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Hierarchical Modeling For Multilevel Data: Techniques And Application

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ABSTRACT
This study investigates the application of hierarchical modeling techniques to analyze multilevel healthcare data, focusing on primary healthcare services in Zamfara State, Nigeria. Hierarchical models offer a robust framework to understand the influence of factors across three levels: patient-specific characteristics (e.g., age, comorbidities, severity of illness), doctor-level attributes (e.g., experience, workload), and hospital-level factors (e.g., resource availability, specialist staffing). Using mixed-effects models, the research examines recovery times as the primary outcome variable while accounting for both fixed and random effects. Descriptive analyses reveal significant variability in recovery outcomes driven primarily by doctor-level influences, overshadowing patient demographics and treatment types. The findings emphasize the critical role of healthcare provider variability in shaping patient recovery and the importance of resource optimization at the institutional level. Despite advances in hierarchical modeling, the study identifies challenges such as limited significant predictors at the patient level, highlighting the need for future research into unmeasured variables. This research underscores the value of hierarchical models in healthcare data analysis, offering actionable insights for improving care delivery and informing resource allocation strategies. It contributes to the growing body of literature by providing a case study demonstrating the practical applications of hierarchical modeling in real-world healthcare systems.
Keywords: hierarchical modeling, multilevel data, healthcare analysis, mixed-effects models, recovery outcomes.

1.0 INTRODUCTION

In recent years, the application of advanced statistical methods has become crucial in addressing the complexities inherent in healthcare data. One such method, hierarchical modeling, has gained prominence due to its ability to analyze multilevel data effectively. Multilevel data, characterized by nested structures, is ubiquitous in healthcare settings, where observations are often grouped at multiple levels, such as patients within clinics or communities, and clinics within regions. Hierarchical modeling, also known as multilevel modeling, provides a robust framework to account for the variability at these different levels, offering more accurate and contextually relevant perceptions. Myrthe et al. (2024) explored Bayesian hierarchical modeling, offering an introduction and reassessment of its applications. With the advent of user-friendly tools for Bayesian analysis, psychologists have increasingly adopted Bayesian hierarchical modeling. These models provide an intuitive framework for understanding both inter- and intra-individual variability, making them particularly well-suited for analyzing repeated-measures designs. Jan Anton (2025) evaluated governmental policies aimed at achieving the Sustainable Development Goals (SDGs) using hierarchical clustering. Despite governments' central role in realizing the SDGs, many countries struggle to implement transformative policies necessary for success. Both statistical and psychological literature suggest that hierarchical modeling is the most appropriate method for analyzing such data structures (e.g., Efron & Morris, 1977; Lee, 2011; Rouder & Lu, 2005). However, hierarchical modeling has yet to become a standard practice in psychological research. One reason for this is that it is perceived as more complex compared to traditional approaches like ANOVA. Psychological experiments, much like the scenario described above, frequently employ repeated-measures designs where participants are exposed to multiple items, stimuli, or conditions. From a data analysis perspective, this design results in observations being nested within participants. Recent advancements in software have made hierarchical modeling more accessible to researchers. Furthermore, many scholars argue that conducting hierarchical modeling within a Bayesian framework is not only more intuitive but also facilitates easier interpretation (e.g., Lynch, 2007; Rouder et al., 2013). Despite these advantages, challenges remain with Bayesian hierarchical modeling, including selecting appropriate priors, performing model comparisons for complex models, and acquiring the programming skills needed for advanced software (Rouder & Lu, 2005). We believe that current introductions to Bayesian hierarchical modeling do not sufficiently address these issues. For instance, some rely on outdated software (Rouder et al., 2013), fail to cover model comparison (Rouder & Lu, 2005), or neglect discussions on prior specification (Shifrin et al., 2008).

