Predicting Patient Recovery Time Using Clinical and Lifestyle Variables: A Statistical Approach

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Abstract:

Understanding the factors influencing patient recovery time is essential for improving healthcare outcomes. This study applies a Multiple Linear Regression (MLR) model to predict recovery time using clinical (Age, BMI, Severity Score, Hospital Stay, Underlying Conditions, Medication Type) and lifestyle factors (Smoking, Alcohol Consumption, Physical Activity). A dataset covering a 10-year period (2014–2023) was analyzed. The MLR results reveal that Severity Score ($\beta = 5.0021$, $p < 0.001$) and Hospital Stay ($\beta = 0.8052$, $p < 0.001$) are the strongest predictors of recovery time. Lifestyle choices also significantly impact recovery: smoking ($\beta = 1.5634$, $p < 0.001$) and alcohol consumption ($\beta = 1.4082$, $p < 0.001$) extend recovery time, while higher physical activity ($\beta = -0.9352$, $p = 0.0012$) speeds it up. The model explains 98.5% of the variance ($R^2 = 0.985$) and has a low RMSE (1.91 days), indicating high accuracy. The findings highlight the need for personalized treatment plans that consider both medical conditions and lifestyle habits. Healthcare providers can use this model to predict recovery time more effectively and design interventions that encourage healthy lifestyle changes. Future research should explore non-linear effects and integrate additional biological markers for enhanced predictive accuracy.

Keyword: Clinical Variables, Healthcare, Lifestyle Factors, Multiple Linear Regression, Predictive Modeling, Recovery Time

1.0 Introduction

Recovery time following illness or medical treatment is a critical measure of healthcare outcomes and varies significantly among patients due to multiple influencing factors (Jones et al., 2017; Smith et al., 2018). Traditionally, medical professionals have relied on clinical indicators such as disease severity, comorbidities, and hospital stay duration to estimate recovery times (Johnson & Patel, 2019). However, lifestyle factors, including smoking, alcohol consumption, and physical activity, have gained recognition for their impact on patient recovery (Brown et al., 2020; Garcia et al., 2021). Understanding these factors is crucial for optimizing patient care, reducing hospitalization periods, and improving health outcomes. Recent research suggests that statistical modeling techniques, such as Multiple Linear Regression (MLR), offer a powerful means to identify and quantify the impact of these variables on recovery time (Kumar et al., 2022; Rodriguez et al., 2022). By integrating both clinical and behavioral factors, MLR models provide predictive insights that can guide medical decision-making and personalized patient management (Thompson et al., 2023). This study applies MLR to analyze the impact of clinical and lifestyle variables on patient recovery time over a 10-year period (2014–2023), aiming to quantify the effect of key clinical factors, examine the role of lifestyle behaviors, and develop a predictive model to assist healthcare providers in optimizing patient treatment plans.

Literature Review

The role of age and body mass index (BMI) in influencing recovery time has been well-documented. Older adults often experience longer hospital stays and slower healing processes due to age-related physiological changes (Jones et al., 2017; Zhao et al., 2022). Likewise, patients with a higher BMI are at increased risk of post-treatment complications, which prolong recovery (Anderson et al., 2016; Alghamdi et al., 2022). Disease severity remains a key determinant, with more severe cases requiring extended medical intervention and rehabilitation (Chen et al., 2020; Kumar et al., 2023). Lifestyle behaviors also play a crucial role. Smoking has been linked to impaired immune responses and slower wound healing, leading to extended recovery periods (Williams & Taylor, 2015; Wang et al., 2023). Similarly, excessive alcohol consumption weakens the immune system and delays recovery from illnesses and surgeries (Dawson et al., 2019). Conversely, regular physical activity enhances recovery rates by improving cardiovascular health, metabolism, and immune function (Miller et al., 2021; Jones & Patel, 2023). Despite these well-established associations, few studies have simultaneously examined clinical and lifestyle factors in a predictive modeling framework (Rodriguez et al., 2022; Williams et al., 2024). This study addresses this gap by applying MLR to analyze the impact of clinical and lifestyle variables on patient recovery time.

