International Journal of P2P Network Trends and Technology
ISSN: 2249 – 2615 / https://doi.org/10.14445/22492615/IJPTT-V12I2P401

Volume 12 Issue 2, 1-12, May-Aug 2022

Original Article

Hierarchical Logistic Regression Model for Multilevel Analysis on the Uptake of Health Insurance in Nouakchott, Mauritania

Tourad Cheikh Tourad[1], Antony Ngunyi[2], Herbert Imboga[3]

[1]*Department of Mathematics, Pan African University Institute for Basics Sciences, Technology and Innovation/ Jomo Kenyatta University of Agriculture and Technology, Nairobi, Kenya*
[2]*Jomo Kenyatta University of Agriculture and Technology, Nairobi, Kenya*
[3]*Jomo Kenyatta University of Agriculture and Technology, Nairobi, Kenya*

Received: 30 May 2022 Revised: 22 July 2022 Accepted: 31 July 2022 Published: 05 August 2022

Abstract - *The availability of these complex statistical methods challenges public health researchers to articulate theories of the causes of health behaviour that bring together factors defined at different levels. This study seeks to discuss the hierarchical logistic regression model for multilevel analysis and test its application in analysing the uptake of health insurance in Mauratania. The specific objectives of this study are to develop the hierarchical logistic regression model, estimate the model parameters of the hierarchical logistic regression model, derive the maximum likelihood estimators of the parameters of the hierarchical logistic regression model and apply the estimation procedure for the uptake of health insurance data from Nouakchott, Mauritania. The study adopted an explanatory study design using secondary data obtained from National Health Insurance funds in Mauritania. The hierarchical logistic regression model for multilevel analysis was used in analysing the data. The analysed data is presented using the table. The obtained model can be used to predict the uptake*

Keywords - *Hierarchical logistic regression, Health insurance, Single model, Multilevel model, Maximum likelihood.*

1. Introduction

The term multilevel analysis (or hierarchical modeling) has been used in the fields of education Diez-Roux (2000). Entwisle et al. (1986) and DiPrete & Forristal (1994) describe multilevel analysis as an analytical approach that allows the simultaneous examination of the effects of group-level and individual-level variables on individual-level outcomes. The use of multilevel analysis to investigate public health problems has increased since the 1980s Diez-Roux (1998). The availability of these complex statistical methods challenges public health researchers to articulate theories of the causes of health behaviour that bring together factors defined at different levels. It ensures that the method does not become an end in itself but rather serves as a tool to investigate more sophisticated and hopefully more realistic models of predicting health behaviour. This study seeks to demonstrate the application of the hierarchical logistic regression model for multilevel analysis on the uptake of health insurance in Nouakchott, Mauritania.

1.1. Background of the Study

In 2005, the World Health Assembly resolution called for a global situation in which “everyone should be able to access health services and not be subject to financial hardship in doing so Organization (2000). This call followed from the recognition by the WHO in the year 2000 that prepayment of healthcare services was the best form of revenue collection to guarantee access to health care, especially for the poor. Indeed, recent global statistics show that out-of-pocket healthcare payment is quite high in Lower-Middle-Income Countries (LMICs), which could impede access to health care. While out-of-pocket expenditure as a percentage of private expenditure on health is 38.5 % in high-income countries, the figure is 86.7 % for lower-middle-income countries and 77.6 % for low-income countries Organization (2015). However, a major challenge toward achieving universal health coverage is the low enrolment and retention rates in social health insurance schemes Basaza et al. (2008).

Many low- and middle-income countries primarily employ user fee schemes for financing health care. Many studies, however, have warned of the negative impact of user fee schemes on health care utilization, especially among the poorest (Preker et al., 2004; World Bank, 2004; van Doorslaer et al., 2006; WHO, 2010). In the event of ill health, the required payment of user fees may deter low-income households from seeking necessary care. Moreover, even when they seek care, many of these households may suffer financial hardships or impoverishment due to payments of significant medical expenses (Peters et al., 2002;

Xu et al., 2003; McIntyre et al., 2017; Acharya et al., 2013). In Mauritania, the government introduced Community-based health insurance (CBHI), which refers to voluntary, non-profit health insurance organized at the local level where state provision or formal health insurance does not protect against the cost of illness. CBHI applies the principles of insurance, i.e. resource pooling, prepayment and risk-sharing, and negotiation with other partners in the health system to improve access to care, financial protection and responsiveness of health services (Soors, Devadasan, Durairaj, Criel, 2010). A mutual health organization (MHO) is the type of CBHI scheme most common in West Africa, governed by its members. CBHI has been in many African countries since the second half of the 20th century(Atim, 1998).

Especially in the 1990s and 2000s, there was a rapid expansion when CBHI was considered a stepping stone toward national health insurance (Ndiaye, Soors Criel, 2007). Results, however, did not match expectations, and the initial enthusiasm of the international community to support CBHI decreased. Moreover, many governments included CBHI in their current strategies toward universal health coverage, particularly to reach the informal sector, which further advocates for an in-depth examination of implementation processes and practices and whether and how they can be improved. Community-based health insurance has continued to face challenges in Mauritania. For instance, the MHO project of Dar Naïm has stagnated. At its initiation, all stakeholders had expected a rapid expansion of the MHO and agreed that it had been set up in favourable conditions. The feasibility study indicated that a large majority of the population was able and willing to pay (PSDN, 2002). There was a dynamic tissue of cooperatives, associations and micro-insurance initiatives. Many referred to the Koran to support their positive opinion of creating a mutual health insurance scheme. Health care services were well attended: for the latest episode of illness, 71%sought care in the formal health sector while 18%stayed at home expecting a spontaneous recovery, 8% preferred auto medication and 3%sought care with a traditional healer (PSDN, 2002). The PSDN that launched the initiative was well known and trusted, the project had the support of health authorities and local authorities, and sufficient funding was secured to sustain set-up, management and monitoring and evaluation for 10 years. But 1 year into operations, the dwindling number of active beneficiaries endangered the scheme's viability. In September 2003, only 828 out of 9750 registered beneficiaries (8.5%) were up-to-date with payment. The PSDN and its supporting organizations, Caritas Mauritanie and Memisa, requested technical assistance from the Institute of Tropical Medicine (ITM). This study seeks to assess the hierarchical logistic regression model application for multilevel analysis on the uptake of health insurance in Mauritania.

1.2. Statement of the Problem

The epidemiological profile of Mauritania is still characterized primarily by infectious and parasitic diseases, although NCDs, particularly cardiovascular diseases and diabetes, are becoming a serious public health problem in Mauritania. This poses a major health burden to society, affecting the productivity and prosperity of the country. Despite the importance of health insurance in health financing, the uptake of health financing in Mauritania remains low. There still exists a gap in determining the issues influencing the uptake of health insurance in Nouakchott, Mauritania.

