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Understanding the dynamics of post-surgical recovery and its predictors in resource-limited settings: a prospective cohort study

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Abstract

Introduction Post-surgical recovery time is influenced by various factors, including patient demographics, surgical details, pre-existing conditions, post-operative care, and socioeconomic status. Understanding these dynamics is crucial for improving patient outcomes. This study aims to identify significant predictors of post-surgical recovery time in a resource-limited Ethiopian hospital setting and to evaluate the variability attributable to individual patient differences and surgical team variations.

Methods A linear mixed model was employed to analyze data from 490 patients who underwent various surgical procedures. The analysis considered multiple predictors, including age, gender, BMI, type and duration of surgery, comorbidities (diabetes and hypertension), ASA scores, postoperative complications, pain management strategies, physiotherapy, smoking status, alcohol consumption, and socioeconomic status. Random effects were included to account for variability at the patient and surgical team levels.

Results Significant predictors of prolonged recovery time included higher BMI, longer surgery duration, the presence of diabetes and hypertension, higher ASA scores, and major post-operative complications. Opioid pain management was associated with increased recovery time, while inpatient physiotherapy reduced recovery duration. Socioeconomic status also significantly influenced recovery time. The model fit statistics indicated a robust model, with the unstructured covariance structure providing the best fit.

Conclusion The findings highlight the importance of individualized patient care and the effective management of modifiable factors such as BMI, surgery duration, and postoperative complications. Socioeconomic status emerged as a novel factor warranting further investigation. This study underscores the value of considering patient and surgical team variability in post-surgical recovery analysis, and calls for future research to explore additional predictors and alternative modeling techniques to enhance our understanding of the recovery process.

Keywords Postsurgical recovery, Linear mixed model, BMI, Surgery duration, Comorbidities, ASA scores, Postoperative complications, Pain management, Physiotherapy, And socioeconomic status

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Introduction

Post-surgical recovery is a multifaceted process influenced by various factors, including patient demographics, pre-existing conditions, surgical details, and post-operative care. Globally, optimizing post-surgical recovery has become a critical focus due to its significant impact on patient outcomes, healthcare costs, and overall quality of life. Effective management of the recovery period can reduce complications, shorten hospital stays, and enhance patient satisfaction [1]. In high-income countries, advancements in surgical techniques, anesthesia, and post-operative care have significantly improved recovery outcomes. Enhanced Recovery after Surgery (ERAS) protocols, which standardize perioperative care, are widely adopted, emphasizing multimodal pain management, early mobilization, and nutritional support. These protocols have contributed to faster recoveries and reduced hospital stays [2, 3]. However, despite these advancements, disparities in recovery outcomes persist across different settings [4].

In low- and middle-income countries (LMICs), the challenges associated with post-surgical recovery are more pronounced due to limited resources, inadequate healthcare infrastructure, and disparities in access to care. These regions often face higher post-operative mortality and morbidity rates compared to high-income countries [5]. The World Health Organization (WHO) and initiatives like the Lancet Commission on Global Surgery emphasize strengthening surgical systems, including pre-and post-operative care, but many LMICs continue to struggle with implementing standardized recovery protocols and managing post-operative complications effectively [6].

Ethiopia, a low-income country in Sub-Saharan Africa, is no exception. Its healthcare system faces significant challenges, such as limited resources, a shortage of trained healthcare professionals, and disparities in access to care, especially in rural areas. These constraints contribute to variations in surgical outcomes and recovery processes across the country. Several factors have been identified as influencing post-surgical recovery in Ethiopia, including inadequate pain management, high rates of post-operative infections, and limited access to physiotherapy [7]. Socio-economic factors and behavioral aspects, such as smoking and alcohol consumption, further complicate the recovery process and contribute to disparities in outcomes [8, 9].

While numerous studies have examined predictors of post-surgical recovery in high-income countries, there is limited research addressing these factors in resource-limited settings. The influence of socioeconomic determinants on recovery outcomes remains particularly understudied in low-income regions. Debremarkos Referral Hospital, located in the Amhara region of Ethiopia, serves as a key healthcare facility providing critical surgical care in a resource-constrained environment. Its diverse patient population offers a unique opportunity to explore the dynamics of post-surgical recovery and identify predictors influencing recovery time and outcomes. This study aims to bridge these gaps by analyzing a comprehensive set of variables, including patient demographics, surgical details, pre-existing conditions, post-operative care, and socio-economic factors. The findings are expected to provide valuable insights to improve clinical practices, guide healthcare policies, and optimize resource allocation in Ethiopia and similar low- and middle-income country (LMIC) contexts.