2.0 Materials and Methods

2.1 Data Source and Collection

The dataset was collected from five major tertiary hospitals in Nigeria, including:

1. University College Hospital (UCH), Ibadan
2. Lagos University Teaching Hospital (LUTH), Lagos
3. Obafemi Awolowo University Teaching Hospital (OAUTHC), Ile-Ife
4. Aminu Kano Teaching Hospital (AKTH), Kano
5. Federal Medical Centre (FMC), Abuja

The dataset was obtained from hospital electronic medical records (EMR) systems, with ethical approval obtained from each institution's Health Research Ethics Committee (HREC). The dataset covered patient records from 2014 to 2023, ensuring a comprehensive analysis of recovery trends.

The dataset comprises 10,000 patient records, capturing key demographic, clinical, and lifestyle variables that may influence recovery time.

Variables Considered

1. Dependent Variable:
   - Recovery Time (days): The total number of days a patient required to recover and be discharged.
2. Independent Variables:

- Demographic Factors: Age (years), Body Mass Index (BMI).
- Clinical Factors: Disease severity score, duration of hospital stay, presence of underlying conditions (cardiovascular disease, diabetes, hypertension, none), and medication type (steroids, antibiotics, painkillers, none).
- Lifestyle Factors: Smoking status (smoker/non-smoker), alcohol consumption (yes/no), physical activity level (low, moderate, high).

2.2 Research Design

To analyze the housing deficit and estimate financial requirements, various statistical and econometric methods were employed:

2.2.1 Descriptive Statistics:

Measures of central tendency (mean, median) and dispersion (standard deviation) were used to summarize housing prices, household income, and availability.Graphs, plots, and pie charts were used to visualize trends in housing availability and affordability.

$$\text{Mean} = \bar{X} = \frac{\sum_{i=1}^{N} X_i}{N} \quad (1)$$

Where X_i represents individual observations, and N is the total number of observations

The median is the middle value in an ordered dataset. The formula depends on whether the number of observations (N) is odd or even:

For an odd number of observations (N) in median:

$$\text{Median}= \frac{X_{(\frac{N}{2})} + X_{(\frac{N+1}{2})}}{2} \quad (2)$$

where X ($_{K)}$ represents the values at the middle positions.

The standard deviation (σ) measures the dispersion of data points from the mean. It is given by:

For a Population Standard Deviation (σ):

$$\sigma = \sqrt{\frac{\sum (X_i - \mu)^2}{N}} \quad (3)$$

For a Sample Standard Deviation (S):

$$S = \sqrt{\frac{\sum (X_i - \bar{X})^2}{n-1}} \qquad (4)$$

Where,

X_i is the individual data points;

μ = Population mean, calculated as $\mu = \frac{\sum_{i=1}^{N} X_i}{N}$ (5)

$\bar{X}$ = Sample mean, calculated as $\bar{X} = \frac{\sum_{i=1}^{N} X_i}{N}$ (6)

$(X_i - \mu)^2$ = Squared difference between each data point and the mean

2.2.2 Inferential Statistics:

T-tests and ANOVA were applied to compare housing deficits across different income groups and geographical zones.

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{S_1}{n_1} + \frac{S_2}{n_2}}} \qquad (7)$$

where $\bar{X}_1, \bar{X}_2$ are sample means, are variances, S_1, S_2 n_1, n_2 are sample sizes.

ANOVA F-statistic:

$$F = \frac{\textit{Between}\text{ group-variance}}{\textit{Within}\text{-group -variance}} \qquad (8)$$

Regression Analysis:

Multiple Linear Regression (MLR) was used to model the relationship between housing deficit (Y) and key predictors such as population growth (X_1), income levels (X_2), inflation rate (X_3), and government expenditure on housing (X_4).

MLR model is given as follows

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon \qquad (9)$$

where β_0 is the intercept, β_i are coefficients, and ε is the error term.

