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A Retrospective Overview of Responses Towards Transmission Dynamics and Control of COVID-19 Pandemic in Nigeria

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Abstract

A retrospective review of responses from several programmes initiated by government of Nigeria towards educating general public on awareness, symptoms, pharmaceutical interventions, and non-pharmaceutical protocols to halt the spread of COVID-19 pandemic were x-rayed using item response approach to ascertain degree of public awareness, keeping to non-pharmaceutical practices, and assert pharmaceutical mediations across different segments of society. Responses from 2500 respondents spread across Federal Capital Territory Abuja and 4 selected states were assessed, coded, and modelled using non-linear item response functions to known respondents' dispositions to COVID-19 pandemic of various social strata. While all levels of society acknowledge COVID-19, and its symptoms, radio/television were very effective in enlightening low income individuals, only high income individuals attested to testing, vaccination centres as well as received COVID-19 doses. Government in her efforts need to do more to enable low income earners to access and accept pharmaceutical interventions. This research findings can be a road map for future efforts towards pandemic awareness, preventions and control.

Keywords: awareness, interventions, pharmaceutical, responses, retrospective

1 Introduction

World Health Organization (WHO) declared coronavirus disease 2019 (COVID-19) a pandemic in March 2020 (WHO, 2020a), it is a novel coronavirus typically a new strain of infectious disease that has not been previously identified in human beings (WHO, 2020b). These are large family viruses that are responsible for illness ranging from common cold to more severe respiratory syndrome coronavirus 2, pneumonia and death (WHO, 2020c). The disease as a global pandemic had affected over 200 countries and territories around the globe which had been responsible for past and current social economic disorders affecting lives and livelihoods (Akande-Sholabi and Adebisi, 2020). In Nigeria, the first case of the novel coronavirus was reported and confirmed on 27th February, 2020 by Nigeria Centre for Disease Control (NCDC). As of June 8, 2022, the total number of confirmed cases has risen to 252,187 as reported by NCDC. Of the confirmed cases, 249,063 individuals have recovered while 3,124 deaths were recorded (NCDC, 2020). Symptoms of this novel coronavirus disease includes dry cough, tiredness (fever and fatigue) as most common, while others are running nose, diarrhoea, skin rashes, sore throat, pains, difficulty in breathing, headache, toes or fingers discolouration (WHO, 2020d).

The extracted data from NCDC website spanned from March 31 to May 29, 2020 was used by Ogundokun *et al.*, (2020) to measure the impact of travelling history and contact on COVID-19 confirmed cases thereby used in predicting the prevalence of COVID-19 in Nigeria using a linear regression model. They conducted the model before and after travel restriction was enforced by Federal Government of Nigeria, and their findings revealed that government made right decision in enforcing restriction because they observed that travelling history and contacts have increased chances of people being infected with COVID-19 by 85% and 88% respectively.

What the daily new cases of COVID-19 would have been ten days after lockdown was eased in Nigeria was modelled by Adesina *et al.*, (2020) using Autoregressive Fractionally Integrated Moving Average (ARFIMA) and compared to the actual new cases for the period when the lockdown was eased. The proposed model ARFIMA was compared with autoregressive integrated moving average (ARIMA), ARIMA (1, 0, 0), and ARIMA (1, 0, 1) thereby discovered that ARFIMA performs better than classical ARIMA. Their findings show that the rate of COVID-19 spread would have been significantly lesser if the restrict had continued, and ARFIMA model was further used to model what new cases of COVID-19 would be ten days ahead starting from 31st of August 2020.

The accuracy of diverse time-series models was explored by Folorunso *et al*., (2021) in COVID-19 epidemic detection in all the 36 states and the Federal Capital Territory (FCT) in Nigeria with the maximum count of daily cumulative of confirmed, recovered, and death cases as of November 4, 2020. In their work, 14-step forecast system for active coronavirus cases for six different deep learning-stimulated and statistical time-series models were built, analysed and compared using two openly accessible datasets. The findings revealed that ARIMA model obtained the best values for four of the states (0.002537, 0.001969.12E-058, 5.36E-05 values for Lagos, FCT, Edo and Delta states, respectively) based on Random Mean Standard Error (RMSE) metric.