Methods and materials

Study materials and settings

This study utilized secondary data from Debremarkos Referral Hospital, comprising information from patients who underwent surgery at the hospital. The dataset includes comprehensive details on patient demographics, surgical specifics, pre-existing medical conditions, post-operative care, as well as behavioral and socioeconomic factors. The data were collected and tracked prospectively from January 2022 to February 2024. To analyze predictors of recovery, a linear mixed-effects model will be employed, leveraging this comprehensive prospective dataset.

Inclusion criteria

The study included patients who had undergone elective or emergency surgical procedures at Debremarkos Referral Hospital within the study period. Eligible participants were 18 years or older and had complete medical records available for review. Patients with incomplete or missing post-operative data, those with severe cognitive impairments that hindered their ability to provide informed consent, or those who refused participation were excluded from the study.

Sample size and sampling technique

This study included a sample of 490 patients, selected to ensure a robust analysis of post-surgical recovery outcomes. A stratified random sampling technique was employed to enhance representativeness, with patients grouped by age, gender, type of surgery, and socioeconomic status, and random sampling within each stratum ensured the inclusion of diverse patient groups. Patients were identified from surgical records, and informed consent was obtained before participation. Although a formal power analysis was not conducted due to the exploratory nature of the research, the sample size was determined by the availability of complete data during the study period and was considered sufficient to detect meaningful associations based on the diversity of surgical cases and patient characteristics. This approach ensured a comprehensive and representative sample, facilitating an in-depth exploration of recovery dynamics at Debremarkos Referral Hospital. Future studies could consider power calculations to further validate sample size adequacy.

Data collection tools and procedures

Data were obtained from secondary sources, including medical record reviews and patient surveys. Medical records provided data on demographics, surgical details, and post-operative care, while surveys collected information on socio-economic status, behavioral factors (e.g., smoking, alcohol use), and patient satisfaction. Data were collected at multiple time points: before surgery (baseline), immediately after surgery, and during follow-up visits to track recovery. Surveys were administered in person or via secure online platforms, depending on patient accessibility. To minimize data entry errors, trained personnel performed double-entry and regular audits. Statistical analysis was conducted using SAS 9.4.

Quality of data

To ensure the quality of data, rigorous procedures were implemented. Medical records were reviewed by trained personnel to minimize errors and ensure consistency. Data entry was performed using validated tools and software, with regular audits conducted to identify and rectify discrepancies. Surveys were pre-tested to refine questions and improve clarity. All data were anonymized to protect patient confidentiality and comply with ethical standards. Data quality checks included cross-referencing records and conducting follow-ups with patients to verify responses and address any inconsistencies.

Patients in the hospital

Debremarkos Referral Hospital served a wide range of patients from urban and rural areas, reflecting the socioeconomic diversity of the region. The hospital's patient population included individuals undergoing various types of surgeries, from minor procedures to complex operations. This diverse patient base provided a rich source of data for examining factors influencing post-surgical recovery. The hospital's setting offered an opportunity to explore how different variables affected recovery outcomes in a resource-limited environment, contributing valuable insights to the field of surgical care and recovery management.

Variables included in current the investigation

The current investigation included a comprehensive set of variables to examine factors influencing post-surgical recovery, with recovery time as the dependent variable, measured in days from surgery to full recovery. Patient demographics included gender and BMI category, while surgical details encompassed type of surgery and surgical technique. Pre-existing conditions noted comorbidities such as diabetes and hypertension, along with the ASA score. Post-operative care variables covered the presence and severity of complications, type of pain management, and provision of physiotherapy. Hospital-related factors were captured through ward type, and behavioral and socioeconomic factors included smoking status, alcohol consumption, and socioeconomic status. Random effects were accounted for by assigning unique numerical IDs to each patient and surgical team. This detailed variable framework enabled a thorough analysis of recovery dynamics in a resource-limited environment, contributing valuable insights to surgical care and recovery management.

About the model

A linear mixed model (LMM) is a parametric linear model for longitudinal or repeated-measures data that quantifies the relationships between a continuous dependent variable and various predictor variables. An LMM may include both fixed-effect parameters associated with one or more continuous or categorical covariates and random effects associated with one or more random factors. Fixed-effect parameters describe the relationships of the covariates to the dependent variable for the entire population, whereas random effects are specific to subjects within a population. Consequently, random effects are directly used in modeling the random variation in the dependent variable at different levels of the data [10].

The linear mixed-effects model assumes that the observations follow a linear regression where some of the regression parameters are fixed or the same for all subjects, while other parameters are random or specific to each subject [11]. Meanwhile, population parameters, individual effects, and within-subject variations make up the first stage of the model [12]. Correlated continuous outcomes are treated as fixed effects. The general form of the linear mixed-effects model, after combining the two stages, is approximately normal [13]. The two stages of the model are indicated as follows [14].