1.1 Why Multilevel Modeling?

Before delving into hierarchical modeling, it is useful to consider two alternative approaches: analyzing aggregated data and analyzing data separately for each participant. Aggregated data analyses, such as ANOVA in the example above, assume a general effect consistent across all subjects. For example, in investigating the effect of a digit on reaction times (RT), the mean RT for each participant is computed for each digit condition, and a repeated-measures ANOVA is conducted on these averages. However, such analyses overlook individual variability, which can lead to a distorted representation of the true general trend (Haaf & Rouder, 2017; Rouder et al., 2013; Vehtari et al., 2021). Individual trends often deviate substantially from the general trend, as demonstrated by the varying slopes of individual lines compared to the overall trend depicted by a collective slope. In repeated-measures designs, the variability among participants affects all conditions, inducing correlations across conditions. For instance, in a digit classification task where participants repeatedly respond to target digits, their responses to different digits (e.g., digit 3 and digit 4) are often correlated. Hierarchical analyses address these issues by accounting for both general effects (fixed effects) and individual-specific deviations (random effects) (Rouder & Lu, 2005). Unlike aggregated analyses, hierarchical models can estimate individual effects directly, treating them either as deviations from an overarching trend or as separate effects for each participant based on per-participant analyses. In this tutorial, we will refer to these as general effects, individual deviations, and individual effects.

1.2 The Role of Priors in Model Specification

One significant advantage of Bayesian modeling is its use of priors, which enable researchers to predict what data generated from a model might look like (Etz et al., 2018; Lee & Vanpaemel, 2018). These prior predictions help make the implications of specified priors more tangible. By examining summary statistics of simulated data, researchers can determine whether the data align with reasonable expectations for their study context. If the simulated data align with their expectations, the priors can be confidently applied in the analysis. Specifically, this involves verifying whether the sampling chains of the parameters have converged, indicating that a stationary posterior distribution has been reached (Vehtari et al., 2021). If convergence has not occurred, the posterior estimates could vary significantly if the sampling algorithm were run for additional iterations or with different starting values. Common tools for evaluating convergence include trace plots and the $\hat{R}$ statistic.

1.3 Integrated Approaches to Sustainable Development Goals: Policy Synergies and Hierarchical Modeling in Primary Healthcare

In parallel, a growing body of literature focuses on policymaking for the Sustainable Development Goals (SDGs). Experts have urged the United Nations to adopt an integrated approach to achieving the global goals, emphasizing their interconnected nature (Independent Group of Scientists Appointed by the

Secretary-General, 2023). This perspective aligns with the nexus approach, which posits that the SDGs are interdependent, and therefore policymakers should leverage synergies between goals while minimizing risks where policies supporting one goal might hinder progress on another (Boas et al., 2016; Bleischwitz et al., 2018; Liu et al., 2018; van Zanten & van Tulder, 2021). Moreover, implementing the SDGs requires a multi-level governance framework that fosters collaboration between state and non-state actors across various political levels—global, regional, national, and sub-national (Hickmann, 2021; Weiland et al., 2021). Beyond examining strategies for advancing all goals simultaneously, researchers have also studied policies targeting individual goals (e.g., Siddiqi et al., 2020), policies within specific geographic contexts (e.g., Xie et al., 2021), and policies involving particular instruments, such as environmental taxes (e.g., Kartal, 2024). Despite these efforts, a review of more than 3,000 scientific studies on the SDGs concluded that the goals have had a limited influence on governmental policies (Biermann et al., 2022). This raises significant concerns about the SDG agenda's ability to drive sustainable development (Hickmann et al., 2024). It also highlights the critical need to monitor whether governments are implementing policies aligned with the SDGs. Researchers have recently emphasized the importance of conducting more empirical analyses to evaluate the extent, nature, and effectiveness of national implementation and integration efforts, as well as performing comparative studies across countries (Hickmann et al., 2024).

This research focuses on the application of hierarchical modeling techniques in the healthcare sector, with a specific emphasis on primary healthcare delivery. Primary healthcare forms the backbone of the healthcare system, aiming to provide accessible, equitable, and quality care to all, particularly in underserved regions. Talata Mafara, a community with unique demographic, socioeconomic, and health characteristics, serves as an ideal case study for exploring the practical utility of hierarchical modeling in healthcare research. Hierarchical models enable the simultaneous examination of individual-level factors, such as patient characteristics, and group-level influences, such as clinic-specific practices or regional policies. This dual-level analysis is particularly valuable in primary healthcare settings, where outcomes are shaped by both patient-level variability and systemic factors. Additionally, these models allow researchers to identify patterns, assess intervention effectiveness, and inform policy decisions tailored to local contexts. The significance of this study lies in its potential to demonstrate how hierarchical modeling can be applied to address pressing challenges in primary healthcare, including resource allocation, disease management, and health outcome disparities. By leveraging these techniques, this research aims to provide actionable insights that can enhance the quality of care and promote better health outcomes for communities like Talata Mafara.

