1 and as a result of analyses performed with analysis of variance (ANOVA) to determine whether there is a difference between the periods or not, consumable items with significant differences were included in the study. According to the ANOVA for all dependent variables, there was a difference in consumption between COVID and N-COVID periods. It was observed that there was no difference between the two periods of TTSURGLV variable.

Due to the fall in patient and surgery numbers predicted for normal periods (N-COVID) during the COVID-19 period, a reduction occurred in the consumption of EXGLV and total powdered and non-powdered TTSURGLV. In conclusion, the reduction in the number of patients attending treatment and/or accepted for treatment compared to normal periods caused a reduction in the number of surgeries performed. Though the consumption of medical supplies in the normal period was all at the same level (apart from TTSURGLV), the unpredicted and very variable consumption in the pandemic period can be seen in Figure 1.

**Multiple Linear Regression Method**

The aim of the study was to determine a method which will allow the prediction of medical supply consumption in a hospital during a normal period (N-COVID) and a pandemic period (COVID-19). The demand prediction methods are divided into two as quantitative and qualitative (Chapman, 2006). Qualitative estimations are predictions produced from information without a well-defined analytic structure. It may be especially beneficial where there are no previous data, like for a new product or one without a sales history. Qualitative methods use methods like market research, naïve, Delphi, and expert opinions. Quantitative methods include time-series and association models. Time-series prediction models make estimations for the future according to data from the past. Estimation methods like moving average, trend analysis, and exponential smoothing are time-series methods. Associated models are predictions made linked to factors or variables affecting the outcome values (Nahmias, 2008). The most commonly used method is LRA which is a mathematical expression of the relationship between the variable with future values to be predicted and a variable affecting this predicted variable. In situations with more than one independent variable,

**Table 1.**
*Statistical Descriptive Monthly Data for Medical Supplies from January 2019 to March 2022 (Data Used)*

| Variables | Variable Type | Total ($n$ = 39) | COVID Group ($n$ = 25) | N-COVID Group ($n$ = 14) | $p$ |
|---|---|---|---|---|---|
| NDOC | Independent | 96.92 ± 7.84 | 100.64 ± 4.04 | 90.29 ± 8.68 | .000* |
| | | 99 (95–102) | 80.75 (78–94) | 94 (80.75–99) | |
| NNUR | Independent | 389.1 ± 65.7 | 403 ± 63.1 | 364.3 ± 64.9 | .077 |
| | | 377 (330–439) | 383 (362.5–468.5) | 338.5 (315.8–438.3) | |
| NEMP | Independent | 44 ± 6.34 | 40.44 ± 3.787 | 50.36 ± 4.8 | .000* |
| | | 42 (40–50) | 41 (38.5–42.5) | 52.5 (46.5–53.25) | |
| NPAT | Independent | 33,000 ± 4984 | 31,729 ± 4883 | 35,269 ± 4464 | .031* |
| | | 32,839 (29,246–36,747) | 31,791 (28,491–34,007) | 36,204 (32,492–38,270) | |
| NSUR | Independent | 2188.4 ± 383.3 | 2101.9 ± 380.3 | 2342.8 ± 349.7 | .059 |
| | | 2203 (1884–2440) | 2105 (1872–2307) | 2343.5 (2054.8–2566.5) | |
| NCOV | Independent | 427.4 ± 570.4 | 667 ± 591 | 0 ± 0 | .000* |
| | | 213 (0–774) | 387 (231–1081) | 0 (0–0) | |
| HDSF | Dependent | 509.3 ± 270.5 | 641.4 ± 249.2 | 273.6 ± 77.1 | .000* |
| | | 449 (295–650) | 605 (457–792) | 289.5 (212.3–324.3) | |
| MRUBSUR | Dependent | 38,676 ± 20,044 | 50,321 ± 15,125 | 17,882 ± 5063 | .000* |
| | | 38,950 (18,250–47,500) | 46,970 (40,215–61,100) | 17,500 (14,800–21,425) | |
| MN95 | Dependent | 1899 ± 1859 | 2948 ± 1506 | 23.7 ± 49.1 | .000* |
| | | 2088 (15–2897) | 2752 (2156–3237) | 9 (3.8–20) | |
| EXGLV | Dependent | 399,613 ± 62,954 | 417,552 ± 64,813 | 367,579 ± 45,885 | .015* |
| | | 385,000 (360,511–433,704) | 400,800 (364,178–450,150) | 375,600 (354,400–387,050) | |
| TTSURGLV | Dependent | 10,439 ± 2147 | 10,713 ± 2261 | 9950 ± 1906 | .293 |
| | | 10,300 (9041–11,633) | 10,657 (9193–12,791) | 10,209 (8885–10,956) | |

*Note:* Values are expressed as mean ± standard deviation or median (interquartile range: Q1–Q3).
*Significant $p$-value <.05.
COVID = coronavirus disease; EXGLV = examination glove; HDSF = hand disinfectant; MN95 = number of mask 95; MRUBSUR = medical/surgical mask; NCOV = number of COVID-19 patients; NDOC = number of doctors; NEMP = number of employees; NNUR = number of nurses; NPAT = number of patients; NSUR = number of surgeries; TTSURGLV = total surgical gloves.

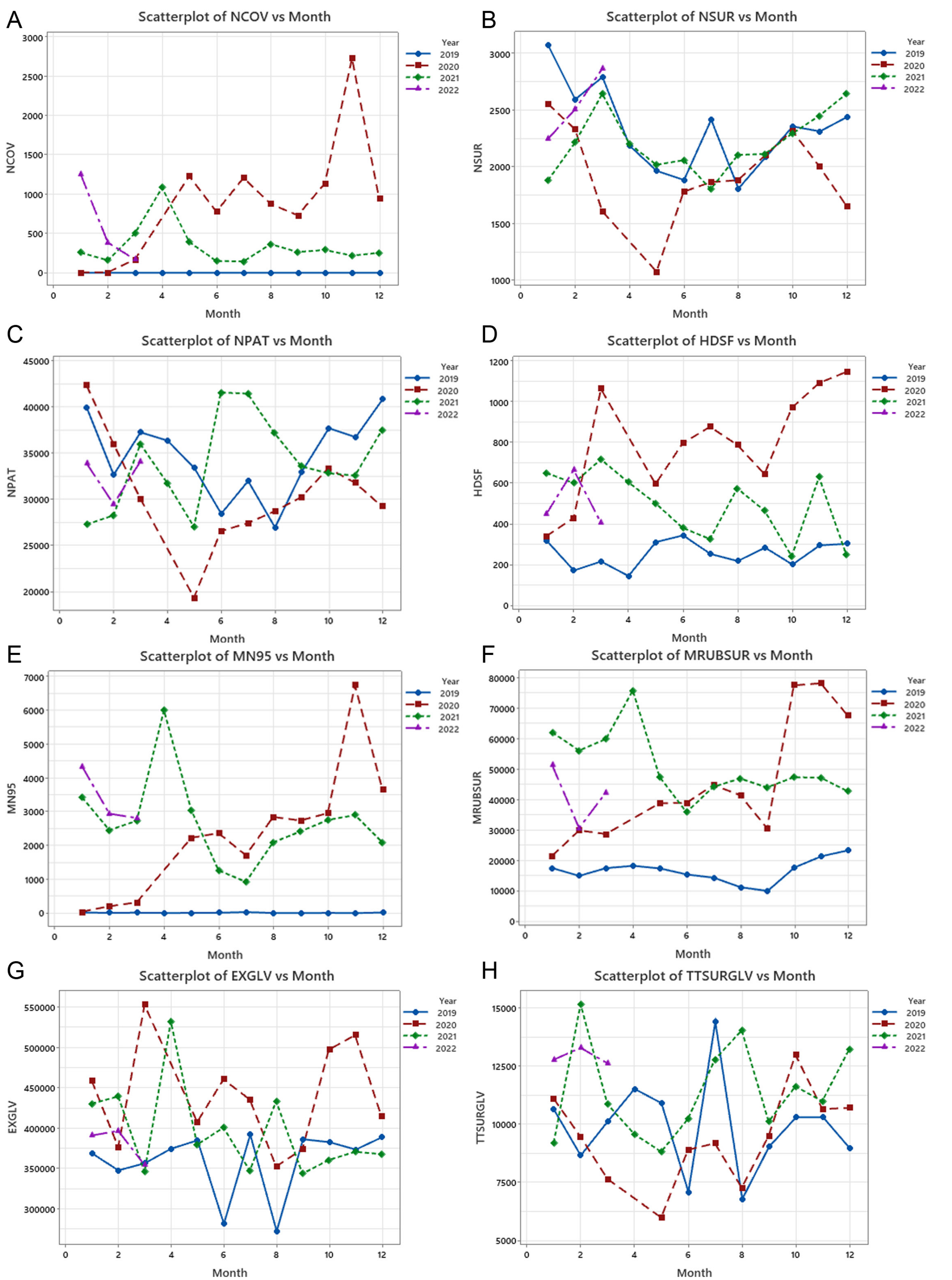



**Figure 1.**
*Consumption by Years, Actual Data for Medical Supplies From 2019 January to March 2022. EXGLV = examination glove; HDSF = hand disinfectant; MN95 = number of mask 95; MRUBSUR = medical/surgical mask; NCOV = number of COVID-19 patients; NPAT = number of patients; NSUR = number of surgeries; TTSURGLV = total surgical gloves.*

the multiple linear regression analysis (MLRA) method is applied. Example studies using this method may be investigated (Flynn et al., 2010). The MLRA is a method used for decision-making in a very broad area. For example, MLRA methods may be used to estimate sales (Chahal et al., 2018), to decide on prices for products (Čeh et al., 2018), to determine the quality levels of products (Binoj et al., 2021), to predict energy consumption (Aranda et al., 2012; Bianco et al., 2009), and to predict COVID-19 case numbers (Rath et al., 2020).