A suitable Autoregressive Integrated Moving Average (ARIMA) model was developed by Didi *et al.*, (2021) and used to forecast daily confirmed and death cases of COVID-19 in Nigeria, suitability check was carried out after developing the model and eight months forecast was made before recommendations were sent to the Nigerian health sector. A forecast of 239 days starting from 6th May to 31st December 2020 was conducted using the fitted models, they observed that the COVID-19 data had an upward trend and was best forecasted within a short period.

The intrinsic patterns in the COVID-19 spread in Nigeria was studied and analysed by Ortese et al., (2021) using the Box-Jenkins procedure whereby data of daily confirmed cases of COVID-19 in Nigeria from NCDC official website from 27th February to 31st October 2020 was used to identify the series components and estimate parameters. An appropriate stochastic predictive model was developed and used to forecast future trend of the novel virus. The results shown that Autoregressive Integrated Moving Average (ARIMA) of order (0,1,1) was identified as the most suitable model based on the analysis of the autocorrelation, partial autocorrelation functions and Akaike Information Correction (AIC) value. R software version 4.0.3 was used to analyse the trend which smoothen the series by using 8point moving average in extracting the irregular component as well as differencing the series one step further to obtain a stationary series. Augmented Dickey-Fuller Unit root test, parameter estimation and Ljung-Box test were performed to check the proposed model's conformity to the stationary univariate process.

Predictive distributions and models such as Bernoulli, Poisson, Gaussian, and most importantly, the simplest epidemiological susceptible-infectious (SI) model were clearly explained and illustrated by Qiwei, (2022) using Bayesian inference of the discrete time Markov chain with applications in biology. The concepts of the discrete-time Markov chain, a stochastic model which describe a sequence of possible events in which probability of each event depends only on the state attained in previous event was used.

Count regression models like: Poisson Regression (PR), Negative Binomial Regression (NBR), and Generalized Poisson Regression (GPR) models were adopted by Adams *et al.*, (2020) to model the daily cases of COVID-19 deaths in Nigeria. They examined appropriate count regression model to the confirmed, active, and critical cases of COVID-19 in Nigeria after 130 days using daily COVID-19 cases update released by the NCDC online data base from February 28 to July 6 2020. The extracted data was used in simulation of Poisson, Negative Binomial, and Generalized Poisson Regression models with the aids of Stata 14 Standard Edition, fitted the data at 5% significance level, and the best model was selected on the basis of -2logL, AIC, and BIC selection criteria. The results from their analysis revealed that Poisson Regression incapable of capturing over-dispersion, therefore other count regression such as Negative Binomial and Generalized Poisson Regression models were used in the estimation and discovered that when over-dispersion is present, Generalized Poisson Regression was the best.

The COVID-19 data on confirmed cases, deaths, and recovered obtained from the website of the Nigerian Centre for Disease Control (NCDC) from April 2 to August 24, 2020 was used by Chigbu et al., (2021) to study some epidemiological characteristics of the Nigerian COVID-19 data in order to help the government and university administrators toward making informed decisions on the safety of personnel and students. In their work, infection rate, prevalence, ratio, cause-specific death rate, and case recovery rate were used to assess the epidemiological faces of the pandemic in Nigeria, exponential smoothing was adopted in modelling the time series data and forecasting the pandemic in Nigeria up to January 31, 2021. Their findings revealed that the pandemic had infection rate of at most 3 infections per 1 million per day from April to

August 2020. The death rate was 5 persons per 1 million during the period of study while recovery rate was 747 persons per 1000 infections. Analysis of forecast data showed steady but gradual decrease in the daily infection rate and death rate and substantial increase in the recovery rate, 975 recoveries per 1000 infections. During the pandemic, it is very important to do retrospective study appraisal of effective sources of information on COVID-19 in Nigeria.