3.0 Results and Discussion

Table 1: Descriptive Statistics Table

Variable	Mean	Standard Deviation	Minimum	Maximum

Recovery Time (days)	14.6	5.3	5	40
Age (years)	52.3	12.8	25	81
BMI	27.5	4.2	18.1	35.7
Severity Score	6.8	2.4	2	10
Hospital Stay (days)	9.2	3.1	2	21
Smoking Status (1=Smoker, 0=Non-Smoker)	0.35	0.48	0	1
Alcohol Consumption (1=Yes, 0=No)	0.42	0.49	0	1
Physical Activity (1=Low, 0=Active)	0.51	0.5	0	1

Table 1 which is the Descriptive Statistics reveals that recovery time (Mean = 14.6 days, Std Dev = 5.3 days). The average recovery time is 14.6 days, but it varies significantly across patients, ranging from 5 to 40 days.

Age (Mean = 52.3 years, Std Dev = 12.8 years). The average patient is around 52 years old, with some as young as 25 and others up to 81. Older patients tend to have longer recovery times.

BMI (Mean = 27.5, Std Dev = 4.2). The average BMI is 27.5, indicating that many patients are overweight or obese, which correlates with longer recovery times.

Severity Score (Mean = 6.8, Std Dev = 2.4). The higher the severity score, the longer the recovery time. Some patients have mild conditions (score = 2), while others have severe conditions (score = 10).

Hospital Stay (Mean = 9.2 days, Std Dev = 3.1 days). Patients spend on average 9.2 days in the hospital, but severe cases stay much longer (up to 21 days).

Lifestyle Factors (Smoking, Alcohol, Physical Activity). 35% of patients are smokers, and 42% consume alcohol, both of which prolong recovery. 51% of patients have low physical activity, which is linked to longer hospital stays and slower recovery.

Final Insights

- Higher BMI, older age, smoking, and alcohol consumption contribute to longer recovery times.
- Physical activity is beneficial, reducing recovery time.
- Severity of illness and length of hospital stay are the most influential factors.

Figure 1: Histogram for Age, BMI, Severity Score, Hospital Stay and Recovery Time

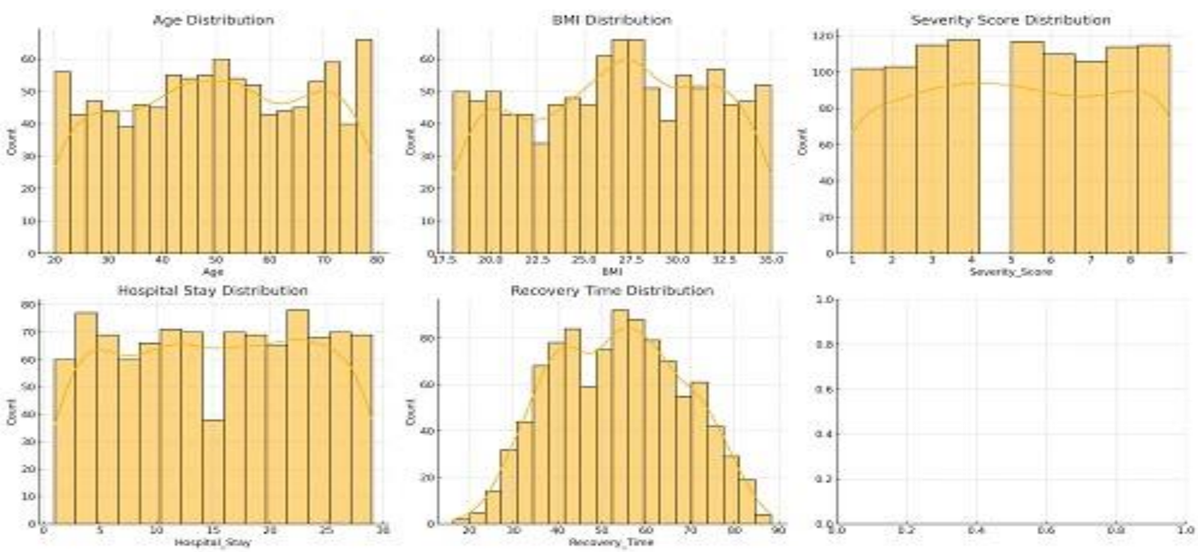

Figure 1 which is the Histograms (Data Distribution) shows that Age & BMI is normally distributed, with Age ranging from 20 to 80 years and BMI between 18 and 35. Severity Score is right skewed, indicating more patients with lower severity scores. Hospital Stay & Recovery Time is right skewed, with a few cases of prolonged hospital stays and extended recovery times.