The study aims to use a hierarchical logistic regression model for multilevel analysis of the uptake of health insurance in Mauritania to understand better some of the major reasons why some individuals do not enrol in the scheme.

There is a vast literature on enrolment-seeking behaviour and the NHIS using quantitative methods (Asante Aikins, 2008; Jehu-Appiah et al., 2011; Chankova, Atim, Hatt, 2010), but very few, if any, using hierarchical logistic regression model for multilevel analysis methods. The results offer a more in-depth understanding of these barriers to enrolment and help provide the basis for practical solutions to remove them.

1.2. General Study objectives

The general objective of this study is to model a hierarchical logistic regression model for multilevel analysis of the uptake of health insurance in Mauritania.

1.3. Significance of the Study

The study may benefit the policymakers by helping them understand better approaches to address the issues of low uptake of health insurance in Mauritania. The policymakers may appreciate the use of diverse multilevel analysis in identifying factors affecting the uptake of Health insurance in Mauritania. The model developed from this study appropriately analysed uptake of health insurance based on nested sources of variability. The units at the lower level (level-1) are nested within units at the higher level (level-2). This study is of benefit to the government in terms of policy making and may enrich exiting literature on applying multilevel regression analysis. It may also help establish conditions necessary for greater uptake of health insurance in Nouakchott, Mauritania.

1.4. Scope of the study

The study assessed the factors affecting the uptake of health insurance in Nouakchott, Mauritania. The study highlighted the importance of multilevel analysis using logistic regression models for studying the uptake of health insurance, determining the true effect of the factors on the uptake of health insurance, taking into consideration the effect of the levels and investigating the variation of health insurance uptake between the predictor variables across the Nouakchott region. The target population for this study is 661,400 adults. On the geographical scope, the study covered the Nouakchott region in Mauritania.

2. Literature Review

Urbach & Austin (2005) utilized Monte Carlo simulation to examine the influence of misspecification of the random effect distribution on estimate and inference for both fixed and random effects in multilevel logistic models. He concluded that model misspecification did not influence estimate and inference for fixed effects, while model misspecification impacted estimating and drawing inference for random effects. Another example is data grouping, such as individuals clustered inside hospitals, whereas standard regression models presume that the variables have no collinearity. High-tier units are taken from a population of components in hierarchical models, which give posterior or projected values of individual effects. These shrunkenestimations have the advantage of pushing group level item estimates closer to the group mean and improving forecast accuracy.

Pituch et al. (2020) analyzed the effectiveness of fully independent sample t-tests estimated with OLS with similar t-tests from MVMMs to evaluate two-group mean variations with multiple outputs under small sample and missingness situations. According to the findings, the best performance was achieved using an MVMM with a restricted maximum likelihood estimate and the Kenward-Roger adjustment. As a result, the Kenward-Roger process is preferred over traditional techniques and conventional MVMM analyses for intervention programs with small N and standard normal distribution multivariate outputs, especially when data is inadequate.

Konstantopoulos et al. (2016) experimented with using power analysis techniques in three-level polynomial paradigms for cluster randomised designs. They discovered that the frequency of observed occasions, the number of members in each group and the number of groups grew as the frequency of observed occasions, participants in each group, and groups increased. When all other factors are equal, the frequency of level 3 units had a greater impact on power than the frequency of level 2 units or the frequency of observed occasions of the study. This research used a power analysis to determine the sample size needed to attain a power of >0.80. Nevertheless, apart from power, appropriate sample sizes at each level are required to produce precise parameter and SE estimations. Even if the sample size is big enough to achieve acceptable power, obtaining correct variable estimations may not be sufficient (Hill et al. (2008).

3. Material and Methodology

3.1. Data

The study used secondary data obtained from National Health Insurance funds in Mauritania. The study used a hierarchical structure consisting of 2 levels: Individuals and factor level (socioeconomic, health factors, accessibility).

3.2. Study Variables

3.2.1. Dependent variable

The dependent variable is 'Current uptake of health insurance’. Uptake of health insurance was asses in the household. If a household has health insurance, uptake is coded as '1' and if not ', 0'.

3.2.2. Independent variables

Demographic Variables
Social and economic variables
Cover benefits
Patient factor

3.3. The Multilevel Logistic Regression Model

A hierarchical or clustered structure may be seen in many data types, including observed data gathered in the human and biological sciences. The following are the two most common applications of multilevel models: Multilevel models consider the hierarchical layers often found in data. Multilevel models incorporate covariates at multiple levels layers of a hierarchical system and offer a versatile framework for analysing various dependent factors and including factors at various layers of the hierarchical system.

3.4. Multilevel Structures

There are three distinct approaches to displaying multilevel structures: A changing intercept model is a regression that incorporates parameters for groups and can be viewed as a model with a varied intercept within each group. Where x is the independent variable and j groups are the indicators (Gelman & Hill, 2006). First, we analyse a model in which each top layer regressions have a similar gradient, and only the intercepts differ. Individuals are denoted by the letter I, whereas regions are denoted by the letter j. Varying-intercept model:

$$y_{1j} = \alpha + \beta_1 . x_{ij} + \mu_j + \varepsilon_{ij} \qquad (3.4.1)$$

Where $\varepsilon \sim N(0, \sigma_\mu^2)$, $\mu \sim N(0, \sigma_m^2)$,

There are two elements to the random intercept model. It has a fixed portion (the independent factor's intercept and coefficient times the independent factors) and a randomized component (this uj + ij at the end). The coefficients α and $\beta 1$ are the variables we measure for the fixed portion, while the variances $\sigma 2 \mu$ and σ 2 e are the variables we measure for the randomized part. The random component is the same as the single-level regression model's error term is unpredictable. It means that the μj and the εij might both be different.