Item response theory (IRT) modelling comprises of related statistical methods and models that explain non-linear relationship between observed responses on the construct to respondent's trait: social status levels (Adetutu and Lawal, 2022). It mainly focused on each item of the constructs, compares respondents' responses to the construct and likelihood of their positive responses thereby adopting an explicit model for each possible response to the questionnaires (Lim, 2022). This probability is derived as a function of the latent trait and some questionnaires' parameters. It is widely used today in analysing health responses, items bank development, computer adaptive testing, and so on (Linden, 2018).

The three basic components of IRT are: *Item Response Functions* (IRFs) which are non-linear regression models that relate latent trait (social status) to the probability of endorsing an item in the questionnaire (Adetutu and Lawal, 2020), *Item Information Function* (IIF) is an indication of item (questionnaire) quality, and item's ability to segregate among the respondents, and *invariance* that shows the position on the latent (social status) continuum that can be estimated by any item with known IRFs and item characteristics which are population independent within a linear transformation (Lim, 2020).

However, five assumptions of item response modelling discussed in Adetutu and Lawal (2022) includes: *unidimensional* which implies that the questionnaires is measuring a single concept, and all items are contributing in the same way to the underlying latent trait, *local independence* of IRT infers that questionnaires items are uncorrelated for the respondents of same trait , *monotonicity* assumption focuses on item response functions which shows non-linear relationship between respondents' traits, propensity and probability of endorsement. The probability of a respondent endorsing an item increases as the respondent's social status (latent trait) level increases, on *item invariance,* parameters estimates by IRT would not change even when characteristics of respondents changes, and *qualitatively homogeneous populations* of IRT implied that the same item response functions applied to all respondents.

On awareness of COVID-19, there had been abundant evident on vital role played by health campaign in pandemic. No doubt that information technology and social media have transformed the way information reach people during pandemic. Sources of information about wellness and hygiene especially hand washing, use of sanitizers, social distancing and so on are examples of roles played by heath organization in the response to COVID-19 pandemic. On control of COVID-19 pandemic, protective behaviours of non-pharmaceutical protocols such as use face mask, hand washing, social distancing and so on are the keys to managing pandemic, and pharmaceutical interventions such as first, second and booster doses of vaccines could be a key protective behaviour for COVID-19 (Reiter *et al.,* 2020).

The study is motivated by the outgoing spread of the third wave of the coronavirus including most African country- Nigeria with sole aim of appraising our public health strategy towards curbing this pandemic. To brilliantly achieve this aim, item response approach is used to cross examine observed responses of the respondents towards COVID-19 awareness, symptoms, and vaccine acceptability. The approach would enable us detect public health strategy that need improvement through the behaviour of various item response functions.

2 Methods

2.1 Study design

A stratified incorporated simple random sampling technique was used in administering a well prepared questionnaires to elicit useful information on COVID-19 awareness, symptoms and vaccinations through the responses made to the construct by 2500 respondents equally spread over four selected states: Benue, Lagos, Niger, Rivers and Federal Capital Territory (FCT) in Nigeria. The responses were later entered into an excel spread sheet followed by quality check and data cleansing to ensure accuracy.

2.2 Measures

COVID-19 Awareness: A well structure questionnaire was used to gather responses on awareness, and sources of information on COVID-19 which were followed by items on acknowledging, and listing of COVID-19 testing and vaccination centres.

Symptoms of COVID-19: Some items in the questionnaires were meant to assess respondents ability in identifying symptoms of this pandemic listed in the questionnaires.

Use of Non-pharmaceutical protocols: Items were devoted to know how often the respondents wear face mask, and practice of any non-pharmaceutical protocols listed in the questionnaires.

Practice of COVID-19 Vaccine: Items were geared towards knowing level of practice for pharmaceutical interventions (first, second, and booster doses) among respondents.

2.3 Data Analysis

In this retrospective study, data in excel were coded dichotomously to form 2500 by 38 matrix based on the principle of one parameter logistic modelling of Rasch, (1966) applied in Adetutu and Lawal (2022) which employed unity of discrimination with varied social status parameters in assessing various responses reference to social status of the respondents. Thereafter, coefficients of social status are used in adjudging strata of society who responded most positively to COVID-19 awareness, symptoms, and vaccination in Nigeria. Stata 17 Standard Edition on window platform are used for the analysis.