**Method Details**

The use of time-series methods was not appropriate to estimate the medical supply consumption in this study because modeling showing an increasing trend linked to time will cause mistaken estimations in situations where a falling trend begins in the COVID-19 pandemic. The decision was made to use the MLRA method to provide a model to estimate the medical supply consumption in a hospital by noting the number of personnel in the hospital and according to the progression of the pandemic in the whole world and in Turkey (as independent variable) with the aim of estimating consumption. The estimations obtained with the models created as a result of the study will allow hospital management to decide on how much of which items need to be purchased. As a result of this, making the best estimations will assist hospital management to avoid situations where stock is completely consumed and also prevent excess stock costs.

The basic steps and assumptions used in implementing the MLRA method may be listed as follows.

The aim of the MLRA method is to explain the total variance in the dependent variable with the independent variables. Some of the independent variables in MLRA may have insignificant contributions to the model. For this reason, one of the most important topics in the MLRA is to decide on which independent variables best explain the dependent variable. In order to make this decision, the values for the correlation coefficient ($r$) and coefficient of determination ($R^2$) should be examined. The $r$ value shows the level and direction of the correlation between the dependent variables and independent variables. The value of this coefficient varies from −1 to +1. +1 represents a positive strong correlation with increasing direction, 0 implies no correlation, and −1 represents a negative strong correlation with decreasing direction. The correlation between dependent variables and independent variables may be investigated on a matrix plot diagram shown on scatter plot graphs. Based on scatter plots, decisions can be made about whether the correlation between variables is linear, quadratic, or logarithmic. The $R^2$ value shows how much the independent variables explain the variance of the dependent variable. The $R^2$ value varies between 0 and 1. For prediction with a good regression equation, the $R^2$ value is expected to be larger than 0.70. When comparison of regression models including different numbers of independent variables is desired, it is necessary to use the $R^2_{(adj)}$ value. Even if there is no real development in the model, the $R^2$ value always increases when a variable is added to a model. The $R^2_{(adj)}$ value shows the increase only if the mean square error falls as a result of adding a new variable (Montgomery & Runger, 2003).

In line with this aim, it is necessary to determine the independent variables that will explain the dependent variable "most suitably" and remove insignificant variables from the model. This process is called "variable selection." For variable selection, different methods like backward selection, forward selection, and stepwise can be used.

The backward selection method begins by including all independent variables in the model and progresses in steps by eliminating the variable with largest significance $p$-value greater than .05 with the 95% CI until the most effective factor remains. The forward selection method, contrary to the backward election method, chooses the most significant of all factors by adding the factors one by one. The stepwise method applies both the forward and backward methods together to reach a conclusion. Inclusion of all factors in a model in line with expert opinions will cause differences in the results. The success of applying the MLRA method is linked to performing variable selection accurately.

For selection of variables, first, it is necessary to investigate the correlation between the independent variables and dependent variable by applying correlation analysis or matrix plots. It is necessary to include independent variables with strong correlations in the analysis. If there are very strong relationships between the independent variables themselves, it is necessary to not include one of these variables in the model. As a result of the selected independent variables ($X_k$) and the MLRA applied, the equation best explaining the dependent variable ($Y$) is obtained. The regression equation (Equation 1) obtained with the MLRA method can be written as follows (Montgomery & Runger, 2003):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k + \varepsilon \tag{1}$$

where $\beta_0$ is a constant intercept, $\beta_1, \ldots, \beta_k$ are regression coefficients of $k$ independent variables, $\mathcal{E}$ is an error term, and $Y$ is an $nx1$ column vector that represents the $n$ observation value of the dependent variable. Due to prediction of the model from the observed values, the predicted regression model (Equation 2) is shown below (Galwey, 2014):

$$\check{Y} = b_0 + b_1 X_1 + b_2 X_2 + \ldots + b_k X_k i = 1, \ldots n \tag{2}$$

Here, $\check{Y}$ is the predicted dependent variable, $b_0$ is the predicted constant value, $b_k$ is the slope of the $k$th independent variable, $X_i$ is the $i$th variable, and $\mathcal{E}$ is the predicted error.

The matrix notation defining the estimated regression equations (Equations 3-6) are presented as follows:

$$Y = \check{Y} + e = Xb + e \tag{3}$$

$$\sum_{i=1}^{n} \left( Y_i - \hat{Y} \right)^2 = \left( Y - X\beta \right)^T \left( Y - X\beta \right) \tag{4}$$

$$b = (X^T X)^{-1} X^T y \tag{5}$$

$$e = Y - X^T b = Y - \check{Y} \tag{6}$$

The least-square error method is applied to minimize the total error squares and predict regression coefficients. The coefficients in the equation are estimated using the least-squares method to minimize the error ($e$) between the observed values and predicted values. Graph and regression analysis studies were performed using the Minitab statistical software (Minitab, 2021).

To identify the best regression model, the following processes are performed (Araiza-Aguilar et al., 2020; Ghinea et al., 2016; Hair et al., 2010):

1. In order to apply linear regression, linearity, homoscedasticity, independence of the residuals, and normality assumptions are evaluated.
2. Multiple linear regression is applied to all data with the chosen independent variables. With the aim of measuring the model performance, the $R^2_{(adj)}$, residual deviation (*S*), and Mallows' Cp values and normality diagrams are checked. Mallows' Cp provides to select the best independent variables with eliminating the imprecise variables in the model.
3. In the first stage, the MLRA method was applied separately for COVID and N-COVID periods to obtain regression equations.
4. A regression model was created by assessing all periods together.
5. Probability plot diagrams for the residuals between the values predicted by the two different regression equations and the real values were created, and the equation best explaining the consumption of medical supplies was determined.
6. Predictions were performed with the obtained equations and compared with real values. Probability plot and time-series plot diagrams were used to compare real values and values predicted in all the obtained models, and the equations best explaining consumption were chosen by examining the

mean absolute deviation $MAD = (1/n)\left|\sum_{i=1}^{n}\left(Y_i - \check{Y}_i\right)\right|$ (7)

and

mean absolute percentage error $MAPE = \left[(1/n)\sum_{i=1}^{n}\left|\left(Y_i - \check{Y}_i\right)/Y_i\right|\right] \times 100$ (8)

values.

One of the most important aims in completing this study was to ensure prediction of medical supply consumption to assist hospital management in deciding on when and how much medical supplies to purchase.

## Results

Hospital management provided data about the numbers of examination, surgery, COVID-19, doctors, healthcare workers, and administrative personnel during periods with consumption amounts examined. For results, the retrospective analysis from multiple regression analysis methods was used to first examine the correlation coefficients between the independent variables and dependent variable. The independent variables with the strongest correlation had regression analysis performed and were added to the model to determine the final model.

The total sample number collected in the study deals with a 39-month duration (between January 2019 and March 2022). As the COVID-19 pandemic began in Turkey in March 2020, it covers a 25-month period. Additionally, the preceding 14-month period is the period when the COVID-19 pandemic was not effective (January–December 2019 and January–February 2020).

Before the MLRA method, one-way ANOVA was applied to analyze whether there were differences in terms of consumption between the COVID-19 period and non-COVID-19 period. Items with differences between these periods (MN95, HDSF, EXGLV, MRUBSUR, and TTSURGLV) were chosen, and a matrix plot was created to identify independent variables with strong correlations. The COVID and N-COVID periods were considered as a categorical variable. The MLRA was applied via the Minitab 21.1 program with the determined independent and dependent variables. Thus, predictions were provided for the consumption of items for periods with and without the COVID-19 pandemic. The correlations of all materials with each other and significant variables with 95% CI are given in Table 2.

**Prediction of N95 Mask Consumption with Multiple Linear Regression Analysis**

While consumption of MN95 items before the COVID-19 pandemic was so low as to be negligible, consumption increased during the pandemic. When the correlation with independent variables is investigated on the correlation matrix (Table 2), the strongest correlation with $r = .819$ appeared to be with NCOV. The reduction in NSUR and NPAT caused a reduction in the consumption of MN95 items. There appears to be a strong correlation (.72) between the NSUR and NPAT independent variables. In situations with a strong correlation between independent variables in MLRA, it is necessary to remove one of these independent variables from the model. The multicollinearity between independent variables is explained with the variance inflation factor (VIF) value. Varian inflation factor $= 1/1 - R^2$ is calculated, and a high $R^2$ value is possible when there is a strong correlation between two variables. If $R^2 > 0.9$, this means that the VIF value >10. This value represents high multicollinearity. The high VIF value requires that one of the variables should be removed from the model due to two variables displaying the same characteristics.

According to the correlation analysis result, the NPAT, NNUR, NDOC, NEMP, and NCOV independent variables appeared to affect the MN95 dependent variable. As a result of including the effective variables in the model and applying the variable selection method of backward elimination, NCOV and NNUR emerged as the independent variables best explaining MN95 consumption. As a result of the MLRA using Minitab, the following regression equation was obtained for MN95 consumption (Equation 9).

$$\text{COVID MN95} = 4.113\ \text{NNUR} + 1.790\ \text{NCOV} \quad (9)$$

The NCOV and NNUR variables explained 90.60% of the consumption of MN95 items (Table 3). The ANOVA result found $p < .05$ for NCOV, showing it was a significant variable. In the regression Equation (9), every extra healthcare personel produces an increase of 4.113 and every extra COVID patients produces an increase of 1.790 in the consumption of MN95. The MAD and mean percentage absolute error (MAPE) values were calculated for the predictions with Equation 9; the MAD value was 739.48 and the MAPE value was 52.3%.