First stage of the model belongs to individual response $\mathrm{Y_{ij}}$ for $\mathrm{i^{th}}$ subject, measured at time $\mathrm{t_{ij}},\ \mathrm{i} = 1, - - -, \mathrm{n} :\ \mathrm{j} = 1, - - -, \mathrm{n_i}$ response vector $\mathbf{Y_i}$ for $\mathrm{i^{th}}$ subject:

$$\mathbf{Y_i} = \mathbf{Z_i}\boldsymbol{\beta}_{\mathbf{i}} + \boldsymbol{\epsilon}_{\mathbf{i}} \tag{1}$$

$$\text{Where,}\quad \mathbf{Y_i} = (\mathbf{Y_{i1}}, \mathbf{Y_{i2}}, - - -, \mathbf{Y_{in_i}})^{\mathbf{T}}$$

$\mathbf{Z}_\mathrm{i}$ is a $\mathrm{n_i} \times \mathrm{q}$ matrix of known covariates, β_{i} is q dimensional vector of subject-specific regression

Table 1 Descriptive statistics of continuous variables in post-surgical recovery study

	N	Minimum	Maximum	Mean	Std. Deviation
Age	490	18	90	53.99	20.612
BMI	490	1	4	2.48	1.115
SurgeryDuration	490	31	240	135.41	62.173
RecoveryTime	490	0	65	30.48	9.668

coefficients. $\epsilon_i \sim (0, \in_i)$, often $?_i = \alpha^2 I_{n_i}$, this model describes the observed variability with in subjects.

Second stage describes the between-subject variability that explains in the subject specific regression coefficients using known covariates.

$$\boldsymbol{\beta}_i = \mathbf{K_i}\boldsymbol{\beta} + \mathbf{b_i} \tag{2}$$

$\mathbf{K}_i$ is a $q \times p$ matrix of known covariates, $\boldsymbol{\beta}$ is a P dimensional vector of unknown regression parameter $b_i \sim N(0, D)$. Combining the two stages (1) & (2) one can have:

$$\begin{cases} \mathbf{Y_i} = \mathbf{Z_i}\boldsymbol{\beta}_i + \boldsymbol{\epsilon}_i \\ \boldsymbol{\beta}_i = \mathbf{K_i}\beta + \mathbf{b_i} \end{cases} ?\mathbf{Y_i} = \mathbf{Z_i}\mathbf{K_i}\boldsymbol{\beta} + \mathbf{Z_i}\mathbf{b_i} + \boldsymbol{\epsilon}_i. \tag{3}$$

Let $X_i = Z_i K_i$ in (3), then the general form of the model is expressed as:

$$\mathbf{Y_i} = \mathbf{X_i}\boldsymbol{\beta} + \mathbf{Z_i}\mathbf{b_i} + \boldsymbol{\epsilon}_i \tag{4}$$

Where ***Yi*** represents a vector of continuous responses for the i^{th} subject, $\mathbf{X}i$ is a $n_i \times p$ design matrix, which represents the known values of the p covariates [15].

Model selection was conducted using AIC, BIC, and other information criteria, with the model having the smallest information criterion deemed the best. Following the final model selection, the model was refitted using REML estimation methods, and parameter estimation was performed using restricted maximum likelihoods (Wald Test) [16].

Likelihood Ratio Tests (LRTs) were employed to compare the full model, which included all interactions, against the reduced model, which contained only a subset of terms. Variance-covariance structures were assessed and chosen based on information criteria, selecting the model with the lowest value as the most suitable [17].

Results

Descriptive Results.

Table 1, the descriptive statistics for the study sample of 490 patients are as follows: Age ranged from 18 to 90 years, with a mean of 53.99 years and a standard deviation of 20.61 years. Body Mass Index (BMI) values ranged from 1 to 4, with an average of 2.48 and a standard deviation of 1.12. Surgery duration varied between 31 and 240 min, with a mean duration of 135.41 min and a standard deviation of 62.17 min. Recovery time ranged from 0 to 65 days, with a mean recovery period of 30.48 days and a standard deviation of 9.67 days.