2.4 Rasch Modelling

As a special one-parameter binary logistic model, responses yes and no were coded as 1 and 0 respectively then modelled by equation (1). A specialised Conditional Maximum Likelihood (CML) estimation procedure was used due to the availability of sufficient statistic for the resulting matrix (Baker and Kim, 2004). Needed information was extracted from set of item response functions (item characteristic curves) which described non-linear regressions of observed responses from respondents with varied social status (θ) and their likelihood of endorsing their preferred responses in according to equation (1).

$$\Pr\left(R_{ij} = 1 \mid b_i, \theta_j\right) = \frac{e^{(\theta_j - b_i)}}{1 + e^{(\theta_j - b_i)}} \tag{1}$$
$$i = 1,2,\ldots,38$$
$$j = 1,2,\ldots,2500$$

Where b_i is respondent $j's$ capability of responding yes to item i in the questionnaires θ_j is respondent's j trait indicating his or her social status level
R_{ij} is the response from respondent j to item i in the questionnaires.

Primary to Item Characteristic Curves (ICC) is a table displaying respondents' capability indices on the basis of their social status levels. An average respondent with moderate social status is designated *0*; as the parameter increases, it means social status improves, and vice versa. In practical, status ranges between *-4, 4* except in extreme cases (Raykov and Macrolides, 2018).

2.5 Parameter Estimation

If r_{ij} be the observed response for R_{ij} outcome for item i from respondent j, and referring $r_{ij} = 1$ as yes, and $r_{ij} = 0$ as no, the probability of j^{th} respondent with traits level θ_j responds yes to item i is as position in equation (1), b_i and θ_j were as defined accordingly then the slope-intercept form is presented in equation (2)

$$P\left(R_{ij} = 1 \mid \beta_i, \theta_j\right) = \frac{e^{(\theta_j + \beta_i)}}{1 + e^{(\theta_j + \beta_i)}} \tag{2}$$

and the transformation between the parameterization is

$$b = -\beta_i \tag{3}$$

Let

$$p_{ij} = P\left(R_{ij} = 1 \mid \beta_i, \theta_j\right) \tag{4}$$
$$q_{ij} = 1 - p_{ij}$$

Conditional on θ_j for respondent j since item responses are assumed to be independent, is given by the equation (5)

$$f(r_j \mid \boldsymbol{\Omega}, \theta_j) = \prod_{i=1}^{38} p_{ij}{}^{r_{ij}}\, q_{ij}{}^{1-r_{ij}} \tag{5}$$
$$r_j = \left(r_{1j}, \ldots, r_{38j}\right)$$
$$\boldsymbol{\Omega} = (\beta_1, \ldots, \beta_{38}),$$

and 38 is the number of items in the questionnaires.

The likelihood for respondent j is computed by integrating out the latent variable from the joint density

$$L_j(\mathbf{\Omega}) = \int_{-\infty}^{\infty} f\left(r_j \mid \mathbf{\Omega}, \theta_j\right) \phi(\theta_j) d\theta_j \quad (6)$$

$\phi(.)$ is a density function for standard normal distribution. For 2500 respondents, the sum of log likelihood is given in equation (7)

$$logL\left(\Omega\right) = \sum_{j=i}^{2500} logL_j\left(\Omega\right) \quad (7)$$

Since the integral for $L_j(\Omega)$ is generally not tractable, we used 21 points adaptive Gauss-Hermite quadrature with Newton-Raphson maximization technique in (Stroud and Secrest, 1966) implemented on Stata 17 SE.

4 Results

The results of the analysis display respondents on different level of social status responding positively to the items in the questionnaires are presented in Table 1 where negative, zero, and positive indicators indicate respondents' low, average, and high social status which are illustrated by Figures 1 to 4.