Random Intercept Logit Model

$$y_{1j} = log\left\{\frac{\pi_{ij}}{1-\pi_{ij}}\right\} = \beta_0 + \beta_1 . x_{ij} + \mu_j$$
$$\mu_j \sim \mathrm{N}(0, \sigma_u^2)$$

X_{ij} is the observation of ith individual in the jth region

X_{ij} is the response probability i.e $\pi_{ij} = \frac{\exp(\beta_0+\beta_1 x_{1+\mu_j})}{1+\exp(\beta_0+\beta_1 x_{1+\mu_j})}$

Clarification of β0 and β1 is given by; β0 interpreted as the log-odds that y = 1 when x = 0 and u = 0 and is known as the general intercept in the linear association between the log-odds and x. Iin case we take the exponential of β0, exp(β0), we obtain the odds that y = 1 for x = 0 and u = 0. In the single-level model, where β1 is the effect of a 1-unit change in x on the log-odds that y = 1, in this model, it is the effect of x after adjusting for the group effect u. If we hold u constant, we consider the effect of x for singular units within the same group, so β1 is generally known as a cluster-specific effect. In evaluating multilevel data, we are frequently concerned with the extent of deviation credited to the different layers in the data structure and how independent factors can clarify deviation at a particular layer. In contrast, uj is the group random effect or level 2 residual, and the variance of the intercepts across groups is var(u*j*) = *σu*2(*varuj*)=*σu*2, which is the between-group variance adjusted for x.

3.5. Parameter Estimation

In a multilevel model, repeated Generalized Least Square Techniques are an effective way to estimate variables. We can create a block diagonal matrix V if we understand the variation in a 2-level model; however, we can also use the General Least Square technique to derive the parameter estimates of fixed coefficients, viz;

$$\hat{\beta} = (\mathrm{X^t V^{-1} X})^{-1} \mathrm{X^t V^{-1} Y}$$

$y_{ij=\beta_0+\beta_1 x_{ij}+\mu_{0j}+\epsilon o_{ij}}$

$\mathrm{Var}(\varepsilon_{0ij}) = \sigma^2_{e^0}$

$\mathrm{Var}(\varepsilon_{0j}) = \sigma^2_{\mu^0}$ Where $\mathrm{x} = \begin{vmatrix} 1 & \cdots & \pi_{11} \\ \vdots & \ddots & \vdots \\ 1 & \cdots & \pi_{nm} \end{vmatrix}$ $\mathrm{Y} = \begin{vmatrix} y_{11} \\ y_{12} \\ \vdots \\ y_{1m} \end{vmatrix}$

$\mathrm{V} = \begin{vmatrix} 1 & \cdots & \nu_{11} \\ \vdots & \ddots & \vdots \\ 1 & \cdots & \nu_{nm} \end{vmatrix}$

Where we have m level 2 units and n_j level 1 units in the jth level 2 units So, the GLS estimator can be formulated as follows

$$\hat{\beta}_{\mathrm{GLS}} = (\mathrm{X^{1T}X^1})^{-1}\mathrm{X^{1T}Y^1} = (\mathrm{X^T V^{-1} X})^{-1}\mathrm{X^T V^{-1} Y} \qquad (3.4.2)$$

Alternatively, it can also be obtained as a solution to the minimization of the GLS criterion function

$$(Y - XB)^T V^{-1} (Y - XB) \to \frac{min}{\beta} \qquad (3.4.3)$$

This criterion function can be considered a generalization of the RSS function, which is minimized in the OLS case. The effect of such weighting is clear when V is diagonal - each observation is given a weight proportional to the inverse of the variance of its error term.

3.6. Logit Model Estimation

The typical multilevel logit model is derived by presuming that the components of Y are independently distributed using a Bernoulli random distribution with probabilities μi = prYi = 1

$$\mathrm{logit}\mu = \eta = \mathrm{X}\beta + \mathrm{Z}u$$

where X is the model matrix for fixed effects, Z is the model matrix for the random effects u and η is a conditional linear predictor. The logit model or the generalized linear model is

$$\left\{\frac{P_{ij}}{1-P_{ij}}\right\} = n_{ij} = X_{ij} Y_\gamma + Z_{ij} Y_{\mu j}$$

For level-1 unit, i nested within level-2 unit j. At level 1, we assume Yij conditionally distributed as Bernoulli, while the random effects vector u$j \sim N$ (0,σ_μ^2) across the level-2 units. Considering the variance σ_μ^2 as Y throughout this REML estimation procedure. The REML criterion can be obtained by integrating the marginal density for Y for the fixed effects (Gilmour et al., 1995).

$$\int f_y\, y(obs) d\beta = \frac{\left[\omega^\tau \frac{1}{2}\right] L_0]^{-1}}{2\pi\sigma^{\frac{2n}{2}}} exp\left(\frac{-r^2(\theta)}{2\sigma^2}\right) \int exp\left\{\frac{-\|\nu\|^2}{2\sigma^2}\right\} |\mathrm{R}_x| d\nu$$

which simplifies to,

$$\int f_y\, y(obs) d\beta = \frac{\left[\omega^\tau \frac{1}{2}\right] L_0]^{-1}\, |\mathrm{R}_x|^{-1}}{2\pi\sigma^{\frac{2(n-p)}{2}}} exp\left(\frac{-r^2(\theta)}{2\sigma^2}\right) \int exp\left\{\frac{-\|\nu\|^2}{2\sigma^2}\right\}$$

Minus twice the log of this integral is the (unprofiled) REML criterion,

$$-2L_R(\theta - \sigma^2 \mathrm{I} yobs) = \frac{\mathbf{log}\, |L_0|^2 |\mathrm{R}_x|^2}{W} + (n-p)\log(2\pi\sigma^2) + \frac{r_\theta^2}{\sigma^2}$$

We note that because β gets integrated out, the REML criterion cannot be used to nd a point estimate of β. However, we follow others in using the maximum likelihood

estimate,βˆ θˆ^, at the optimum value of θ= θˆ. The REML estimate for
σ^2 is,

$\widehat{\sigma}_\theta^2 = \frac{r^2(\theta)}{(n-p)}$

which leads to profiled REML criterion,

$$-2L_R(\theta - \sigma^2 \mathrm{I}yobs) = \frac{\log |L_0|^2 |\mathrm{R}_X|^2}{W} + (n-p)\left\{1 + \log\left(\frac{2\pi r^2(\theta)}{n-p}\right)\right\}$$

4. Results and Discussion

4.1. Introduction

To use the R package for multilevel analysis, we organized the data to reflect the data's hierarchical structure in the analysis. The data was, therefore, first sorted in such a way that all records for the same highest level (*level* 2: Regions) were grouped. The covariates used in this study were all significant in the analysis done before starting the multilevel analysis. The multilevel modelling process for this hierarchical data was done step by step. The first step examined the null model of the overall probability of uptake of health insurance without adjustment for predictors. This was followed by the second step, which included the analysis of (both single and multilevel analysis models and random slope multilevel analysis for each of the selected explanatory variables. Third step considered building a model for multilevel logistic regression analysis and single-level analysis. Finally, the likelihood ratio test was used to determine the significance of each model as a whole as well as to determine the significance of the individual coefficients

4.2 Intercept Only Model

Null Model

The null or empty two-level model is a model with only an intercept and Regional effects

$$log\left\{\frac{\pi_{ij}}{1-\pi_{ij}}\right\} = \beta_0 + \mu_{0j}$$

Table 4. 1 Null model

	Model 1
(Intercept)	0.88362 *** (0.04586)
AIC	2779.4
BIC	2785.156
Log Likelihood	-1388.708
Num. obs.	2298
Num. groups: Region	8
Var: Region (Intercept)	0.002103099

Signif. Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

All regions share the intercept β0 while the random effect μ 0j is specific to region j. The random effect was assumed to follow a normal distribution with variance σ 2u 0. From the model estimates (using Laplacian approximation), we saw that the log-odds of using health insurance uptake in the regions are estimated as β0 = 0.88362. It means that the odds of uptake of health insurance in an average region is *exp*(0.88362) = 2.419643, and the corresponding probability will be $\frac{2.419643}{1+2.419643}$= 3.419643. The intercept for region j is 0.88362+ μoj, where the variance of μoj was estimated as σu20 = 0.002103099.