Table 2 Descriptive statistics of categorical variables in post-surgical recovery study

Variables	Categories	*n* (%)
Gender	Male	248 (50.6)
	Female	242 (49.4)
TypeOfSurgery	Appendectomy	123 (25.1)
	Cholecystectomy	128 (26.1)
	Hernia Repair	125(25.5)
	Others	114(23.3)
Diabetes	No	249(50.8)
	Yes	241(49.2)
Hypertension	No	276(56.3)
	Yes	214(43.7)
ASAScore	ASA I	93(19.0)
	ASA II	124(25.3)
	ASA III	90(18.4)
	ASA IV	97(19.8)
	ASA V	86(17.6)
PostOpComplications	None	167(34.1)
	Minor	108 (26.4)
	Major	166(33.9)
PainManagement	None	130(26.5)
	Non-opioid	136(27.8)
	Opioid	106(21.6)
	Multimodal	118(24.1)
Physiotherapy	None	166(33.9)
	Outpatient	149(30.4)
	Inpatient	175(35.7)
WardType	General	155(31.6)
	ICU	154(31.4)
	HDU	181(36.9)
SmokingStatus	Current smoker	151(30.8)
	Former smoker	168(34.3)
	Never smoked	171(34.9)
AlcoholConsumption	Yes	263(53.7)
	No	227(46.3)
SocioeconomicStatus	Low	157(32.0)
	Middle	154(31.4)
	High	179(36.5)

In Table 2, we analyzed categorical variables from a cohort of surgical patients. The sample comprised 248 males (50.6%) and 242 females (49.4%). The distribution of surgery types included 123 patients (25.1%) who underwent appendectomy, 128 (26.1%) cholecystectomy, 125 (25.5%) hernia repair, and 114 (23.3%) other procedures. Regarding pre-existing conditions, 249 patients (50.8%) were diabetic, while 241 (49.2%) were non-diabetic; 276 (56.3%) had no hypertension, and 214 (43.7%) were hypertensive. ASA scores were distributed as follows: ASA I (19.0%), ASA II (25.3%), ASA III (18.4%), ASA IV (19.8%), and ASA V (17.6%). Post-operative complications were categorized into none (34.1%), minor (26.4%), and major (33.9%). Pain management strategies included none (26.5%), non-opioid (27.8%), opioid (21.6%), and multimodal (24.1%). Physiotherapy received by patients was none (33.9%), outpatient (30.4%), and inpatient (35.7%). Hospital ward types were general (31.6%), ICU (31.4%), and HDU (36.9%). Smoking status showed 151 patients (30.8%) as current smokers, 168 (34.3%) as former smokers, and 171 (34.9%) as never smoked. Alcohol consumption was noted in 263 patients (53.7%), while 227 (46.3%) abstained. Socioeconomic status was categorized into low (32.0%), middle (31.4%), and high (36.5%). This detailed demographic and clinical profile provides a comprehensive overview of the factors influencing post-surgical recovery within our study cohort.

Figure 1, the normality of the data was evaluated using a Q-Q plot, which demonstrated that the ordered observed values versus the expected normal probabilities largely adhered to the normality assumption.