Residual plot diagrams are important to assess analysis results as they show the fit of data to normal distribution. As MN95 items were almost not used at all during the N-COVID period, normality checks were performed for data from the COVID period, and Figure 2 shows that the residuals for the data were normally distributed and homoscedasticity assumption was proved.

**Table 2.**
*Pearson's Correlations Between Dependent and Independent Variable*

| Variable | | NDOC | NNUR | NEMP | NPAT | NSUR | NCOV | HDSF | MRUBSUR | MN95 | EXGLV | TTSURGLV |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. NDOC | Pearson's *r* | – | | | | | | | | | | |
| | *p* | – | | | | | | | | | | |
| 2. NNUR | Pearson's *r* | .256 | – | | | | | | | | | |
| | *p* | .115 | – | | | | | | | | | |
| 3. NEMP | Pearson's *r* | –.398* | .063 | – | | | | | | | | |
| | *p* | .012 | .703 | – | | | | | | | | |
| 4. NPAT | Pearson's *r* | –.214 | .139 | .09 | – | | | | | | | |
| | *p* | .19 | .399 | .586 | – | | | | | | | |
| 5. NSUR | Pearson's *r* | –.186 | –.191 | –.14 | .72*** | – | | | | | | |
| | *p* | .257 | .243 | .396 | <.001 | – | | | | | | |
| 6. NCOV | Pearson's *r* | .459** | –.026 | –.264 | –.518*** | –.505** | – | | | | | |
| | *p* | .003 | .875 | .105 | <.001 | .001 | – | | | | | |
| 7. HDSF | Pearson's *r* | .502** | .091 | –.188 | –.523*** | –.504** | .735*** | – | | | | |
| | *p* | .001 | .581 | .252 | <.001 | .001 | <.001 | – | | | | |
| 8. MRUBSUR | Pearson's *r* | .538*** | .302 | –.496** | –.153 | –.106 | .519*** | .653*** | – | | | |
| | *p* | <.001 | .062 | .001 | .351 | .52 | <.001 | <.001 | – | | | |
| 9. MN95 | Pearson's *r* | .559*** | .159 | –.526*** | –.444** | –.301 | .819*** | .661*** | .728*** | – | | |
| | *p* | <.001 | .335 | <.001 | .005 | .062 | <.001 | <.001 | <.001 | – | | |
| 10. EXGLV | Pearson's *r* | .304 | .243 | .067 | –.25 | –.355* | .581*** | .668*** | .361* | .5** | – | |
| | *p* | .06 | .136 | .683 | .125 | .026 | <.001 | <.001 | .024 | .001 | – | |
| 11. TTSURGLV | Pearson's *r* | .053 | –.001 | –.387* | .544*** | .61*** | –.252 | –.211 | .285 | –.017 | –.057 | – |
| | *p* | .748 | .994 | .015 | <.001 | <.001 | .122 | .198 | .079 | .916 | .729 | – |

*Note:* *$p < .05$.
**$p < .01$.
***$p < .001$.
EXGLV = examination glove; HDSF = hand disinfectant; MN95 = number of mask 95; MRUBSUR = medical/surgical mask; NCOV = number of COVID-19 patients; NDOC = number of doctors; NEMP = number of employees; NNUR = number of nurses; NPAT = number of patients; NSUR = number of surgeries; TTSURGLV = total surgical gloves.

**Table 3.**
*Multiple Linear Regression Analysis for MN95*

| Variables | Step 1 | | Step 2 | | Step 3 | | Step 4 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | *p* | Coefficient | *p* | Coefficient | *p* | Coefficient | *p* | VIF[b] |
| NDOC | 36.2 | .144 | 26.5 | .125 | | | | | |
| NNUR | 6.53 | .097 | 5.71 | .109 | 6.79 | .063 | 4.113 | .000 | 1.99 |
| NEMP | −94.5 | .094 | −82.7 | .106 | −29.1 | .439 | | | |
| NPAT | −0.0248 | .570 | | | | | | | |
| NCOV | 1.798 | .000 | 1.881 | .000 | 1.928 | .000 | 1.790 | .000 | 1.99 |
| | | | | | | | | | |
| *S* | | 991.872 | | 976.005 | | 1009.75 | | 1001.42 | |
| $R^2$ | | 92.62% | | 92.50% | | 91.59% | | 91.35% | |
| $R^2$ (adjusted) | | 90.77% | | 91.07% | | 90.44% | | 90.60% | |
| Mallows' Cp | | 5.00 | | 3.33 | | 3.80 | | 2.44 | |

*Note:* [a]Coefficient of independent variables in regression equation.
NCOV = number of COVID-19 patients; NDOC = number of doctors; NEMP = number of employees; NNUR = number of nurses; NPAT = number of patients; VIF = variance inflation factor.

**Prediction of Hand Disinfectant Consumption with Multiple Linear Regression Analysis**

Coronavirus disease 2019 is known to cause an increase in the use of HDSF items among patients and healthcare workers as a result of mask, distance, and hygiene rules. In the normal period, only healthcare workers displayed care in using disinfectant items, while after the pandemic, patients attending hospital began to pay attention to the use of disinfectants. Examining the correlation matrix table for HDSF items, significant correlations were observed for NPAT ($r = -.523$), NDOC ($r = .502$), and NCOV ($r = .735$), which were taken as independent variables. When the categorical variable of COVID and N-COVID periods are assessed with all data, the regression Equations 10a and 10b were obtained. These equations explained 91.06% of the consumption of HDSF materials. The *S* value was 176.948 (Table 4). The normality diagram shows that the residuals obtained as a result of the regression equation displayed normal distribution (Figure 3). According to the regression equation, HDSF consumption increased by a mean of 188.3 L in the COVID period. For each increase in the number of doctors and the number of COVID patients, there were a mean 3.009 L and 0.2365 L increase in HDSF consumption, respectively.

$$\text{COVIDHDSF} = 188.3 + 3.009\ \text{NDOC} + 0.2365\ \text{NCOV} \quad (10a)$$

$$\text{N} - \text{COVIDHDSF} = 0.0 + 3.009\text{NDOC} + 0.2365\text{NCOV} \quad (10b)$$

For only the COVID-19 period, the analysis results with NPAT, NDOC, and NCOV variables provided the regression equation in

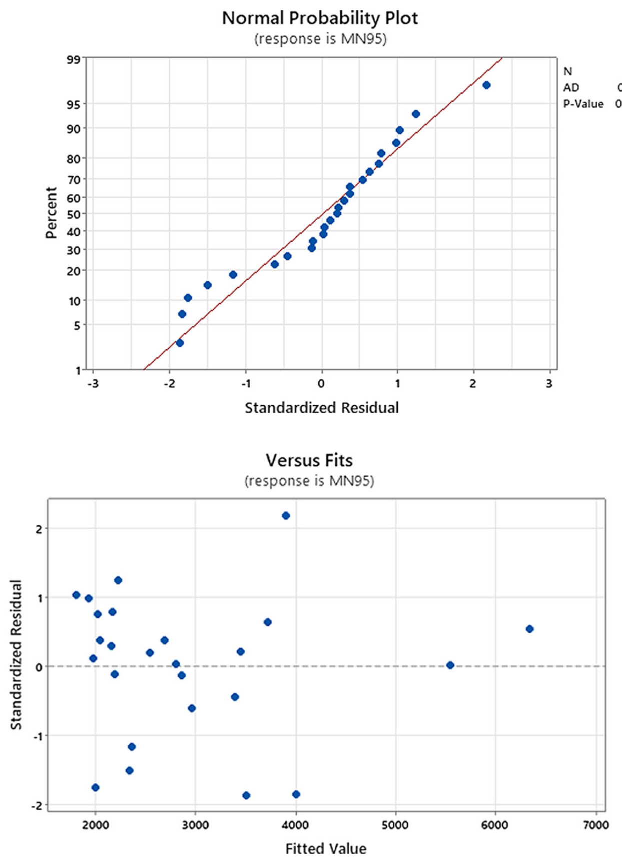
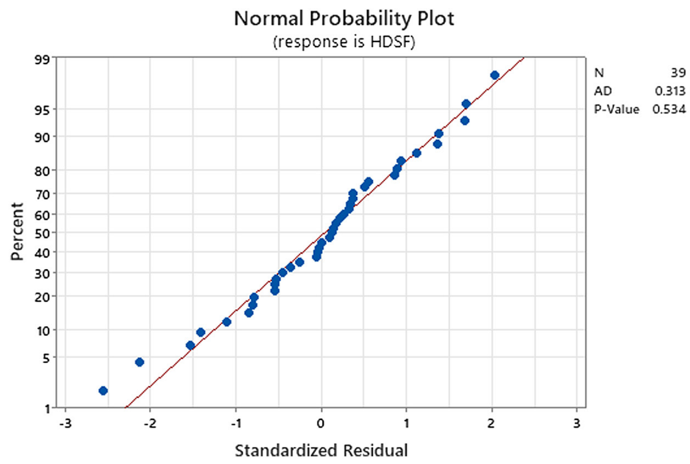



**Figure 2.**
*Residual Plot for MN95. MN95 = number of mask 95.*

**Table 4.**
*Regression Coefficient for HDSF Material*

| Variables | Step 1 | | Step 2 | | |
|---|---|---|---|---|---|
| | Coefficient | *p* | Coefficient | *p* | VIF |
| NPAT | −0.00652 | .248 | | | |
| NDOC | 5.53 | .017 | 3.009 | .000 | 3.20 |
| NCOV | 0.2045 | .002 | 0.2365 | .000 | 2.22 |
| Pandemic | 159.3 | .047 | 188.3 | .015 | |
| | | | | | |
| *S* | | 176.016 | | 176.948 | |
| $R^2$ | | 92.06% | | 91.74% | |
| $R^2$ (adjusted) | | 91.15% | | 91.06% | |
| Mallows' Cp | | 4.00 | | 3.38 | |

*Note:* HDSF = hand disinfectant; NCOV = number of COVID-19 patients; NDOC = number of doctors; NPAT = number of patients; VIF = variance inflation factor.