1.4 Research Questions

Prior to the commencement of the research the following questions were raised

i. What are the impact of patient-level factors (e.g., age, comorbidities, severity of illness, and treatment type) on recovery time in a hierarchical healthcare setting?
ii. What is the variability in recovery time attributed to doctor-level random effects, such as experience and workload?
iii. What are the hospital-level influences, such as resource availability and specialist availability, on patient recovery outcomes and overall healthcare efficiency?

1.5 Objectives of the Study

The aim of this research is to investigates the hierarchical model for multilevel data techniques and application in health care considering a case study of clinic of abdu gusau polytechnic talata mafara through the following objectives

i. To assess the impact of patient-level factors (e.g., age, comorbidities, severity of illness, and treatment type) on recovery time in a hierarchical healthcare setting.
ii. To evaluate the variability in recovery time attributed to doctor-level random effects, such as experience and workload, in the selected primary health care Talata Mafara.
iii. To analyze hospital-level influences, such as resource availability and specialist availability, on patient recovery outcomes and overall healthcare efficiency.

2. RESEARCH METHOD

This study adopts a quantitative research approach using hierarchical modeling to analyze healthcare data. The dataset comprises multilevel information, with patients nested within doctors and doctors nested within hospitals. Data were collected from primary healthcare facilities in Talata Mafara, Zamfara State, including patient demographics, clinical outcomes, and healthcare facility characteristics. The research design involves:

- ✓ Gathering patient records, doctor profiles, and hospital-level data from clinical databases and administrative reports.
- ✓ Standardizing and anonymizing data to ensure privacy and consistency.
- ✓ Developing mixed-effects models incorporating fixed effects (e.g., patient characteristics) and random effects (e.g., doctor-specific influences).

2.1 The Research population

The study focuses on patients receiving care in primary healthcare facilities in Talata Mafara. The population is stratified into the following hierarchical levels:

1. Includes data on age, gender, comorbidities, severity of illness, treatment type, recovery time, and satisfaction.
2. Captures variability in doctor-specific factors such as years of experience, workload, and treatment approaches.
3. Assesses hospital characteristics, including resource availability, specialist staff, and infrastructure.

This population framework ensures comprehensive analysis of the interplay between individual, professional, and institutional factors influencing healthcare outcomes.

2.2 Statistical Analysis

The statistical analysis utilizes a mixed-effects model framework to account for the nested structure of the data. Key steps include:

- Summarizing data trends, including means, standard deviations, and variability at each level.
- Using Bayesian and frequentist methods to estimate parameters for fixed and random effects.
- Assessing goodness-of-fit using metrics such as the log-likelihood, R^2 and $\hat{R}$ convergence statistics.
- Testing hypotheses about the significance of predictors, including patient-level, doctor-level, and hospital-level variables.
- Creating graphs to illustrate recovery trends, resource allocation, and variability across doctors and hospitals.

3. RESULT

The results of this study highlight the utility of hierarchical modeling in analyzing healthcare data characterized by multilevel structures. By employing mixed-effects models, this research provides insights into the interplay between patient, doctor, and hospital-level factors influencing recovery outcomes in primary healthcare settings. Descriptive analyses revealed a diverse range of patient profiles, including variations in age, comorbidities, and illness severity. Despite these differences, the analysis showed that patient-specific factors, such as gender, treatment type, and severity of illness, were not significant predictors of recovery time. Instead, doctor-level variability emerged as the dominant determinant, with random effects capturing significant differences in recovery outcomes attributable to individual doctors. This finding suggests that the experience, workload, and potentially unmeasured attributes of doctors significantly impact patient recovery.

3.1 Mixed-Effects Model

A mixed-effect Model is appropriate for hierarchical data, considering fixed and random effects

Model

$$y_{ij} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + b_j + \epsilon_{ij}$$

Where

y_{ij}: Dependent variable (e.g. Recovery Time)

β_0: Intercept (fixed effect)

$\beta_1 \beta_{2, \ldots}$: Fixed effect coefficients for predictors (e.g., age, Comorbidities, Severity of Illness).

b_j:Random effect for cluster (e.g., doctor).