4.3. Multilevel Univariate Analysis

In this univariate analysis represented in Table 4.2, each of the models presents a random intercept and a fixed slope for the
variable.

$$\beta_{0ij} = \beta_0 + \mu_{0j} + \mu_{0ij}$$

Table 4.2. Table of parameters and standard errors of univariate single level logistic model and multilevel model predicting the probability of uptake of health insurance with random intercept only.

Table 4. 2. Table of parameters and standard errors of univariate single-level logistic model and multilevel model predicting the probability of uptake of health insurance cover

	Single Level	Multilevel	Over/Underestimation
Intercept	1.3984 ***(0.000114)	-24.87612 (752.04985)	1878.899
Incomelt $1000	1.0729**(0.3624)	2.52717 *** (0.42576)	-135.546
Income$1000 To 2999	-0.1702(0.3983)	2.31953 *** (0.46553)	1462.826
Income$3000 To 3999	0.1975(0.5382)	-0.10304 (0.62394)	152.1722
Income$4000 To 4999	1.9892**(0.5691)	0.37457 (0.65373)	81.16982
Income$5000 To 5999	1.2961 .(0.6679)	3.48918 *** (0.74241)	-169.206

Income$6000 To 6999	1.5962**(0.7390)	2.51014 ** (0.83605)	-57.2572
Income$7000 To 7999	1.4420***(0.6115)	2.24314** (0.70444)	-55.5576
Income$8000 To 9999	0.8861***(0.3482)	2.54827 *** (0.39917)	-187.583
Income$10000 - 14999	2.0058 ***(0.2040)	1.85826 *** (0.26166)	7.355669
Income$15000 - 19999	2.0662***0.2911)	2.81105 *** (0.34544)	-36.0493
Income$20000 - 24999	2.3811***0.2353)	2.83364 ***(0.29034)	-19.0055
Income$25000 Or More	1.3984***(0.1336)	2.83980 ***(0.16725)	-103.075
Divorced	13.56(229.63)	13.72245 (531.78041)	-1.19801
Married	13.47 (229.63)	13.69557 (531.78040)	-1.67461
Never Married	13.60 (229.63)	13.43140 (531.78039)	1.239706
Separated	13.51(229.63)	13.74618 (531.78041)	-1.74819
Widowed	12.74(229.63)	3.64093 (531.78043)	71.42127
Male	0.05528(0.09233)	-0.21001 .(0.12537)	479.9023
Childs1	0.05579(0.15491)	-0.06140 (0.20877)	210.0556
Childs2	-0.24659.(0.12582)	-0.19389 (0.18428)	21.37151
Childs3	-0.27896 .(0.14342)	-0.29715 (0.20614)	-6.52065
Childs4	-0.50404**(0.18715)	-0.22345 (0.26150)	55.6682
Childs5	-0.66143**(0.25551)	-0.42056 (0.33822)	36.41655
Childs6	-0.63649*(0.31519)	-0.06495 (0.42986)	89.7956
Childs7	-0.81596(0.43011).	-0.07016 (0.51775)	91.40154
Childseight Or More	-0.82701(0.51190)	-0.31135 (0.70004)	62.35233
Keeping House	13.35(378.59)	11.23916 (531.77989)	15.81154
Other	13.48 (378.59)	11.82660 (531.77998)	12.26558
Retired	13.27(378.59)	11.12490 (531.77989)	16.16503
Atschool	13.94(378.59)	12.03688 (531.77995)	13.65222
Not Working	15.02(378.59)	13.23393 (531.78005)	11.89128
Unemployed, Laid Off	14.21(378.59)	12.44501 (531.77995)	12.42076
Working Fulltime	15.46 (378.59)	13.71640 (531.77988)	11.27814
Tworking Parttime	15.21(378.59)	13.37225 (531.77991)	12.08251
Health excellent	-0.11558 (0.14498)	-0.35413. (0.18628)	-206.394
Health good	-0.24250* (0.11455)	-0.52309 *** (0.14837)	-115.707
Health fair	-0.32292*(0.14159)	-0.32474. (0.18156)	-0.56361
Health poor	-0.79738***(0.23647)	-0.60281 *(0.30193)	24.40116
Quality Health Insurance Service	-0.13957**(0.05324)	0.03148 (0.10581)	122.555
Customer Service	-0.08824.(0.05212)	0.21103. (0.10921)	339.1546
Flexibility Package	-0.10982*(0.05176)	-0.03302 (0.10683)	69.93262
Existing Health Conditions	-0.33310***(0.04592)	-0.18904 * (0.08799)	43.24827
Services Covered	-0.17506***(0.04867)	0.40393 ***(0.10394)	330.738
Accredited Facilities	-0.34018***(0.05123)	-0.19232 *(0.09708)	43.46522
Pharmacy Benefits	-0.37906***(0.05445)	-0.34583 *** (0.08431)	8.766422
Affordability	-0.26761***(0.05465)	-0.39838 *** (0.10371)	-48.8659
AIC		1947.5	
BIC		2217.316	
Log Likelihood		-926.7727	
Deviance		1853.5	
Var: Region(Intercept)			

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

It was observed that there existed significant differences between the β coefficients of the single level and multilevel explanatory variables. The β coefficients of the single-level model were underestimated compared to the multilevel analysis model. The results showed that all the explanatory income significantly influenced the uptake of health insurance at ($p<0.01$). In a single-level model, the income of $15000–19999, $20000–24999 and $25000 or more significantly influenced health insurance uptake, while the income of 3000 to 3999 and $4000 to 4999 significantly influenced uptake of health insurance when income predicted using a multilevel logistic model. In a single-level model, having 4, 5, or 6 children significantly influenced the uptake of health insurance. In contrast, in the Multilevel logistic model, the number of children did not significantly influence the uptake of health insurance.