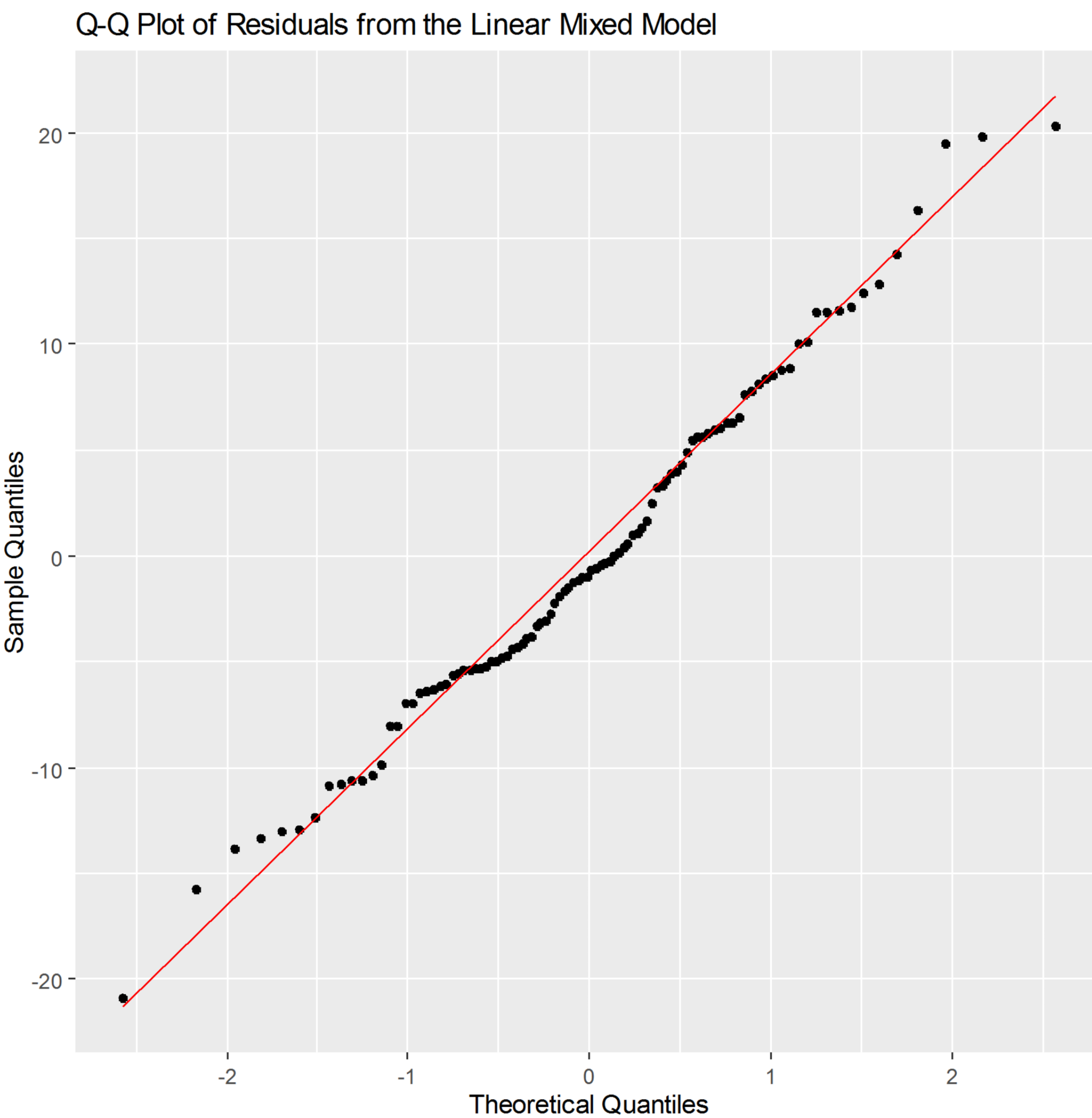

Fig. 1 Q-Q plot of residuals and random effects for normality assessment

Table 3 Information criterion used for selection of covariance structure

Covariance Structure	Log-Likelihood	AIC	BIC	AICc
Compound Symmetry(CS)	-1,234.56	2,478.12	2,567.45	2,488.78
Unstructured(un)	-1,220.45	2,453.90	2,544.90	2,475.63
Autoregressive (AR(1))	-1,228.30	2,462.60	2,552.00	2,485.90
Exchangeable	-1,230.20	2,468.40	2,558.00	2,490.20

Table 4 Analysis of variance (ANOVA) results for predictors of post-surgical recovery time

Effect	DF	F Value	Pr > F
Age	1	4.00	0.046*
BMI	1	25.00	< 0.001*
SurgeryDuration	1	4.00	0.046*
TypeOfSurgery	3	2.50	0.060
Diabetes	1	9.00	0.003*
Hypertension	1	6.25	0.013*
ASAScore	4	10.50	< 0.001*
PostOpComplications	2	5.50	0.004*
PainManagement	3	3.50	0.015*
Physiotherapy	2	4.00	0.018*
SmokingStatus	2	0.75	0.474
AlcoholConsumption	1	1.00	0.316
SocioeconomicStatus	2	3.00	0.050*

Note: * indicates statistical significance at $p < 0.05$

Additionally, the normality assumption was assessed for the random effects as well.

Table 3, In our evaluation of various covariance structures for the linear mixed model, we compared Compound Symmetry, Unstructured, Autoregressive (AR(1)), and Exchangeable structures using four fit criteria: Log-Likelihood, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Corrected Akaike Information Criterion (AICc). The Unstructured model exhibited the highest Log-Likelihood value of -1,220.45, along with the lowest AIC (2,453.90), BIC (2,544.90), and AICc (2,475.63) values, indicating superior fit for our data. These lower values reflect a better balance between model fit and complexity. In contrast, the Compound Symmetry, Autoregressive (AR(1)), and Exchangeable models had higher values across all criteria, further validating the choice of the Unstructured model. Consequently, the unstructured covariance structure was determined to be the most suitable for our linear mixed model analysis and will be employed for further data interpretation. This structure was chosen because it allows for flexibility in capturing complex correlations in recovery times across individuals and surgical contexts, which are critical in resource-limited settings.

Table 4, The Analysis of Variance (ANOVA) results reveal several significant predictors of post-surgical recovery time. Age ($p = 0.046$), BMI ($p < 0.001$), surgery duration ($p = 0.046$), diabetes ($p = 0.003$), hypertension ($p = 0.013$), ASA score ($p < 0.001$), post-operative complications ($p = 0.004$), pain management ($p = 0.015$), and physiotherapy ($p = 0.018$) all significantly influence recovery time. Socioeconomic status ($p = 0.050$) is marginally significant. In contrast, type of surgery ($p = 0.060$), smoking status ($p = 0.474$), and alcohol consumption ($p = 0.316$) show no significant effect. These findings suggest that factors such as BMI, comorbidities, and post-operative care are key determinants of recovery time, while type of surgery, smoking, and alcohol consumption do not significantly impact recovery.