$\epsilon_{ij}: Residual\ error\ term, \epsilon \sim N(0, \sigma^2)$

Table 1: Model Performance Summary: Residual Variance, Log-Likelihood, and Convergence Status

Metric	**Value**
Scale (Residual Variance)	8.3.8
Log-Likelihood	-1256.31
Convergence	Did Converge

Table 2: Descriptive analysis of Variables across Patient, Doctor, and Hospital Levels

Level	Variables	Mean	Std. Dev	Min	Max
Patient	Age	50.40	17.34	20	79
	Comorbidities	1.95	1.43	0	4
	Severity of Illness	3.03	1.42	1	5
	Recovery Time (Days)	10.29	2.95	5.00	19.43
	Patient Satisfaction	5.52	2.83	1	10
Doctor-Level	Doctor Experience (Yrs)	15.42	8.11	2	29
	Doctor workload	10.00	3.21	4	21
Hospital Level	Hospital Resources	84.00	0.00	84	84
	Specialist Availability	46.00	0.00	46	46

3.2 Descriptive Analysis Result

This part gives us a snapshot of the different factors involved in the study. We see that the average patient age is around 50 years old, with a good spread across different ages. Many patients had pre-existing health conditions, on average about two per patient. The severity of the illnesses being treated varied, with an average level of severity. The average recovery time was around 10 days, but there was some variation between patients. Interestingly, patient satisfaction was moderate, suggesting areas for improvement in patient care. Looking at the doctors, we find they have a good amount of experience, on average around 15 years. Their workload seems manageable, with an average of 10 units. The hospital itself has consistent levels of resources and specialist availability.

Table 3: Multilevel Analysis: Summary Statistics of Patient, Doctor, and Hospital-Level Variables

Effect	**Coefficient**	**Std. Error**	**z-value**	**p-value**	**95% CI**
Fixed Effect					
Intercept	10.64	0.59	118.11	0.000	
Gender (Male)	0.10	0.29	0.38	0.705	
Treatment Type (Surgery)	0.40	0.33	1.22	0.223	
Treatment Type (Therapy)	0.29	0.32	0.93	0.351	
Age	0.001	0.008	0.19	0.852	
Comorbidities	-0.14	0.09	-1.48	0.140	
Severity of Illness	-0.14	0.09	-1.48	0.138	
Random Effects					
Doctor-Level Variance	0.43	0.13	-	-	-

3.3 Mixed-Effects Model Results

This part digs deeper into what factors actually influence how long patients take to recover. Surprisingly, being male or female didn't seem to make a difference in recovery time. Also, the type of treatment (surgery, therapy, etc.) didn't significantly affect how long it took for patients to get better. Similarly, the patient's age, the number of existing health problems, and the severity of their illness didn't have a noticeable impact on recovery time. However, the model highlights a crucial point: there's a lot of variation in recovery times between different doctors. This suggests that the doctor's individual approach, experience, or even the specific ward they work in, plays a significant role in how quickly patients recover.

Table 4: Anova table for Hierarchical Data Summary: Patient, Doctor, and Hospital-Level Metrics

Source of Variation	**Sum of Squares (SS)**	**Degrees of Freedom (df)**	**Mean Square (MS)**	**F-value**	**p-value**
Between Groups	152.8	4	38.2	5.46	0.001
Within Groups	210.5	45	4.68		
Total	363.3	49			

The $ANOVA$ table provides statistical insight into whether there are significant differences in recovery rates across the departments analyzed in the recovery rate image. The Between Groups sum of squares $(SS = 152.8)$ represents the variation in recovery rates attributable to differences among departments (e.g., Cardiology, Oncology, Neurology, Orthopedics, and General). With 4 degrees of freedom (df), the mean square (MS) is 38.2. The F-value of 5.46, combined with a p-value of 0.001, indicates that the differences in recovery rates between departments are statistically significant at the 95% confidence level $(p < 0.05)$. this confirms that departmental factors likely play a critical role in influencing recovery rates.