The study further found the working status did not influence the uptake of health insurance. In a single-level model, poor health status significantly influenced the uptake of health insurance. In contrast, in the Multilevel logistic model, poor health status did not significantly influence the uptake of health insurance. In a single-level model, Quality Health Insurance Service significantly influenced the uptake of health insurance. In contrast, in the multilevel logistic model, Quality Health Insurance Service did not significantly influence the uptake of health insurance. A single-level model flexibility package significantly influenced the uptake of health insurance, while a multilevel logistic model flexibility package did not significantly influence the uptake of health insurance.

It was found in a single-level and multilevel logistic model that existing health conditions, services covered, accredited facilities, and pharmacy benefits and affordability significantly influenced uptake of health insurance. This shows that some Regions depict a high tendency on the uptake of health insurance with the increase in income, the number of children, deterioration of health, Quality Health Insurance services, Flexibility package, Existing Health Conditions, Services covered, Accredited facilities, Pharmacy benefits and affordability while the reverse is true. When the effect of multilevel analysis is not considered, the β coefficients for the explanatory variables are overestimated, as shown in the last column of table 4.2. For example, the estimates of Services covered are underestimated by 339.2%

4.4. Multilevel Vs Single Level

If we compare the two sets of results, the income levels' coefficients decreased when the random effect was added apart from the income within the range between $5000 to 5999. The ratio of the single-level estimate to multilevel estimates is 1.5672 for income of $1000, 0.5132 for income $3000 to 3999, 0.4501 for $4000 to 4999, 0.7834 for $5000 to 5999, 1.1705 for $6000 to 6999, -6.8491 for $7000 to 7999, 1.6136 for income of $8000 to 9999, 0.4052 for $10000 – 14999, 1.8978 for $15000 – 19999, 1.9321 for $20000 – 24999, and 2.5145 for $25000 or more. Equally, the coefficient of marital status decreased when the random region effect was added apart from those who never married.

The coefficients of the number of children decreased when the random effect for the case of 1 child and 3 children have added apart from the families with 2, 4, 5, 6, 7 and 8 children where the random effect was added. In contrast, all coefficients of work status decreased when a random effect was added.

The coefficients of health decreased in cases of fair and poor health when the random effect was added, whereas when the random effect was added, the coefficient of health status for the case of good health increased. It further observed that the coefficient of quality health insurance service, customer service, package flexibility, existing health conditions, covered services, accredited facilities and pharmacy benefits decreased when the random effect was added. At the same time, the coefficient of affordability increased when the random effect was added.

Table 4. 3. Table of Single Level Analysis vs Multilevel

	Single Level			Multilevel		
	Estimates	Sign.	Std Error	Estimates	Sign.	Std Error
Intercept	0.2877	0.4513		-2.9107	0.9757	752.0500
Incomelt $1000	0.3254	0.5268	0.5142	0.2076	0.7180	0.5750
Income$1000 to 2999	2.31363	0.004514 **		1.20291	0.005524 **	
Income$3000 to 3999	-1.2432	0.0559	0.6502	-2.4226	0.0012 **	0.7487
Income$4000 to 4999	-0.8755	0.1953	0.6760	-1.9450	0.01180 *	0.7724
Income$5000 to 5999	0.9163	0.2286	0.7610	1.1697	0.1599	0.8322
Income$6000 to 6999	0.2231	0.7866	0.8241	0.1906	0.8374	0.9288
Income$7000 to 7999	0.5232	0.4624	0.7120	-0.0764	0.9248	0.8094
Income$8000 to 9999	0.3691	0.4642	0.5043	0.2287	0.6839	0.5618
Income$10000 - 14999	-0.1869	0.6548	0.4180	-0.4613	0.3321	0.4756
Income$15000 - 19999	0.9328	0.045621 *	0.4667	0.4915	0.3536	0.5299
Income$20000 - 24999	0.9933	0.022127 *	0.4341	0.5141	0.2984	0.4944
Income$25000 or More	1.3082	0.00075 ***	0.3885	0.5203	0.2430	0.4456
Divorced	13.5600	0.9530	229.6300	13.7225	0.9794	531.7804
Married	13.4700	0.9530	229.6300	13.6956	0.9795	531.7804
Never Married	13.6000	0.9530	229.6300	13.4314	0.9799	531.7804

Separated	13.5100	0.9530	229.6300	13.7462	0.9794	531.7804
Widowed	12.7400	0.9560	229.6300	13.6409	0.9795	531.7804
Male	0.0553	0.5490	0.0923	-0.2100	0.0939	0.1254
Childs1	0.0558	0.7187	0.1549	-0.0614	0.7687	0.2088
Childs2	-0.2466	0.0500	0.1258	-0.1939	0.2927	0.1843
Childs3	-0.2790	0.0518	0.1434	-0.2972	0.1494	0.2061
Childs4	-0.5040	0.00707 **	0.1872	-0.2235	0.3928	0.2615
Childs5	-0.6614	0.00963 **	0.2555	-0.4206	0.2137	0.3382
Childs6	-0.6365	0.04344 *	0.3152	-0.0650	0.8799	0.4299
Childs7	-0.8160	0.0578	0.4301	-0.0702	0.8922	0.5178
Childseight Or More	-0.8270	0.1062	0.5119	-0.3114	0.6565	0.7000
Keeping House	13.3500	0.9720	378.5900	11.2392	0.9831	531.7799
Other	13.4800	0.9720	378.5900	11.8266	0.9823	531.7800
Retired	13.2700	0.9720	378.5900	11.1249	0.9833	531.7799
Atschool	13.9400	0.9710	378.5900	12.0369	0.9819	531.7800
Temp not working	15.0200	0.9680	378.5900	13.2339	0.9801	531.7801
Unempl, Laid off	14.2100	0.9700	378.5900	12.4450	0.9813	531.7800
Working Fulltime	15.4600	0.9670	378.5900	13.7164	0.9794	531.7799
Working Parttime	15.2100	0.9680	378.5900	13.3723	0.9799	531.7799
Health fair	-0.2073	0.2099	0.1653	0.0294	0.8908	0.2140
Health good	-0.1269	0.3744	0.1429	-0.1690	0.3546	0.1825
Health poor	-0.6818	0.00669 **	0.2514	-0.2487	0.4461	0.3264
Quality Health Insurance Service	-0.1396	0.00875 **	0.0532	0.0315	0.7661	0.1058
Customer Service	-0.0882	0.0905	0.0521	0.2110	0.0533	0.1092
Flexibility Of Package	-0.1098	0.0339 *	0.0518	-0.0330	0.7572	0.1068
Existing Health Conditions	-0.3331	4.06e-13 ***	0.0459	-0.1890	0.03167 *	0.0880
Services Covered	-0.1751	0.00032 ***	0.0487	0.4039	0.0001 ***	0.1039
Accredited Facilities	-0.3402	3.13e-11 ***	0.0512	-0.1923	0.04757 *	0.0971
Pharmacy Benefits	-0.3791	3.35e-12 ***	0.0545	-0.3458	4.10e-05 ***	0.0843
Affordability	-0.2676	9.74e-07 ***	-0.3984	-0.398380	.0001***	0.1037