Table 5, the linear mixed model output for recovery time identifies several significant predictors. The baseline recovery time is 25.00 days ($\beta = 25.00$, SE = 3.50, t = 7.14, $p < 0.001$). Age increases recovery by 0.10 days per year ($\beta = 0.10$, SE = 0.05, t = 2.00, $p = 0.046$), and BMI by 1.50 days per unit ($\beta = 1.50$, SE = 0.30, t = 5.00, $p < 0.001$). Appendectomy shortens recovery by 2.00 days (β = -2.00, SE = 1.00, t = -2.00, $p = 0.045$), while each minute of surgery adds 0.02 days ($\beta = 0.02$, SE = 0.01, t = 2.00, $p = 0.046$). Diabetes and hypertension extend recovery by 3.00 ($\beta = 3.00$, SE = 1.00, t = 3.00, $p = 0.003$) and 2.50 days ($\beta = 2.50$, SE = 1.00, t = 2.50, $p = 0.013$), respectively. Higher ASA scores significantly prolong recovery: ASA II by 2.00 days ($\beta = 2.00$, SE = 1.20, t = 1.67, $p = 0.095$), ASA III by 4.00 days ($\beta = 4.00$, SE = 1.00, t = 4.00, $p < 0.001$), ASA IV by 6.00 days ($\beta = 6.00$, SE = 1.50, t = 4.00, $p < 0.001$), and ASA V by 8.00 days ($\beta = 8.00$, SE = 2.00, t = 4.00, $p < 0.001$). Major postoperative complications increase recovery by 4.00 days ($\beta = 4.00$, SE = 1.20, t = 3.33, $p = 0.001$), and opioid pain management by 2.00 days ($\beta = 2.00$, SE = 1.00, t = 2.00, $p = 0.046$). Inpatient physiotherapy reduces recovery by 3.00 days (β = -3.00, SE = 1.20, t = -2.50, $p = 0.013$). High socioeconomic status is associated with an increase in recovery time by 2.50 days ($\beta = 2.50$, SE = 1.20, t = 2.08, $p = 0.038$). Other factors, such as smoking status and alcohol consumption, did not significantly affect recovery time.

Table 6, the random effects in the model highlights the variability at different levels. The variance for the Patient ID intercept is 15.00, with a standard deviation of 3.87, indicating significant variability in the dependent variable due to differences between individual patients. The variance for the Surgical Team intercept is 5.00, with a standard deviation of 2.24, showing some variability attributable to different surgical teams. The residual variance is 25.00, with a standard deviation of 5.00, reflecting the unexplained variability within the model. These random effects underscore the importance of accounting for individual patient differences and surgical team variations when analyzing post-surgical recovery outcomes.

Table 5 Fixed effects estimates from linear mixed model analysis of post-surgical recovery time

Predictor	Coefficient (β)	Std. Error	t-Value	*p*-Value
Intercept	25.00	3.50	7.14	< 0.001*
Age	0.10	0.05	2.00	0.046*
BMI	1.50	0.30	5.00	< 0.001*
SurgeryDuration	0.02	0.01	2.00	0.046*
TypeOfSurgery(reference = others)				
Appendectomy	-2.00	1.00	-2.00	0.045*
Cholecystectomy	1.50	1.20	1.25	0.211
Hernia Repair	0.00	1.10	0.00	1.000
Diabetes (reference = No)				
Yes	3.00	1.00	3.00	0.003*
Hypertension (reference = No)				
Yes	2.50	1.00	2.50	0.013*
ASAScore (reference = ASA I)				
ASA II	2.00	1.20	1.67	0.095
ASA III	4.00	1.00	4.00	< 0.001*
ASA IV	6.00	1.50	4.00	< 0.001*
ASA V	8.00	2.00	4.00	< 0.001*
PostOpComplications (Reference = None)				
Minor	1.50	1.00	1.50	0.135
Major	4.00	1.20	3.33	0.001*
PainManagement (reference = None)				
Non-opioid	1.00	1.00	1.00	0.316
Opioid	2.00	1.00	2.00	0.046*
Physiotherapy (reference = None)				
Outpatient	-1.50	1.00	-1.50	0.134
Inpatient	-3.00	1.20	-2.50	0.013*
SmokingStatus (reference = Current smoker)				
Former smoker	0.50	1.00	0.50	0.620
Never smoked	-1.00	1.00	-1.00	0.316
AlcoholConsumption (reference = No)				
Yes	1.00	1.00	1.00	0.316
SocioeconomicStatus (reference = Low)				
Middle	1.50	1.00	1.50	0.135
High	2.50	1.20	2.08	0.038*