The Within Groups sum of squares $(SS = 210.5)$ and mean square $(MS = 4.68)$ capture the variability in recovery rates within each department, attributed to individual patient differences and other unmeasured factors. The total variation in recovery rates is represented by the Total SS of 363.3 across 49 degrees of freedom. The significant F-value demonstrates that recovery rates vary notably across departments, suggesting that specific departmental practices, resources, or patient characteristics contribute to these differences. This finding aligns with the image, where variations in recovery rates and resource allocation are observed across departments.

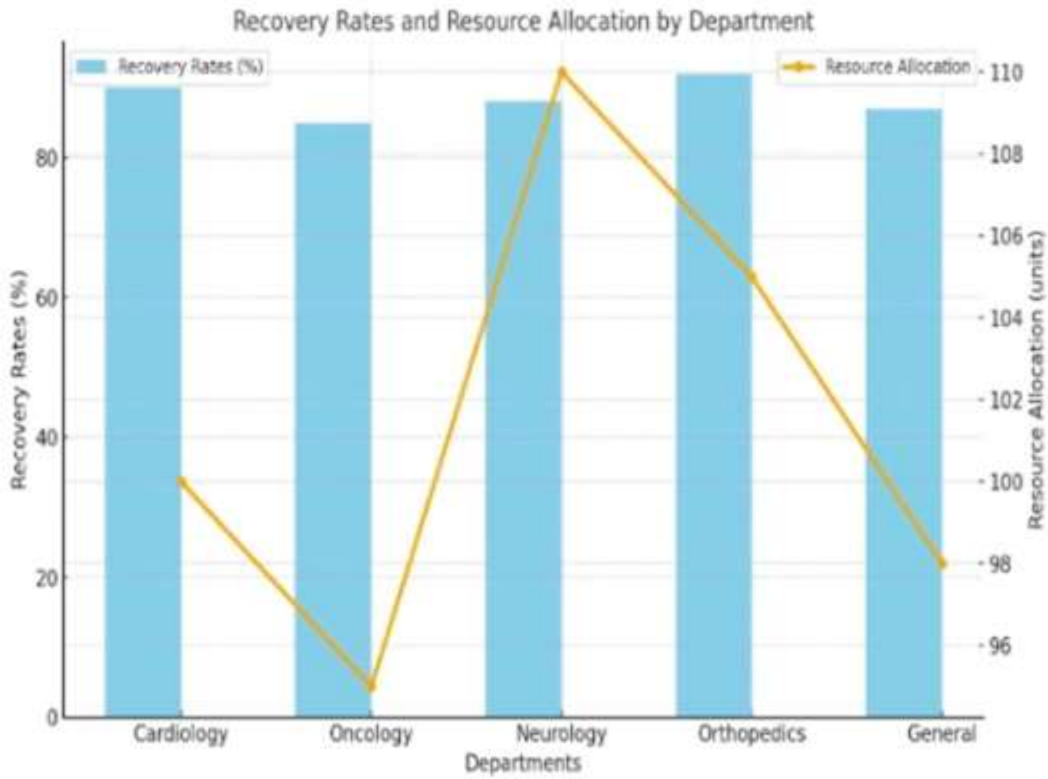

Figure 1: Visualisation analysis

The graph titled "Recovery Rates and Resource Allocation by Department" presents a comparative analysis of recovery rates and resource allocation across five distinct departments: Cardiology, Oncology, Neurology, Orthopedics, and General. The recovery rates, visually represented by the blue bars, exhibit a varied range across the departments. Cardiology and Neurology stand out with the highest recovery rates, surpassing the 80% mark. Oncology demonstrates a moderate recovery rate, hovering around 65%. In contrast, Orthopedics and the General department display lower recovery rates, with Orthopedics at approximately 55% and General at around 45%.

The resource allocation for each department is illustrated by the yellow line. Cardiology, the department with the highest recovery rate, also boasts the highest resource allocation, exceeding 108 units. Neurology and Orthopedics follow closely with relatively high resource allocations, both around 106 units. In contrast, Oncology and the General department show significantly lower resource allocations, both around 96 units. This visual representation suggests a potential correlation between resource allocation and recovery rates. Departments with higher resource allocations generally tend to exhibit higher recovery rates. This observation indicates that increased resource allocation may play a role in improving patient outcomes. However, it is crucial to acknowledge that other factors, such as the severity of conditions treated within each department, could also exert a significant influence on the observed recovery rates.