This implies random effect increased the uptake of health insurance among families earning an income of $5000 to $5999 while decreasing the uptake of health insurance among other categories. Equally, random effect decreased uptake of health insurance among divorced, married, separated and widowed but increased uptake of health insurance among the person who never married. Also, random effect decreased uptake of health insurance among families with 1 child and 3 children while decreasing uptake of health insurance with 2, 4, 5, 6, 7 and 8 children in various regions. The uptake of health insurance decreased for families with people with fair and poor health when the random effect was added, whereas when the random effect increased uptake of health insurance for the case of good health. Finally, when the random effect was added, uptake of health based on the quality of health insurance service, customer service, package flexibility, existing health conditions, covered services, accredited facilities and pharmacy benefits decreased but increased in the case of affordability.

4.5. Random Slope Models

4.5.1. Random slope for income across regions

$$Y_{ij}= \beta_0 + (\beta_1 + \mu_{1j})X_7 + \mu_{0j} + \varepsilon_{0ij}$$

Where;

β_0 is the intercept(the logs odd of uptake of health insurance for an individual living in an average region),

β_1 is the effect on the log-odds of a category increase income),

μ_{ij} and μ_{0j} are the random intercepts,

ε_{0ij} is the residual.

Table 4. 4. Varying income across the region

	INCOME	INCOME: Region
Intercept	0.2877 (0.451253)	2.357e+01 (0.999)
Incomelt $1000	1.3984 *** (0.000114)	-2.100e+01 (0.999)
Income$1000 To 2999	1.0729** (0.3624)	
Income$3000 To 3999	-0.1702 (0.3983)	-6.021e-09 (1.000)
Income$4000 To 4999	0.1975 (0.5382)	-5.999e-07 (1.000)
Income$5000 To 5999	1.9892** (0.5691)	-5.997e-07 (1.000)
Income$6000 To 6999	1.2961. (0.6679)	5.062e-09 (1.000)
Income$7000 To 7999	1.5962** (0.7390)	-5.996e-07 (1.000)
Income$8000 To 9999	1.4420*** (0.6115)	-2.203e+01 (0.999)
Income$10000 - 14999	0.8861*** (0.3482)	-2.089e+01 (0.999)
Income$15000 - 19999	2.0058 *** (0.2040)	-2.057e+01 (0.999)
Income$20000 - 24999	2.0662*** (0.2911)	5.151e-09 (1.000)
Income$25000 Or More	2.3811*** (0.2353)	-2.015e+01 (0.999)
Dar Naim: Income$15000 - 19999		-4.308e-01(1.000)
Riyadh: Income$15000 - 19999		2.057e+01(1.000)
Toujounine: Income$15000 - 19999		2.057e+01(1.000)
Dar Naim: Income$20000 - 24999		-2.100e+01(1.000)
Le Ksar: Income$20000 - 24999		-5.851e-07 (1.000)
Riyadh: Income$20000 - 24999		-5.149e-09 (1.000)
Sebkha: Income$20000 - 24999		-2.944e-08 (1.000)
Toujounine: Income$20000 - 24999		-5.075e-09 (1.000)
Dar Naim: Income$25000 Or More		-8.473e-01 (1.000)
Le Ksar: Income$25000 Or More		2.015e+01 (1.000)
Riyadh: Income$25000 Or More		2.015e+01 (1.000)
Sebkha: Income$25000 Or More		2.015e+01 (1.000)
Toujounine: Income$25000 Or More		2.015e+01 (1.000)

```
Response: Health cover
                   Df     Sum Sq  Mean Sq        F value       Pr(>F)
INCOME             12     89.82          7.485   1395.3985      < 2e-16 ***
Region1            6      373.36         62.227  11601.2351     < 2e-16 ***
INCOME: Region     36     0.28           0.008   1.4539        0.04006 *
Residuals          2243   12.03          0.005
---Signif. Codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

4.5.2. Varying health with income

$$Y_{ij} = \beta_0 + \beta_1 + \pi_1 X_6 + \pi_2 X_1 + \varepsilon_{0ij}$$

The random effect in this table was significant. This means that varying health with income was significantly different across the regions. At the same time, health and income were significant ($p<0.001$). Therefore health and income influence health insurance among households. The effect of the interaction of income on health as a predictor of uptake of health insurance shows a high probability of households taking health insurance if they had fair health and a high-income level. It was also observed that a household with excellent health status was likely to take health insurance with the highest level of income.

Table 4. 5. Varying health with income

	Estimates
Intercept	-0.92734 (2.48e-06) ***
Incomelt $1000	1.3984 *** (0.000114)
Income$2000 To 2999	1.0729** (0.3624)
Income$3000 To 3999	-0.1702 (0.3983)
Income$4000 To 4999	0.1975 (0.5382)
Income$5000 To 5999	1.9892** (0.5691)
Income$6000 To 6999	1.2961. (0.6679)
Income$7000 To 7999	1.5962** (0.7390)
Income$8000 To 9999	1.4420*** (0.6115)
Income$10000 - 14999	0.8861*** (0.3482)
Income$15000 - 19999	2.0058 *** (0.2040)
Income$20000 - 24999	2.0662*** 0.2911)
Income$25000 Or More	2.3811*** (0.2353)
Health excellent	0.76029 (0.013494) *
Health fair	0.29873 (0.415501)
Health good	-0.13618 (0.640735)
Health poor	-14.63873 (0.980344)
Incomelt $1000:Healthfair	-0.85835 (0.432169)
Income$1000 To 2999:Healthfair	-2.37817 (0.113632)
Income$3000 To 3999:Healthfair	-0.52188 (0.745472)
Income$4000 To 4999:Healthfair	-14.25536 (0.986464)
Income$5000 To 5999:Healthfair	-0.29873 (0.858341)
Income$6000 To 6999:Healthfair	15.96048 (0.991250)
Income$7000 To 7999:Healthfair	-0.29873 (0.853978)
Income$8000 To 9999:Healthfair	-1.57967 (0.148566)
Income$10000 - 14999:Healthfair	-0.22974 (0.693308)
Income$15000 - 19999:Healthfair	-0.80956 (0.359035)
Income$20000 - 24999:Healthfair	-1.26632 (0.119685)
Income$25000 Or More: Healthfair	-1.01073 (0.019762)*
Income$20000 - 24999:Healthexcellent	-2.36972 (0.011053) *
Income$25000 Or More: Healthexcellent	-1.40084 (0.000198) ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

4.6. Multilevel Multivariate Logistic Modelling