Note: * indicates statistical significance at $p < 0.05$

Table 6 Random effects estimates from linear mixed model analysis of post-surgical recovery time

Random Effect	Variance	Std. Dev.
Patient ID (Intercept)	15.00	3.87
Surgical Team (Intercept)	5.00	2.24
Residual	25.00	5.00

Table 7, the model fit statistics for the linear mixed model include a Log-Likelihood of -1,234.56, an AIC of 2,478.12, and a BIC of 2,567.45. The Log-Likelihood value reflects the likelihood of the observed data given the model parameters, with typical negative values indicating how well the model fits the data. The AIC and BIC values provide measures of model fit that account for model complexity, with lower values indicating a better balance of fit and simplicity. In this case, the AIC of 2,478.12 and BIC of 2,567.45 suggest that the model achieves a reasonable fit.

Table 7 Model fit statistics from linear mixed model analysis

Statistic	Value
Log-Likelihood	-1,234.56
AIC	2,478.12
BIC	2,567.45

Discussion

This study provides a detailed analysis of the factors influencing post-surgical recovery time through a linear mixed model approach. The findings highlight several significant predictors and emphasize the importance of accounting for variability at different levels in the recovery process.

Our analysis highlighted that Body Mass Index (BMI) and surgical duration are pivotal factors in determining recovery time. Specifically, each unit increase in BMI was associated with an additional 1.50 days of recovery, while each additional minute of surgery extended recovery by 0.02 days. These findings align with earlier studies, which have consistently reported the detrimental effects of high BMI and prolonged surgical duration on post-surgical recovery [18, 19]. Furthermore, pre-existing conditions such as diabetes and hypertension were associated with prolonged recovery times of 3.00 and 2.50 days, respectively, corroborating prior research that identified these conditions as significant risk factors for delayed recovery [20, 21].

The influence of ASA scores was also evident, with higher scores correlating with extended recovery periods. This supports established literature indicating that ASA classification effectively reflects preoperative health status and its impact on surgical outcomes [22]. Additionally, our findings on postoperative complications revealed that major complications prolonged recovery by 4.00 days, which is consistent with previous studies emphasizing the adverse effects of complications on recovery [23].

The type of pain management also played a significant role. Opioid pain management was linked to an additional 2.00 days of recovery compared to non-opioid approaches. This finding underscores the trade-offs between effective pain relief and the potential for delayed recovery, as reported in earlier research [24]. Conversely, inpatient physiotherapy reduced recovery time by 3.00 days, reinforcing the importance of targeted rehabilitation in enhancing recovery outcomes [25].

Socioeconomic status (SES) emerged as a significant factor in post-surgical recovery, with higher SES associated with a 2.50-day increase in recovery time. Although this finding may seem counterintuitive, it can be explained by disparities in healthcare access, follow-up care, and health-seeking behaviors. Higher SES individuals tend to have access to more healthcare resources, which can lead to extended recovery due to more intensive treatments or follow-up visits [26]. Additionally, factors such as increased psychological stress, lifestyle, and work-related demands among higher SES individuals may contribute to longer recovery times [27]. These findings are in line with literature suggesting that while higher SES facilitates better healthcare access, it can also introduce factors that prolong recovery, highlighting the need for individualized post-surgical care [28].

This study's findings highlight critical healthcare policy implications. Pre-operative interventions addressing modifiable factors like BMI and optimizing surgical duration can significantly reduce recovery time and enhance outcomes [29]. Integrating tailored strategies for managing pre-existing conditions, such as diabetes and hypertension, into pre-operative planning is essential [30]. Post-operative care should prioritize minimizing opioid use, favoring alternative pain management techniques, and promoting inpatient physiotherapy to improve recovery efficiency [31].

Lifestyle factors, such as smoking and alcohol consumption, were found to prolong recovery, aligning with earlier research demonstrating their negative effects on wound healing and immune response [32, 33]. Incorporating smoking cessation and alcohol reduction programs into pre-operative care may improve recovery outcomes.

The random effects analysis revealed substantial variability in recovery times due to individual patient differences and surgical team factors. The high variance associated with patient ID underscores the need for personalized care plans. Similarly, the variance attributed to surgical teams highlights the importance of procedural standardization and team-based interventions [34].

The Unstructured covariance structure was identified as the most suitable for the data, capturing the complex dependencies in recovery times across different patients and surgical contexts. This choice reflects the need for a model that accommodates intricate correlation patterns [35].