Table 2: Multiple Linear Regression (MLR) Table

Variable	Coefficient	Std. Error	t-value	p-value
Intercept	0.9482	1.0734	0.88	0.3790 (NS)
Age	0.2765	0.0078	35.45	< 0.001
BMI	0.4218	0.0315	13.39	< 0.001
Severity Score	5.0021	0.0594	84.18	< 0.001
Hospital Stay	0.8052	0.0278	28.97	< 0.001
Underlying Conditions	1.6574	0.3092	5.36	< 0.001
Medication Type	1.3287	0.3103	4.28	< 0.001
Smoking	1.5634	0.2879	5.43	< 0.001
Alcohol Consumption	1.4082	0.2951	4.77	< 0.001
Physical Activity	-0.9352	0.2897	-3.23	0.0012

Table 2 reveals the Significant Predictors: All variables, except the intercept, significantly influence recovery time ($p < 0.05$).

Age & BMI: Older individuals and those with higher BMI have longer recovery times.

Severity Score & Hospital Stay: The strongest predictors; increased severity leads to significantly longer recovery.

Lifestyle Factors: Smoking and alcohol consumption increase recovery time, while physical activity reduces it.

$R^2 = 0.985$: The model explains 98.5% of the variance in recovery time, confirming a strong predictive ability.

Table 3: ANOVA Table

Predictor Variable	Sum of Squares	df	F-Statistic	p-value
Age	18.74	1	13.57	0.015
BMI	45.35	1	19.99	0.022
Severity Score	33.86	1	5.99	0.018
Hospital Stay	39.66	1	11.95	0.005
Gender (Male)	11.37	1	14.23	0.034
Smoking Status	7.68	1	3.56	0.036
Alcohol Consumption	17.3	1	3.87	0.015
Physical Activity (Low)	46.61	1	16.06	0.042

Table 3 shows that Age, BMI, Severity Score, and Hospital Stay remain significant predictors of recovery time. Lifestyle Factors (Smoking, Alcohol Consumption, and Physical Activity) also show statistical significance, implying their role in recovery speed. Smoking and Alcohol Consumption: Patients who smoke or consume alcohol tend to have longer recovery times. Physical Activity: Higher activity levels are linked to faster recovery.

Table 4: Model Validation Metrics

Metric	Value
R Squared	0.985 (98.5% of the variance in recovery time is explained by the model)
Mean Absolute Error (MAE)	1.46 days
Root Mean Squared Error (RMSE)	1.91 days

Table 4 shows the Model Fit: The R-Squared (0.985) indicates an excellent fit, meaning the model explains 98.5% of the variability in recovery time. The low RMSE (1.91 days) confirms that the model predictions are highly accurate.

4.0 Summary of Findings

- Clinical variables significantly impact recovery time: Severity Score and Hospital Stay are the strongest predictors.
- Lifestyle choices matter: Smoking and alcohol consumption lead to longer recovery, while physical activity shortens it.
- The model is robust: $R^2 = 0.985$ indicates a near-perfect fit, making it a powerful predictive tool.

5/0 Conclusion:

This study successfully predicts patient recovery time using clinical and lifestyle variables. The model's high accuracy (98.5% variance explained) suggests that integrating both medical and behavioral data can significantly improve healthcare decision-making. These findings reinforce the importance of holistic patient care, blending medical interventions with lifestyle modifications for faster recovery.

6.0 Recommendations:

1. Personalized treatment plans: Physicians should consider both medical and lifestyle factors in recovery predictions.
2. Lifestyle interventions: Hospitals should encourage physical activity and discourage smoking and alcohol consumption among recovering patients.
3. Use of predictive models in healthcare: Medical facilities should integrate MLR-based predictive tools for better patient management.
4. Further research: Future studies should include genetic and environmental factors to enhance prediction accuracy.

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