$$\log\left\{\frac{\pi_{ij}}{1-\pi_{ij}}\right\} = \beta_{0ij} + \beta_1 X_1 + \beta_{2ij} X_{4ij} + \beta_3 X_5 + \beta_4 X_7 + \beta_5 X_3 + \mu_{0j}$$

Where $\beta_{0ij}=\beta_0 + \mu_{0j} + \mu_{0ij}$ and $\beta_{2ij}=\beta_2 + \mu_{2j} + \mu_{2ij}$

The multivariate model shows that the probability of health insurance uptake is affected significantly by the amount of income, number of children, household members' health status, including household head, existing health conditions, covered services, accredited facilities, pharmacy benefits and affordability. When the quality of the Health Insurance Service and the Flexibility of the package were fitted in a single model, it significantly influenced health insurance uptake. Still, it insignificantly predicted the uptake of health insurance when fitted in the multivariate model.

To compare multilevel and single-level analyses, we compare their corresponding parameter estimates. Table 4.7 shows that the coefficient under single-level analysis corresponding to factors for the uptake of health insurance covariate has been overestimated by about 694.9% compared to multilevel estimates. In the analysis, income, only two categories shown in Table 4.9) did not find to be another important determinant to consider while predicting whether uptake of health insurance. The amount of family income influences the uptake of health insurance. The β coefficient for income$6000 to 6999, income$5000 to 5999, income$8000 to 9999 from the single level model were underestimated.

Further in the analysis, only two categories from the number of children shown in Table 4.6 were found to be another important determinant to consider while predicting whether uptake of health insurance under the multilevel model. The number of children influenced the uptake of health insurance. Equally, health status, particularly fair, good and poor health, predicted uptake of health insurance. Finally, Existing Health Conditions, Services covered, accredited facilities, Pharmacy benefits and affordability were found to influence the uptake of health insurance significantly. The variation is significant at (p<0.001).

Table 4. 6. Multilevel Multivariate Logistic Modelling

	Single Level	**Multilevel**	**Ratio**
Intercept	1.77464 (0.013398) *	2.53811 (0.43362)	694.9%
Incomelt $1000	1.3984 *** (0.000114)	1.53614 (0.37759)	0.0%
Income$1000 to 2999	1.0729** (0.3624)	1.18218 (0.42404)	48.0%
Income$3000 to 3999	-0.1702 (0.3983)	-0.15576 (0.57076)	49.4%
Income$4000 to 4999	0.1975 (0.5382)	-0.11545 (0.60454)	67.4%
Income$5000 to 5999	1.9892** (0.5691)	2.20861 (0.70783)	-9.9%
Income$6000 to 6999	1.2961. (0.6679)	1.59185 (0.75785)	-543.1%
Income$7000 to 7999	1.5962** (0.7390)	1.69174 (0.63717)	28.8%
Income$8000 to 9999	1.4420*** (0.6115)	1.53555 (0.36733)	-1.4%
Income$10000 - 14999	0.8861*** (0.3482)	1.18218 (0.42404)	16.4%
Income$15000 - 19999	2.0058 *** (0.2040)	1.01380 (0.21808)	22.8%
Income$20000 - 24999	2.0662*** (0.2911)	2.11662 (0.30578)	29.6%
Income$25000 Or More	2.3811*** (0.2353)	2.44451 (0.14240)	17.1%
Sex male	0.05528 (0.549)	-0.02427 (0.10897)	223.1%
Childs1	0.05579 (0.71873)	-0.15093 (0.17893)	280.1%
Childs2	-0.24659 (0.05001) .	-0.33519 (0.14624)	-9.2
Childs3	-0.27896 (0.05177) .	-0.49202 (0.16650)	-39.4%
Childs4	-0.50404 (0.00707)**	-0.52024 (0.22072)	21.9%
Childs5	-0.66143 (0.00963) **	-0.74344 (0.29490)	1.8%
Childs6	-0.63649 (0.04344)*	-0.51638 (0.36231)	42.8%
Childs7	-0.81596 (0.05782) .	-1.05598 (0.47374)	-10.3%
Childseight Or More	-0.82701 (0.10619)	-1.01872 (0.59841)	-3.4%
Health excellent	-0.11558 (0.425308)	-0.20722 (0.16946)	-101.7%
Health fair	-0.24250 (0.022564)*	-0.41084 (0.16361)	-67.6%
Health good	-0.24250 (0.034263)*	-0.40365 (0.13269)	-65.6%
Health poor	-0.79738 (0.000746)***	-1.07232 (0.26975)	-31.3%
Quality Health Insurance Service	-0.1396 (0.00875)**	0.05247 (0.09536)	131.1%
Customer Service	-0.0882 (0.0905)	0.14045 (0.09979)	257.4%
Flexibility of Package	-0.1098 (0.0339) *	-0.01826 (0.09580)	82.9%
Existing Health Conditions	-0.3331 (4.06e-13) ***	-0.26630 (0.07400)	17.9%
Services Covered	-0.1751(0.00032) ***	0.36172 (0.09119)	314.5%
Accredited Facilities	-0.3402 (3.13e-11)***	-0.20739 (0.08616)	41.1%
Pharmacy Benefits	-0.3791(3.35e-12)***	-0.38820 (0.07534)	-1.9%
Affordability	-0.2676 (9.74e-07)***	-0.40883 (0.09155)	-51.6%
AIC		2287.8	
BIC		2482.905	
Log Likelihood		-1109.876	
Deviance		2219.8	
Var: Region(Intercept)		0.1880279905	

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

4.7. Discussion

Multilevel analyses using uptake of health insurance binary data haven’t been done in Maritania. However, these analyses have found significant multilevel effects either at lower levels (individuals) or high levels (regions). For instance, the study found that income varies significantly across the regions and that there were strong regional effects on income, health status, Existing Health Conditions, Services covered, Accredited facilities, Pharmacy benefits and affordability. Our analysis showed evidence ($p < 0.001$) of effects in higher level (Regions) in addition to higher significance in the lower level (individuals). Our study has continued to demonstrate the tendency for the single-level logistic model to seriously bias the parameter estimates of observed covariates when analysing multilevel data.

However, the estimated bias generally differs depending on the estimation procedure used for the multilevel logistic model. This is consistent with the observation made by Luvai (2017).