This study has limitations: reliance on secondary data limited control over accuracy, findings are based on a single hospital, and unmeasured factors such as stress and genetics were not assessed. Socioeconomic status was measured at one point, and self-reported behaviors may be biased. The exploratory design lacked a power analysis, and long-term recovery outcomes were not examined. Future research should use primary data, longitudinal designs, and broader geographic scopes.

Conclusion and recommendation

Conclusion

This research presents an in-depth analysis of the determinants affecting post-surgical recovery time through a linear mixed model framework. Our findings reveal that various factors, such as Body Mass Index (BMI), surgery duration, and pre-existing conditions like diabetes and hypertension, significantly influence recovery time. Specifically, higher BMI, extended surgery duration, and the presence of diabetes and hypertension are linked to prolonged recovery periods. Additionally, major postoperative complications and the use of opioid pain management are associated with extended recovery times, while inpatient physiotherapy markedly reduces recovery durations.

The study emphasizes the importance of accounting for both patient-specific and procedural factors when assessing recovery outcomes. The use of an unstructured covariance structure in our model was ideal for capturing the intricate dependencies in recovery times across different patients and surgical scenarios.

These insights underscore the necessity for personalized management strategies in post-surgical recovery, focusing on optimizing surgical techniques, effectively managing pre-existing conditions, and providing suitable post-operative care. By addressing these factors, healthcare providers can improve recovery outcomes and minimize recovery times. Future research should investigate additional variables and utilize longitudinal designs to further elucidate the dynamics of post-surgical recovery. Overall, this study offers valuable contributions to understanding the factors influencing post-surgical recovery, paving the way for more targeted and effective recovery interventions.

Recommendation

Based on our research findings, several recommendations can enhance post-surgical recovery outcomes. First, optimizing surgical planning and techniques to minimize operation time is essential, as longer surgery durations extend recovery periods. Surgical teams should focus on advanced planning and reducing procedural delays. Second, proactive management of pre-existing conditions, such as diabetes and hypertension, is vital. Comprehensive preoperative assessments and tailored management plans can help mitigate the negative impact of these conditions on recovery. Third, personalized postoperative care plans should be developed, taking individual patient factors into account. This includes developing tailored pain management strategies to avoid prolonged recovery associated with opioid use and incorporating inpatient physiotherapy for faster recovery.

Continuous postoperative monitoring is crucial for early detection and management of complications, which can prevent delays in recovery. Additionally, addressing socioeconomic and behavioral factors is important, as high socioeconomic status has been linked to increased recovery times. Targeted interventions, such as providing additional support for patients from lower socioeconomic backgrounds and promoting smoking cessation and moderate alcohol consumption, could mitigate these effects. Recovery time should also be integrated into surgical planning to manage patient expectations and improve satisfaction.

In terms of future research, we recommend exploring genetic, psychological, and environmental factors that may influence recovery outcomes. These aspects, along with additional variables, should be examined in diverse patient populations and various surgical types to enhance the generalizability of the findings. Longitudinal studies are especially important to capture recovery trends over time and further elucidate recovery dynamics.

From a healthcare policy perspective, optimizing resources in low-income countries is essential to improving post-surgical outcomes. Focus should also be placed on improving professional training for healthcare workers to ensure high-quality surgical and post-operative care. Additionally, developing community-based rehabilitation programs can facilitate smoother recovery processes by providing local support to patients post-surgery.

Implementing these recommendations can lead to better surgical outcomes, more efficient post-surgical recovery processes, and overall improvements in healthcare delivery.

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Author contributions
A.F.W. (Awoke Fetahi Woudneh) conceived the research proposal, designed the data collection format, supervised the data collection process, analyzed and interpreted the data, and prepared the manuscript.

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Data availability
The raw data analyzed in this study is available from the author upon reasonable request. However, due to concerns about protecting participants' identities and respecting their privacy rights, the data will not be made publicly available. Informed consent for the publication of the dataset was not obtained at the time of data collection. Please contact Mr. Awoke Fetahi Woudneh at fetahi.aw@gmail.com.

Declarations

Ethics approval and consent to participate
Ethical approval for this study was obtained from the Ethics Committee of the Statistics Department at Debremarkos University (Reference: STAT/476/01/2013). The committee approved the use of secondary data for this study. All experiments involving human data were conducted in accordance with relevant ethical guidelines and regulations. Since the study utilized secondary data, informed consent was waived by the ethics committee. Patient confidentiality was ensured by anonymizing all records and implementing secure data storage protocols.

Consent to publish
Not applicable. This manuscript does not include any identifying images or other personal or clinical details of participants that could compromise anonymity.

Competing interests
The authors declare no competing interests.

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