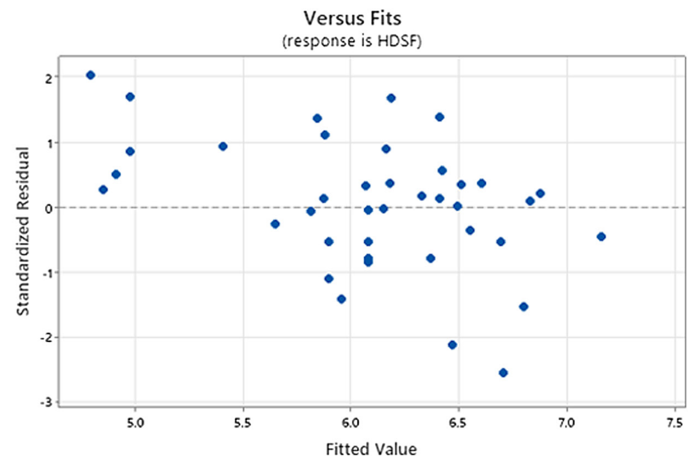




**Figure 3.**
*Residual Plot for HDSF. HDSF = hand disinfectant.*

Equation 11a. Analysis results for only the N-COVID period provided the regression equation for HDSF material in Equation 11b.

$$\mathrm{COVIDHDSF} = 0.01308\mathrm{NPAT} + 0.3296\,\mathrm{NCOV} \tag{11a}$$

$$\mathrm{N-COVIDHDSF} = 0.007687\mathrm{NPAT} \tag{11b}$$

To determine the model best explaining HDSF consumption, consumption was predicted with Equations 10a and 10b and Equations 11a and 11b. The MAD and MAPE values were calculated for the predictions and real values, and the model with smallest values was accepted. For predictions with Equations 10a and 10b, the MAD value was 122.35 and the MAPE value was 28.3%. For predictions with Equations 11a and 11b, the MAD value was 141.82 and the MAPE value was 31.2%. When compared to the models, the first model (10a, b) had smaller MAPE and MAD values. Therefore, Equations 10a and 10b with low MAPE and MAD values were chosen to predict HDSF consumption in the coming months.

### Prediction of Examination Glove Consumption with Multiple Linear Regression Analysis

Examination gloves are changed after every patient is examined. Examination gloves are known to be most intensely used by doctors and healthcare workers. The consumption of EXGLV items in the N-COVID period was most associated with the NPAT variable with .783 correlation and .05 *p*-value obtained in correlation analysis (Table 5). Consumption, which could be explained by patient numbers in the N-COVID period, can be observed to have a large increase from March 2020 with the attendance of COVID patients. For this reason, it was observed from the data in Table 2 that the NPAT variable along with NDOC, NNUR, and NCOV variables may be effective. Due to the differences in these variables and knowing patient number is one of the implementations affecting the use of gloves, three regression equations were obtained as a result of analyses with the NPAT, NDOC, NNUR, and NCOV variables. Equation 12 shows the equation when all data are assessed together, while Equation 13a shows the equation predicting the N-COVID period and Equation 13b shows the regression equation obtained for the COVID period.

$$\mathrm{COVID\,\&\,N-COVIDEXGLV} = 3923\mathrm{NDOC} + 38.1\,\mathrm{NCOV} \tag{12}$$

$$\mathrm{N-COVIDEXGLV} = 10.333\mathrm{NPAT} \tag{13a}$$

$$\mathrm{COVIDEXGLV} = 10.541\mathrm{NPAT} + 113.7\,\mathrm{NCOV} \tag{13b}$$

According to Equation 12, consumption of EXGLV items appear to be affected by NDOC and NCOV variables. For each increase in doctor numbers, there is a monthly increase of 3923 items, and each increase in COVID patient numbers will cause a 38.1 increase in the EXGLV consumption. If we consider EXGLV consumption in only the N-COVID period, for each increase in patient numbers, there will be a 10.333 item increase in EXGLV consumption. According to data in Table 6, the $R^2_{(adj)}$ value is 97.95%, *S* value is 57,896.6, and Mallows' Cp value is 2.52 for Equation 12. The model in Figure 4 shows that the residuals have normal distribution. Due to obtaining different equations, in order to determine the model best explaining EXGLV consumption, predictions were calculated with Equation 12 and Equations 13a and 13b. The MAD value was 46,643.86 and the MAPE value was 11.8% for Equation 12. The MAD value was 50,361.26 and the MAPE value was 12.0% for the predictions obtained with Equations 13a and 13b. The decision was made to continue with the model obtained with the equation best explaining EXGLV consumption in Equation 12.

### Prediction of Medical Face Mask Consumption with Multiple Linear Regression Analysis

The supply of masks, gloves, protective equipment, and disinfectant products has been risky during the pandemic period. Because of this, even the businesses that we normally supply have had trouble getting supplies. Interviews have been set up with the managers of the factories that produce these goods, but they have provided unfavorable feedback. For instance, whereas we requested 10,000 masks, only 2000 were delivered. In addition, each item's price varies because no manufacturer maintains a regular stock. The rubberized mask's unit cost was 0.08 Turkish liras (TL) in January 2020, but it rose to 2.30 TL in March. The hospital planted 110,000 masks in April 2020 to make up for the absence of masks.

Masks are sold as two types: medical face masks and tie band surgical masks. As both items can be substituted for the other, consumptions of both items were collected as the name of MRUBSUR. In April 2020, which is the beginning time of the COVID pandemic period, 28,630 masks were used, despite the fact that there were 2154 COVID patients, due to both the difficulties experienced in the mask training and the absence of the obligation to wear a mask. This row was omitted from the study, and

**Table 5.**
*Table Correlation Coefficient for N-COVID Period*

| **Pearson's correlations** | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | | **TTSURGLV** | **EXGLV** | **MN95** | **MRUBSUR** | **HDSF** | **NDOC** | **NNUR** | **NEMP** | **NPAT** | **NSUR** |
| 1. TTSURGLV | Pearson's *r* | – | | | | | | | | | |
| | *p* | – | | | | | | | | | |
| 2. EXGLV | Pearson's *r* | .685** | – | | | | | | | | |
| | *p* | .007 | – | | | | | | | | |
| 3. MN95 | Pearson's *r* | .027 | .153 | – | | | | | | | |
| | *p* | .927 | .601 | – | | | | | | | |
| 4. MRUBSUR | Pearson's *r* | .138 | .411 | .72** | – | | | | | | |
| | *p* | .637 | .144 | 0 | – | | | | | | |
| 5. HDSF | Pearson's *r* | −.1 | .184 | .62* | .55* | – | | | | | |
| | *p* | .74 | .53 | .02 | .04 | – | | | | | |
| 6. NDOC | Pearson's *r* | −.14 | .196 | .31 | .3 | .412 | – | | | | |
| | *p* | .626 | .502 | .28 | .31 | .143 | – | | | | |
| 7. NNUR | Pearson's *r* | −.03 | .476 | .36 | .68** | .363 | .78** | – | | | |
| | *p* | .924 | .086 | .21 | .01 | .203 | .001 | – | | | |
| 8. NEMP | Pearson's *r* | .14 | .487 | .23 | .3 | .685** | .574* | .495 | – | | |
| | *p* | .633 | .078 | .43 | .3 | .007 | .032 | .072 | – | | |
| 9. NPAT | Pearson's *r* | .397 | .783*** | .13 | .61* | .175 | .142 | .537* | .275 | – | |
| | *p* | .16 | <.001 | .67 | .02 | .549 | .629 | .048 | .342 | – | |
| 10. NSUR | Pearson's *r* | .388 | .442 | .08 | .28 | −.02 | −.2 | −.01 | −.02 | .7** | – |
| | *p* | .171 | .114 | .78 | .33 | .958 | .485 | .978 | .942 | .01 | – |

*Note:* *$p < .05$.
**$p < .01$.
***$p < .001$.
EXGLV = examination glove; HDSF = hand disinfectant; MN95 = number of mask 95; MRUBSUR = medical/surgical mask; NDOC = number of doctors; NEMP = number of employees; NNUR = number of nurses; NPAT = number of patients; NSUR = number of surgeries; TTSURGLV = total surgical gloves.

**Table 6.**
*Regression Coefficients for EXGLV Material*

| **Variables** | **Step 1** | | **Step 2** | | **Step 3** | | |
|---|---|---|---|---|---|---|---|
| | **Coefficient** | ***p*** | **Coefficient** | ***p*** | **Coefficient** | ***p*** | **VIF** |
| NPAT | 2.42 | .191 | 2.64 | .128 | | | |
| NDOC | 3089 | .000 | 2959 | .000 | 3923 | .000 | 1.63 |
| NCOV | 57.9 | .006 | 55.6 | .006 | 38.1 | .018 | 1.63 |
| Pandemic | −9831 | .700 | | | | | |
| | | | | | | | |
| *S* | 57,496.3 | | 56,814.1 | | 57,896.6 | | |
| $R^2$ | 98.19% | | 98.18% | | 98.06% | | |
| $R^2$ (adjusted) | 97.98% | | 98.03% | | 97.95% | | |
| Mallows' Cp | 4.00 | | 2.15 | | 2.52 | | |

*Note:* EXGLV = examination glove; NCOV = number of COVID-19 patients; NDOC = number of doctors; NPAT = number of patients; VIF = = variance inflation factor.

the computation was done in order to produce accurate results in the MLRA analysis.