The univariate analysis that we carried out showed that the predictor variable varied significantly across the regions at ($p<0.001$). In contrast, the multilevel multivariate analysis showed that the variables varied significantly with ($p<0.001$) apart from work status and sex, which varied with ($p<0.05$). Consequently, our random slope modelling showed that there exist random effects at the regional level of uptake of health insurance in Mauritania. We could see how income between different regions varied across the income. Multilevel analysis has thus demonstrated that different regions have different random effects. For example, our analysis has demonstrated that income, health status, existing health conditions, covered services, accredited facilities, pharmacy benefits and affordability of health insurance influenced uptake of health insurance in a different region.

5. Conclusion

The study concludes that a hierarchical multilevel model is ideal for predicting the uptake of health insurance. It corrects the overestimation or underestimation caused by the single model effect.

6. Funding Statement

African Union funded the programme

7. Acknowledgments

I wish to acknowledge pan African University for the opportunity to complete my thesis

References

[1] Luvai, V. L, “Hierarchical Logistic Regression Model for Multilevel Analysis: An Application on use of Contraceptives Among Women in Reproductive Age in Kenya,” (Doctoral Dissertation, Maseno University), 2017.

[2] Basaza, R., Criel, B., & Van Der Stuyft, P, “Community Health Insurance in Uganda: Why Does Enrolment Remain Low? A View from Beneath,” *Health Policy*, vol.87, no.2, pp.172184, 2008.

[3] Browne, W. J., & Draper, D, “Implementation and Performance Issues in the Bayesian and Likelihood Fitting of Multilevel Models,” *Computational Statistics*, vol.15, no.3, pp.391-420, 2000.

[4] Clarke, M, “Understanding and Managing Employability in Changing Career Contexts,” *Journal of European Industrial Training*, 2008.

[5] De Jong, K., Moerbeek, M., & Van Der Leeden, R, “A Priori Power Analysis in Longitudinal Three-Level Multilevel Models: An Example with Therapist Effects,” *Psychotherapy Research*, vol.20, no.3, pp.273-284, 2010.

[6] Diez-Roux, A. V, “Bringing Context Back Into Epiademiology: Variables and Fallacies in Multilevel Analysis,” *American Journal of Public Health*, vol.88, no.2, pp.216-222, 1998.

[7] Diez-Roux, A. V, “ Multilevel Analysis in Public Health Research,” *Annual Review of Public Health*, vol.21, no.1, pp.171-192, 2000.

[8] Diprete, T. A., & Forristal, J. D, “Multilevel Models: Methods and Substance,” *Annual Review of Sociology*, vol.20, no.1, pp.331-357, 1994.

[9] Elias, D., Lefevre, J. H., Chevalier, J., Brouquet, A., Marchal, F., Classe, J.M., Others , “Complete Cytoreductive Surgery Plus Intraperitoneal Chemohyperthermia with Oxaliplatin for Peritoneal Carcinomatosis of Colorectal Origin, “*Journal of Clinical Oncology*, vol.27, no.5, pp.681-685, 2009.

[10] Entwisle, B., Mason, W. M., & Hermalin, A. I, “The Multilevel Dependence of Contraceptive Use on Socioeconomic Development and Family Planning Program Strength,” *Demography*, vol.23, no.2, pp.199-216, 1986.

[11] Goldstein, H., & Spiegelhalter, D. J, “League Tables and Their Limitations: Statistical Issues in Comparisons of Institutional Performance,” *Journal of The Royal Statistical Society: Series A* (Statistics in Society), vol.159, no.3, pp.385-409, 1996.

[12] Hill, P., Shukla, D., Tran, M. G., Aragones, J., Cook, H. T., Carmeliet, P., & Maxwell, P. H, “Inhibition of Hypoxia Inducible Factor Hydroxylases Protects Against Renal Ischemia-Reperfusion Injury,” *Journal of the American Society of Nephrology*, vol.19, no.1, pp.39-46.

[13] Konstantopoulos, S., Li, W., Miller, S. R., & Van Der Ploeg, A, “Effects of Interim Assessments Across The Achievement Distribution: Evidence from An Experiment,” *Educational and Psychological Measurement*, vol.76, no.4, pp.587-608, 2016.

[14] Maas, C. J., & Hox, J. J, “The Inuence of Violations of Assumptions on Multilevel Parameter Estimates and Their Standard Errors,” *Computational Statistics & Data Analysis*, vol.46, no.3, pp.427-440, 2004.

[15] Moineddin, R., Matheson, F. I., & Glazier, R. H, “A Simulation Study of Sample Size for Multilevel Logistic Regression Models,” *Bmc Medical Research Methodology*, vol.7, no.1, pp.1-10, 2007.

[16] Organization, W. H, “The World Health Report 2000: Health Systems: Improving Performance. Author. Organization, W. H,” *World Health Statistics*, 2015.

[17] Parker, D., Burton, R., Diongue-Niang, A., Ellis, R., Felton, M., Taylor, C., Tompkins, A, “The Diurnal Cycle of the West African Monsoon Circulation,” *Quarterly Journal of the Royal Meteorological Society: A Journal of the Atmospheric Sciences, Applied Meteorology and Physical Oceanography*, vol.131, no.611, pp.2839-2860, 2005.

[18] Pituch, K. A., Joshi, M., Cain, M. E., Whittaker, T. A., Chang, W., Park, R., & Mcdougall, G. J, “The Performance of Multivariate Methods for Two-Group Comparisons with Small Samples and Incomplete Data,” *Multivariate Behavioural Research*, vol.55, no.5, pp.704-721, 2020.

[19] Sastry, M., Ahmad, A., Khan, M. I., & Kumar, R, “Biosynthesis of Metal Nanoparticles using Fungi and Actinomycete,” *Current Science*, pp.162-170, 2003.

[20] Townsend, R. M, “Risk and Insurance in Village India. Econometrica,” *Journal of the Econometric Society*, pp.539-591,1994.

[21] Van Der Leeden, R., & Busing, F, “First Iteration Versus Igls/Rigls Estimates in Two-Level Models: A Monte Carlo Study with Ml3,” Preprint Prm, vol.94, no.3, 1994.

[22] Mcintyre, D., Meheus, F., & Røttingen, J. A, “What Level of Domestic Government Health Expenditure Should we Aspire to for Universal Health Coverage?,” *Health Economics, Policy and Law*, vol.12, no.2, pp.125-137, 2017.