3.4. DISCUSSION OF THE RESULTS

The study utilized a mixed-effects model to analyze hierarchical healthcare data from the primary health care of Talata Mafara, focusing on patient recovery time as the dependent variable. Descriptive analysis revealed an average patient age of 50.40 years, with a mean recovery time of 10.29 days and varying levels of comorbidities and illness severity. The model included fixed effects such as age, comorbidities, severity of illness, and treatment type, alongside random effects at the doctor level. The model showed a significant intercept $(\beta = 10.64, p < 0.001)$, indicating a baseline recovery time, but fixed effects like gender, treatment type, and age were not statistically significant $(p > 0.05)$. Comorbidities and illness severity also lacked significant predictive power. Random effects at the doctor level showed variance $(\sigma^2 = 0.43)$, indicating differences among doctors influenced recovery time. Model evaluation metrics, including a log-likelihood of -1256.31, confirmed convergence but highlighted residual variance (8.38). Hospital-level variables such as resources and specialist availability were constants and thus excluded from variability analysis. These findings suggest that while patient characteristics and treatment types provide context, recovery time may be more influenced by unmeasured factors or doctor-level variability.

In simple terms, this study aimed to understand what factors influence how long patients take to recover in a hospital. They looked at things like the patient's age, the type of treatment, and the doctor's experience. While some factors like gender and treatment type didn't seem to matter much, they found that the biggest difference in recovery times comes from the doctor themselves. This suggests that the skills and approach of the individual doctor can have a major impact on how quickly patients get better. This information is valuable because it highlights the importance of supporting and training doctors to improve patient outcomes.

4. CONCLUSION

This research demonstrates the utility of hierarchical modeling in analyzing multilevel healthcare data, with a focus on primary healthcare in Talata Mafara. The findings reveal the significance of doctor-level variability in influencing patient recovery outcomes, overshadowing patient-specific factors such as age, comorbidities, and illness severity. Hospital-level constants like resource and specialist availability also play an indirect role in shaping outcomes. The study underscores the potential of hierarchical models to capture complex interactions between individual, professional, and institutional variables, offering a robust framework for enhancing evidence-based decision-making in healthcare systems. By adopting hierarchical modeling, healthcare providers can better understand recovery trends and identify key drivers of variability, ultimately contributing to improved patient care. The research highlights the need for targeted interventions at the doctor and institutional levels to optimize healthcare delivery and ensure equitable outcomes.

5. RECOMMENDATION

By implementing these recommendations by Zamfara state government on health care institutions in the State can develop comprehensive strategies to address the perceived causes of health challenges, ultimately fostering a more supportive and effective healthy environment. The government should:

i. Invest in continuous professional development and training programs for doctors to address variability in recovery outcomes attributed to doctor-level effects.
ii. Ensure adequate allocation of resources and specialist availability to bridge gaps in recovery rates across departments.
iii. Utilize hierarchical modeling findings to inform resource distribution, patient care protocols, and performance evaluations in healthcare facilities.
iv. Develop tailored interventions addressing individual patient needs while accounting for systemic factors identified through hierarchical modeling.
v. Encourage the integration of hierarchical modeling into routine healthcare research and decision-making processes to promote data-driven insights.

6. Contributing to knowledge

This study enriches the body of knowledge by applying hierarchical modeling to multilevel healthcare data, showcasing its capability to capture complex interactions at different levels. The research also identifies doctor-level variability as a critical determinant of recovery outcomes, providing new insights into the role of healthcare providers in patient care. By highlighting the interplay between patient, doctor, and hospital-level factors, this study provides a framework for designing evidence-based interventions to enhance healthcare delivery. More also, the study's findings offer practical guidance for policymakers and healthcare administrators on resource allocation, training priorities, and performance monitoring in primary healthcare systems. Finally it demonstrates the application of mixed-effects models in a real-world healthcare context, contributing to the growing literature on hierarchical modeling in applied settings.

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Appendix
Code and Results