Regression Equations 14a and 14b were obtained by considering all data in the analysis results performed with NDOC, NEMP, and NCOV variables affecting the variation in MRUBSUR items. According to Equations 14a and 14b, for each increase in the number of nurses, there will be a 50.26 item increase in the consumption of MRUBSUR items, and if the number of COVID patient increases, the consumption rate will be increased 14.49 items. Additionally, during the COVID period, there was a mean 19,741 item increase in monthly use.

$$\text{COVID MRUBSUR} = 19{,}741 + 50.26\ \text{NNUR} + 14.49\ \text{NCOV} \quad (14a)$$

$$\text{N-COVID MRUBSUR} = 0.0 + 50.26\ \text{NNUR} + 14.49\ \text{NCOV} \quad (14b)$$

As a result of MLRA performed due to the effect of NPAT and NNUR variables in correlation analysis results for the MRUBSUR items in the N-COVID period, Equation 15a was predicted.

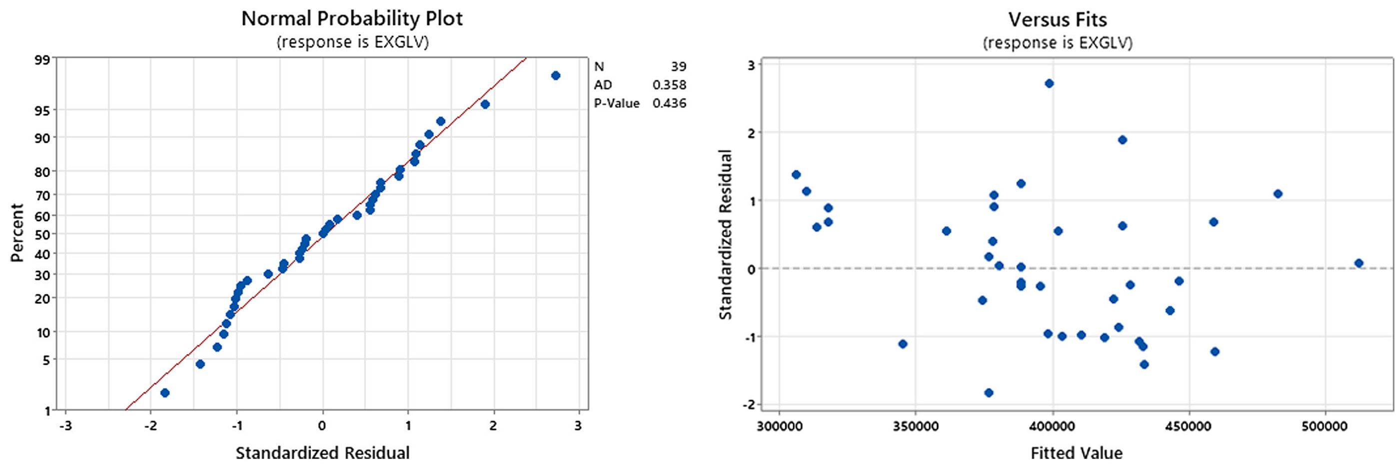



**Figure 4.**
*Residual Plot for EXGLV. EXGLV = examination glove.*

According to data in Table 7, the R_((adj))^2 value is 94.80%, S value is 9637.78 and Mallows' Cp value is 1.99 for MRUBSUR. But in COVID-19 period, NCOV variable was found significant in using MRUBSUR items and Equation 15b was obtained. This equation shows that the predicted MRUBSUR comsumption increases by 16.40 for every Covid patient added.

$$\text{N-COVID MRUBSUR} = 49.2(\text{NNUR}) \quad (15a)$$

$$\text{COVID MRUBSUR} = 96.12\ \text{NNUR} + 16.40\ \text{NCOV} \quad (15b)$$

If we consider MRUBSUR consumption only in the N-COVID period, for each increase in the number of healthcare workers, there will be an increase of 49.2 masks used monthly. If we only consider the COVID period, every increase in the number of healthcare workers will cause a monthly increase of 96.12 for MRUBSUR consumption, and if the number of COVID patients increases, the consumption rate will be increased 16.40 items. Due to obtaining different equations, with the aim of determining the model best explaining MRUBSUR consumption, predictions were calculated with Equations 14a and 14b and Equations 15a and 15b. The MAD value was 7057.56 and the MAPE value was 20.0% for Equations 14a and 14b. For predictions with Equations 15a and 15b, the MAD value was 7281.67 and the MAPE value was 20.2%. The decision was made to predict using the equations best explaining the MRUBSUR consumption for the COVID and N-COVID periods (in other words, Equations 14a and 14b).

Figure 5 shows the probability plot, the data form an approximately straight line along the line. The normal distribution appears to be a good fit to the data for MRUBSUR variable.

**Prediction of Surgical Glove Consumption with Multiple Linear Regression Analysis**

It is known that TTSURGLV items are generally used for surgeries. The equation best explaining consumption was Equation 16 ($R^2_{(adj)}$ = 96.28%) obtained as a result of analysis including the NEMP, NPAT, and NSUR variables considered to affect the consumption of this item in the regression model. Table 8 shows the MLRA results for TTSURGLV. This equation shows that for every surgery, a mean 4.721 gloves were used. The regression equations obtained for N-COVID and COVID periods are given in Equations 17a and 17b.

The model in Figure 6 shows that the residuals have normal distribution.

**Table 7.**
*Regression Coefficients for MRUBSUR*

| Variables | Step 1 | | Step 2 | | Step 3 | | |
|---|---|---|---|---|---|---|---|
| | Coefficient | *p* | Coefficient | *p* | Coefficient | *p* | VIF |
| NDOC | 1 | .996 | | | | | |
| NEMP | −213 | .563 | −212 | .319 | | | |
| NNUR | 77.9 | .011 | 77.9 | .009 | 50.26 | .000 | 2.93 |
| NCOV | 15.51 | .000 | 15.52 | .000 | 14.49 | .000 | 2.25 |
| Pandemic | 16,531 | .025 | 16,553 | .003 | 19,741 | .000 | 4.39 |
| | | | | | | | |
| *S* | | 9779.63 | | 9634.74 | | 9637.78 | |
| $R^2$ | | 95.35% | | 95.35% | | 95.21% | |
| $R^2$ (adjusted) | | 94.64% | | 94.80% | | 94.80% | |
| Mallows' Cp | | 5.00 | | 3.00 | | 1.99 | |

*Note:* MRUBSUR = medical/surgical mask; NCOV = number of COVID-19 patients; NDOC = number of doctors; NEMP = number of employees; NNUR = number of nurses; VIF = variance inflation factor.

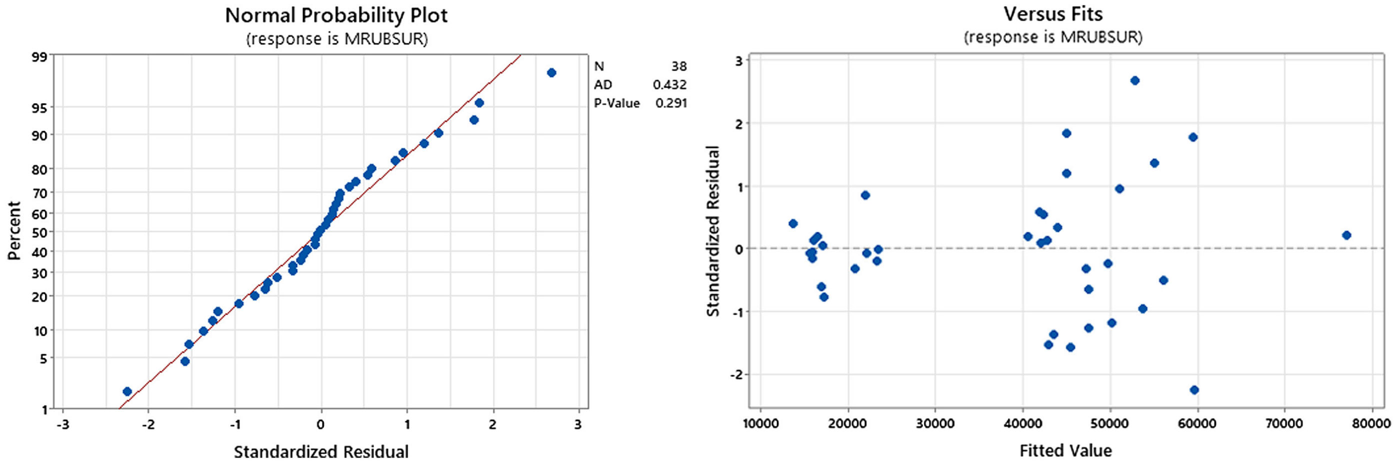



**Figure 5.**
*Residual Plot for MRUBSUR. MRUBSUR = medical/surgical mask.*

**Table 8.**
*Regression Coefficients for TTSURGLV Material*

| Variables | Step 1 | | Step 2 | | |
|---|---|---|---|---|---|
| | **Coefficient** | ***p*** | **Coefficient** | ***p*** | **VIF** |
| NEMP | 13.1 | .656 | | | |
| NSUR | 4.464 | .000 | 4.721 | .000 | 1.00 |
| *S* | | 2056.77 | | 2035.04 | |
| $R^2$ | | 96.40% | | 96.38% | |
| $R^2$ (adjusted) | | 96.20% | | 96.28% | |
| Mallows' Cp | | 2.00 | | 0.20 | |

*Note:* NEMP = number of employees; NSUR = number of surgeries; TTSURGLV = total surgical gloves; VIF = variance inflation factor.

$$\text{TTSURGLV} = 4.721\ (\text{NSUR}) \tag{16}$$

Equation 17a for the N-COVID period and Equation 17b for the COVID period were obtained from the results of the MLRA applied separately for the TTSURGLV items. While there was 4.204 TTSURGLV used per surgery in the N-COVID period, in the COVID period this use was modeled as 5.091 items.

$$\text{N-COVID TTSURGLV} = 4.204\ (\text{NSUR}) \tag{17a}$$

$$\text{COVID TTSURGLV} = 5.091\ (\text{NSUR}) \tag{17b}$$

Due to obtaining different equations, with the aim of deciding which model best explained TTSURGLV consumption, predictions were calculated with Equation 16 and Equations 17a and 17b. The MAD value was 1577.73 and the MAPE value was 15.1% for Equation 16. For prediction with Equations 17a and 17b, the MAD value was 1352.95 and the MAPE value was 12.6%. The decision was made to predict TTSURGLV consumption with the models for equations best explaining the COVID and N-COVID periods (in other words, Equations 17a and 17b.

**Prediction of All Medical Supplies for the Next Period**

Figure 7 shows the predicted values obtained with different models due to MLRA for medical supplies and actual consumption. The curves shown with blue lines represent the actual consumption values. The red lines show the graph of values predicted in models obtained by considering all periods together.

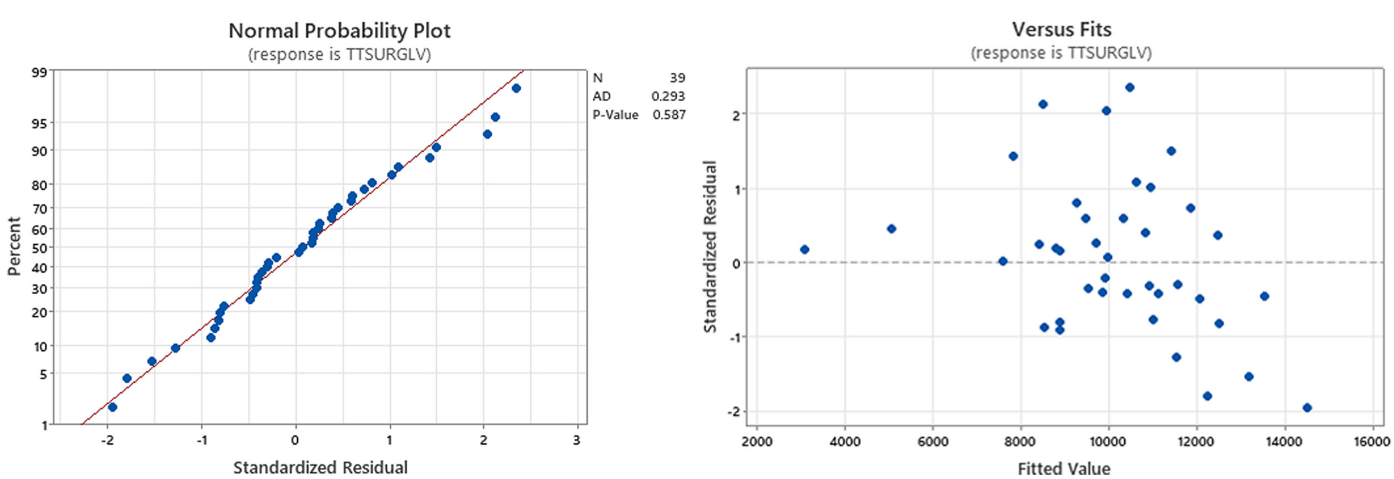



**Figure 6.**
*Residual Plot for TTSURGLV. TTSURGLV = total surgical gloves.*

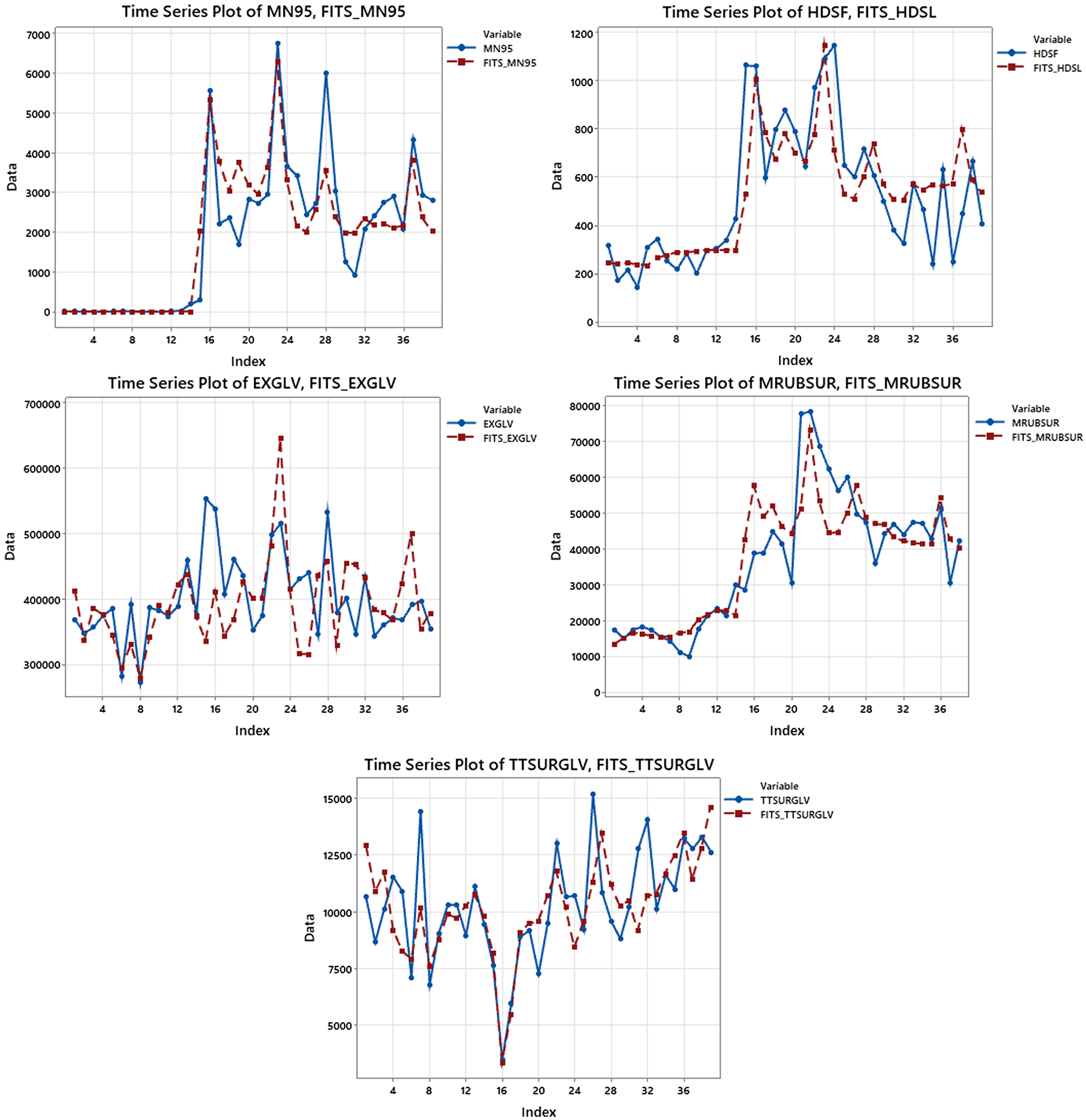



**Figure 7.**

*Predicted and Actual Consumptions for All Medical Supplies. MN95 = number of mask 95; HDSF = hand disinfectant; EXGLV = examination glove; MRUBSUR = medical/surgical mask; TTSURGLV = total surgical gloves.*

The Minitab software is used to apply the prediction response optimizer tool for future periods. Response optimization aids in finding the combination of variable settings that jointly optimize a particular response or a group of responses. When assessing the effects of various variables on a response, this is helpful. If response optimizer is employed, Figure 8 is obtained based on the MLRA results. By adjusting the red line to the right or left in this diagram according to the NDOC, NNUR, and NCOV while choosing the COVID period, hospital management may forecast how much medical supply will be used. According to individual and composite desirability, you can determine how well a set of variables satisfies the objectives you have set for the responses. Composite desirability (*D*) assesses how the circumstances optimize a collection of replies, while individual desire (*d*) assesses how the conditions optimally optimize a single response. Desirability is measured on a scale from 0 to 1. Zero signifies that one

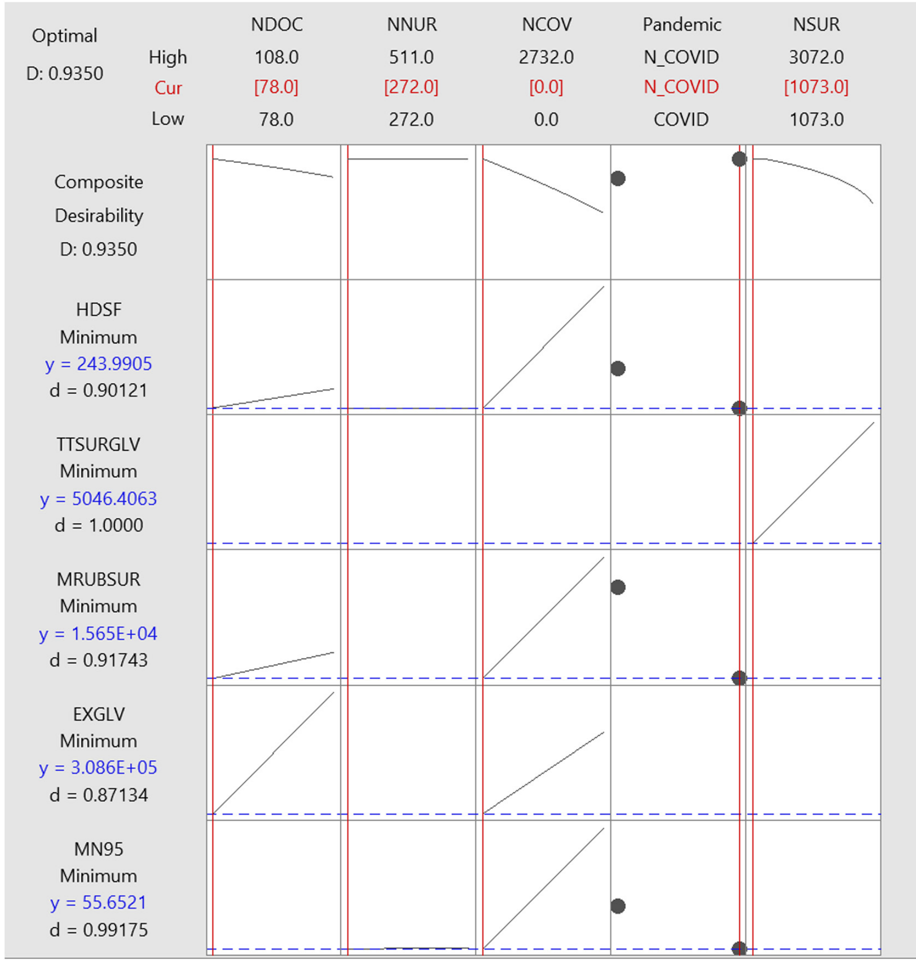



**Figure 8.**
*Response Optimizer of All Medical Supplies for N-COVID Period. EXGLV = examination glove; HDSF = hand disinfectant; MN95 = number of mask 95; MRUBSUR = medical/surgical mask; NCOV = number of COVID-19 patients; NDOC = number of doctors; NNUR = number of nurses; NSUR = number of surgeries; TTSURGLV = total surgical gloves.*

or more responses fall outside of the permissible range, whereas 1 represents the optimum situation. The composite desirability in this case (0.9350) is quite close to 1, indicating that the settings appear to produce favorable outcomes for all responses taken together.

## Discussion

The desire was to assist hospital management in making purchasing decisions by performing predictions about the future with consumption figures obtained from the hospital. The COVID-19 pandemic affected the number of patients and number of surgeries, which can be seen from the data in Table 1 and Figure 1. As the COVID-19 numbers increased, the number of patients and surgeries reduced. Decisions taken by the government affected these numbers. At the beginning of the COVID-19 period in April, all hospitals were transformed to pandemic hospitals and did not accept patients except in emergency situations. Non-critical surgeries were postponed. Mask, distance, and hygiene rules were implemented to intervene against COVID-19. For this reason, the demand for some supplies increased during the pandemic. Supply problems were encountered due to this increase, and some items had to be purchased at very different prices. Especially when masks could not be obtained, hospitals were forced to sew their own masks. Over time, suppliers proliferated and capacity increased. The reduction in pandemic numbers linked to the progression of the pandemic and implementation of preventive measures will affect the supply chain. All suppliers and hospital management in the world and Turkey have the opportunity to be able to implement correct purchasing policies by monitoring the progression of the pandemic. This is an important reason for the inability to use time-series estimation methods to predict consumption. The multiple regression analysis is a method accepted for use to predict the dependent variable linked to more than one independent variable. The desire is to predict consumption by finding the effect of variance in medical supply consumption that will form due to independent variables; for this reason, consumption of medical supplies considered to be linked to the pandemic was included.

## Conclusion and Recommendations

In conclusion, the MLRA was used to create mathematical models to predict the consumption of medical supplies in a hospital in Turkey. The data were gathered from January 2019 to March 2022 that included the COVID-19 and non-COVID periods. Correlations were observed between the NPAT, NSUR, and NCOV variables in the analysis of samples. Independent variables with high multicollinearities were not used in the models.

In this study, regression models were used to predict the monthly consumption of medical supplies in a hospital linked to the consumption of medical supplies during the COVID and N-COVID periods and NDOC, NNUR, NEMP, NPAT, NCOV, and NSUR. Regression models were obtained to predict the consumption of MN95, EXGLV, HDSF, TTSURGLV, and MRUBSUR items in future periods. While examining the best model in order to predict consumption during the COVID and non-COVID periods, we analyzed periods separately and together. We selected the best model according to the MAPE and MAD values that gives the smallest deviation values.

This study shows that the use of MN95 has a strong relationship with the number of COVID patients. According to the obtained regression equation, NCOV and NNUR variables explained 90.60% of MN95 usage. The change in HDSL consumption is explained by the NDOC and NCOV variables at the level of 91.06%. It is seen that there is a constant increase of 188 L in the COVID-19 period and varies depending on the number of doctors and COVID patients. It was observed that EXGLV changed with a strong correlation depending on the NPAT variable in the N-COVID period. It has been realized that NDOC, NNUR, and NCOV variables are effective in the COVID-19 period. With all these variables, three different regression models were obtained as a result of MLRA. Among these models, the model with the lowest MAPE and MAD values was selected. According to this model, EXGLV consumption can be estimated according to the change in NDOC and NCOV numbers. The NDOC, NNUR, NEMP, and NCOV variables were chosen as effective variables for the estimation of MRUBSUR consumption. It is seen that the best model obtained with these variables explains the variability of 94.80% with the NNUR and NCOV variables. The variable TTSURGLV was explained by the model with 96.28% depending on the number of surgeries. While the consumption per surgery was 4204 in the N-COVID period, the usage increased to 50,921 in the COVID period. It will be possible to obtain better results with more data.

This study will assist the prediction of consumption of medical supplies during pandemic periods in hospitals. Predictions of medical supply consumption will contribute to purchasing decisions and stock policies. Uncertainty is accepted for these models, considering that other factors affecting the consumption of medical supplies were not checked in this study and that the study is based on a relatively small sample.

Future studies will perform optimization studies and simulation studies minimizing stock costs for medical supplies to decide minimum stock levels.

**Peer-review:** Externally peer-reviewed.

**Author Contributions:** Concept – İ.S., R.Y.; Design – İ.S.; Supervision – R.Y.; Resources – İ.S., Ç.S.E.; Materials – İ.S., Ç.S.E.; Data Collection and/or Processing – Ç.S.E., İ.S.; Analysis and/or Interpretation – İ.S.; Literature Search – İ.S.; Writing Manuscript – İ.S.; Critical Review – R.Y.

**Declaration of Interests:** The authors state that there is no conflict of interest.

**Funding:** The author declares that this study had received no financial support.

**Hakem Değerlendirmesi:** Dış bağımsız.

**Yazar Katkıları:** Fikir – İ.S., R.Y.; Tasarım – İ.S.; Denetleme – R.Y.; Kaynaklar – İ.S.; Malzemeler – İ.S., Ç.S.E.; Veri Toplanması ve/veya İşlemesi – S.Ç.E., İ.S.; Analiz ve/veya Yorum – İ.S.; Literatür Taraması – İ.S.; Yazıyı Yazan – İ.S.; Eleştirel İnceleme – R.Y.

**Çıkar Çatışması:** Yazarlar çıkar çatışması bildirmemişlerdir.

**Finansal Destek:** Yazarlar bu çalışma için finansal destek almadıklarını beyan etmiştir.

## References

Araiza-Aguilar, J. A., Rojas-Valencia, M. N., & Aguilar-Vera, R. A. (2020). Forecast generation model of municipal solid waste using multiple linear regression. *Global Journal of Environmental Science and Management*, 6(1), 1–14. [CrossRef]

Aranda, A., Ferreira, G., Mainar-Toledo, M. D., Scarpellini, S., & Llera Sastresa, E. (2012). Multiple regression models to predict the annual energy consumption in the Spanish banking sector. *Energy and Buildings*, 49, 380–387. [CrossRef]

Bianco, V., Manca, O., & Nardini, S. (2009). Electricity consumption forecasting in Italy using linear regression models. *Energy*, 34(9), 1413–1421. [CrossRef]

Binoj, J. S., Manikandan, N., Thejasree, P., Varaprasad, K. C., Prem Sai, N., & Manideep, M. (2021). Machinability studies on wire electrical discharge machining of Nickel alloys using multiple regression analysis. *Materials Today: Proceedings*. *Proceedings*, 39, 155–159. [CrossRef]

Catalina, T., Iordache, V., & Caracaleanu, B. (2013). Multiple regression model for fast prediction of the heating energy demand. *Energy and Buildings*, 57, 302–312. [CrossRef]

Čeh, M., Kilibarda, M., Lisec, A., & Bajat, B. (2018). Estimating the Performance of Random Forest versus Multiple Regression for Predicting Prices of the Apartments. *ISPRS International Journal of Geo-Information*, 7(5), 168. [CrossRef]

Chahal, H., Jyoti, J., & Wirtz, J. (2018). Understanding the role of business analytics: Some applications. In *Understanding the role of business analytics*. Springer. [CrossRef]

Chapman, S. N. (2006). *The fundamentals of production planning and control (pp. 18)*. Pearson Education, Inc.

Chaurasia, V., & Pal, S. (2020). COVID-19 pandemic: Arima and regression model-based worldwide death cases predictions. *SN Computer Science*, 1(5), 288. [CrossRef]

Cihan, P. (2022). The machine learning approach for predicting the number of intensive care, intubated patients and death: The COVID-19 pandemic in Turkey. *Sigma Journal of Engineering and Natural Sciences – Sigma Mühendislik ve Fen Bilimleri Dergisi*, 1. [CrossRef]

Cohen, J., & Rodgers, Y. V. M. (2020) Contributing factors to personal protective equipment shortages during the COVID-19 pandemic. *Preventive Medicine*, 141(September), 106263. [CrossRef]

Crivellari, A., Beinat, E., Caetano, S., Seydoux, A., & Cardoso, T. (2022). Multi-target CNN-LSTM regressor for predicting urban distribution of short-term food delivery demand. *Journal of Business Research*, 144, 844–853. [CrossRef]

Demirkol Akyol, Ş. (2022). Covid-19 pandemisi sürecinde hijyen ürünleri üreten bir firmada tedarik zinciri ağı tasarımı. *European Journal of Science and Technology*, 35, 387–394. [CrossRef]

Ekingen, E., & Demir, B. (2021). Covid-19 salgın döneminde bir kamu hastanesinde kişisel koruyucu ekipman kullanımındaki değişimlerin incelenmesi. *İnönü Üniversitesi Sağlık Hizmetleri Meslek Yüksek Okulu Dergisi*, 9(2), 642–654. [CrossRef]

Flynn, B. B., Huo, B., & Zhao, X. (2010). The impact of supply chain integration on performance: A contingency and configuration approach. *Journal of Operations Management*, 28(1), 58–71. [CrossRef]

Furman, E., Cressman, A., Shin, S., Kuznetsov, A., Razak, F., Verma, A., & Diamant, A. (2021). Prediction of personal protective equipment use in hospitals during COVID-19. *Health Care Management Science*, 24(2), 439–453. [CrossRef]

Galwey, N. W. (2014). *Introduction to mixed modelling: Beyond regression and analysis of variance* (2nd ed). [CrossRef]

Ghinea, C., Drăgoi, E. N., Comăniţă, E. D., Gavrilescu, M., Câmpean, T., Curteanu, S., & Gavrilescu, M. (2016). Forecasting municipal solid waste generation using prognostic tools and regression analysis. *Journal of Environmental Management*, 182, 80–93. [CrossRef]

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate data analysis. In *Vectors*. [CrossRef]

Johnson, M. (2020). Wuhan 2019 novel coronavirus - 2019-nCoV. *Materials and Methods*, 10, 1–5. [CrossRef]

Mena, C., Karatzas, A., & Hansen, C. (2022). International trade resilience and the Covid-19 pandemic. *Journal of Business Research*, 138, 77–91. [CrossRef]

Minitab. (2021). *Minitab Statistical Software Release 18 for Windows*. Minitab 21 Release. https://www.minitab.com/en-us/

Montgomery, D. C., & Runger, G. C. (2003). Applied statistics and probability for engineers. In *Journal of the Royal Statistical Society, Series A* (Vol. 158). John Wiley & Sons, Inc. [CrossRef]

Nahmias, S. (2008). Production and operation analysis. In (pp. 56-58) *McGraw-Hill/Irwin Series Operation and Decision Science*.

Olsen, A. A., McLaughlin, J. E., & Harpe, S. E. (2020). Using multiple linear regression in pharmacy education scholarship. *Currents in Pharmacy Teaching and Learning*, 12(10), 1258–1268. [CrossRef]

Rath, S., Tripathy, A., & Tripathy, A. R. (2020). Prediction of new active cases of coronavirus disease (COVID-19) pandemic using multiple linear regression model. *Diabetes and Metabolic Syndrome*, 14(5), 1467–1474. [CrossRef]

Rhee, S. W. (2020). Management of used personal protective equipment and wastes related to COVID-19 in South Korea. *Waste Management and Research*, 38(8), 820–824. [CrossRef]

Roshan, R., Feroz, A. S., Rafique, Z., & Virani, N. (2020). Rigorous hand hygiene practices among health care workers reduce hospital-associated infections during the COVID-19 pandemic. *Journal of Primary Care and Community Health*, 11, 2150132720943331. [CrossRef]

Uyanık, G. K., & Güler, N. (2013). A study on multiple linear regression analysis. *Procedia – Social and Behavioral Sciences*, 106, 234–240. [CrossRef]

van der Laan, E., van Dalen, J., Rohrmoser, M., & Simpson, R. (2016). Demand forecasting and order planning for humanitarian logistics: An empirical assessment. *Journal of Operations Management*, 45(1), 114–122. [CrossRef]

World Health Organization (WHO). (2020). *Emergency Global Supply Chain System (COVID-19) catalogue*. https://www.who.int/publications/i/item/emergency-global-supply-chain-system-(covid-19)-catalogue

World Health Organization (WHO). (2020). Rational use of personal protective equipment for coronavirus disease 2019 (COVID-19) and considerations during severe shortages. *Who*, 1–7. https://apps.who.int/iris/handle/10665/331695

# Genişletilmiş Özet

**Amaç:** Bu çalışmanın amacı, COVID-19 pandemisi ile birlikte tüketimi artan hijyen ve koruyucu sarf malzemelerin ilerleyen ve gelişen dönemlerdeki talebini tahmin etmektir, ayrıca benzer durumlar için örnek olabilecek bir model oluşturmaktır.

**Yöntem:** Bu çalışma için İstanbul gibi metropol bir şehirde nüfus yoğunluğunun en fazla olduğu bölgelerden birinde bulunan özel bir hastanenin hijyen ve koruyuculuk sağlayan sarf malzeme tüketimlerine ait veriler ele alınmıştır. Verileri dikkate alınan hastane, 2020 Mart – Eylül aylarında pandemi hastanesi olarak fonksiyon üstlenmiştir. Hastane yönetimi ile yapılan görüşmeler sonrasında tedarik yönetimi farklılaşan fakat daha öncesinde yüksek derece önem oluşturmayan (ABC analizi içinde C grubu malzeme olarak dikkate alınabilen), COVID-19 salgınında tüketimlerinin etkilendiği düşünülen sarf malzemeleri olarak maske cerrahi bağcılıklı, maske lastikli, maske N95, el dezenfektanı, muayene eldiveni, ameliyat eldiveni malzemeleri dikkate alınmıştır. Bu çalışmada, bir hastanenin COVID-19 dönemi ve COVID-19 olmayan dönemi sarf malzeme tüketimleri bağımlı değişken olarak, doktor, sağlık çalışanı, idari personel, hasta, COVID-19 hastası, ameliyat sayıları bağımsız değişken olarak tanımlanmış ve hastanenin aylık sarf malzeme tüketimlerini tahmin etmek için çok değişkenli regresyon modelleri kullanılmıştır. Bu çalışma kapsamında COVID-19 pandemisinin olduğu Mart 2020-Mart 2022 tarihlerini içeren 25 aylık bir dönem ile pandemi öncesi döneme ait olan Ocak 2019-Şubat 2020 tarihleri arasındaki 14 aylık döneme ait sarf malzemelerin tüketim rakamları ele alınmıştır. Regresyon analizi çalışmaları için Minitab Statistical Software (Minitab, 2019) kullanılmıştır.

**Bulgular:** Bilinmeyen bulaşıcı hastalıklar ortaya çıktıkça, araştırmacılar salgın ve salgın ile ilgili bilim konularında modelleme ve tahmin çalışmaları yapmaya başlarlar. Yapılan bu modelleme ve tahmin çalışmaları halk sağlığı hizmetlerinin ve medikal ihtiyaçların planlamasında faydalı olmuştur ve gelecekte de olacaktır. Özellikle de veri biliminin gelişmesiyle birlikte çok sayıda tahmin yöntemi salgın alanında kullanılmaya başlamıştır.

Bu çalışmada, hastaneden elde edilen sarf malzemelerin tüketim rakamları ile geleceğe yönelik tahminler yapılarak hastane yönetiminin satın alma kararlarına yardımcı olmak istenmiştir. Elde edilen veriler doğrultusunda COVID-19 pandemisinin hastaneye muayene için gelen hasta sayısını ve ameliyat sayısını etkilediği gözlenmiştir. COVID-19 sayıları arttıkça hasta ve ameliyat sayısı azalmıştır. Çoklu regresyon analizi sonucunda; hastaneye normal muayene için gelen hasta sayısı, ameliyat sayısı ve COVID-19 hasta sayısı arasında güçlü bir korelasyon olduğu görülmektedir. N95 maskesinin COVID-19 olmayan dönemde neredeyse hiç kullanılmamaktayken COVID-19 pandemisi ile birlikte ciddi miktarda tüketiminde artış olduğu ve regresyon analizi sonucunda da COVID-19 hasta sayısına bağlı olarak değiştiği ortaya çıkmıştır. El dezenfektanının tüketimindeki değişimi en iyi açıklayan faktörlerin doktor sayısı ve COVID-19 hasta sayısı olmuştur. Muayene eldiveninin COVID-19 pandemi öncesinde tüketimin muayene edilen hasta sayısına bağlı olarak değiştiği, fakat COVID-19 pandemi döneminde tüketimin doktor sayısı, sağlık personeli sayısı ve COVID-19 hasta sayısına bağlı değiştiği hesaplanmıştır. Aynı şekilde, cerrahi bağcıklı ve lastikli maske kullanımını en iyi açıklayan değişkenler sağlık personeli sayısı ve COVID-19 hasta sayısı olmuştur. Ameliyat eldivenin tüketiminin ise ameliyat sayısına göre değişkenlik gösterdiği elde edilmiştir. Bu çalışma ile pandemi döneminde alınması gereken maske, mesafe ve hijyen önlemleri doğrultusunda kullanılması gereken sarf malzemelerin tüketimlerinin tahmin edilmesinde yardımcı olacak tahmin modelleri önerilmiştir. Bu tahminler, hastanelerin sarf malzemelerinin satınalma ve sipariş politikalarına katkı sağlayacaktır. Bunun sonucunda, en iyi tahminlemeyi yaparak hem stoksuz kalmamak hem de fazla stok maliyetini engellemek üzere hastane yönetimine yardımcı olunacaktır.