Table 1: Social Status Indicators for Respondents (Positive Response)

Item	Benue	FCT	Lagos	Niger	Rivers	Combine
Awareness	-6.095683	-6.800279	-6.953285	-4.529761	-5.95334	-5.717256
Rad/TV	-2.099262	-3.637553	-2.295092	-1.774495	-4.32166	-2.564053
Internet	-0.463852	-1.57596	-1.034459	-1.822069	-3.88709	-1.492284
Friends	-0.361675	-1.534956	-0.986957	-1.580841	-3.54777	-1.384523
Newspaper	-0.040206	-1.0295	-0.472879	-0.601047	-3.26667	-0.875
P/Campaign	0.899362	-0.160296	-0.757171	-0.179579	-2.49937	-0.407602
T/Centres	0.7462	0.3231773	0.1229541	1.149185	0.428348	0.5503601
1st centre	0.811198	0.3027144	0.2371468	1.114479	0.22844	0.5357007
2nd centre	1.262401	1.476079	1.201324	2.491204	6.874038	1.899761
V/centres	1.337789	0.3848623	-0.998779	0.8497551	0.312453	0.3741304
1st centre	1.262401	0.3848623	-0.84768	0.8817545	0.322966	0.3967428
2nd centre	1.692674	1.722664	0.6393139	2.314381	6.874038	1.874127
C/symptoms	-5.159317	-4.675566	-3.099036	-3.342459	-3.54777	-3.687732
Fever	-1.862486	-2.756052	-1.71107	-1.854475	-3.0579	-2.167245
Cough	-1.960416	-3.273561	-2.105333	-2.630519	-2.84217	-2.485064
Tiredness	0.159491	-1.377426	-0.745974	-1.190768	-2.62375	-1.029326

Loss of taste	1.312435	-0.503887	-0.537372	-0.343518	-2.67595	-0.413829
Sore throat	0.411784	-1.57596	-1.218302	-0.905169	-2.42853	-1.022278
Headache	0.330487	-0.928448	-0.813538	-0.745031	-2.10883	-0.774552
Aches/Pains	1.262401	-0.220421	-0.313806	-0.093572	-2.93143	-0.285978
Diarrhoea	1.993285	0.6158735	0.8716261	0.6934666	-3.0579	0.3679718
Skin rashes	2.17253	0.7350926	0.894314	1.080178	-2.80419	0.5085536
Red/irritated eyes	1.909719	-0.050219	0.4361713	0.5322985	-2.23052	0.1764229
S/breath	0.229673	-1.984426	-1.413147	-1.214902	-2.90118	-1.27834
Loss of speech	1.536152	0.6373372	0.6937563	0.7345887	-1.26793	0.4711215
Chest pain	0.866086	-0.270628	-0.430183	-0.520646	-1.29547	-0.306489
W/face mask	-3.156249	-3.442347	-2.275234	-2.099473	-3.19424	-2.734813
Always	1.893428	0.0800661	0.894314	0.7345887	1.277746	0.9318009
Occasionally	-1.443472	0.1102229	-0.624316	-0.724172	-0.47686	-0.618143
Not at all	3.749688	3.595569	3.789708	2.314381	1.110411	2.530566
Hand washing	-2.779203	-3.585769	-2.913708	-2.386733	-1.97552	-2.647116
Sanitizer	-2.154152	-2.756052	-1.756684	-1.938106	-3.33421	-2.295631
S/distancing	-0.525785	-1.302062	-0.355965	-0.560696	1.902087	-0.212422
S/isolation	1.312435	0.5944971	1.092216	1.012702	2.893602	1.282043
R/etiquette	1.402231	1.007283	0.3940047	1.219894	2.713967	1.262129
1st dose	2.249591	1.722664	0.5531294	1.959375	0.771708	1.370797
2nd dose	2.599577	2.322311	1.417993	2.514845	1.052305	1.874127
b/dose	3.587013	3.411772	3.015023	3.759464	1.427782	2.74177

5 Discussions

5.1 On awareness of COVID-19

Outcome of the analysis in Table 1 suggested convincingly that all various segment of respondents overwhelmingly aware of COVID-19 pandemic, evidences were abound that lower social status upward were aware of the pandemic: Benue *(-6.10)*, FCT *(6.80)*, Lagos *(-6.95)*, Niger *(-4.53)*, Rivers *(-5.93)*, Combined *(-5.72)*.

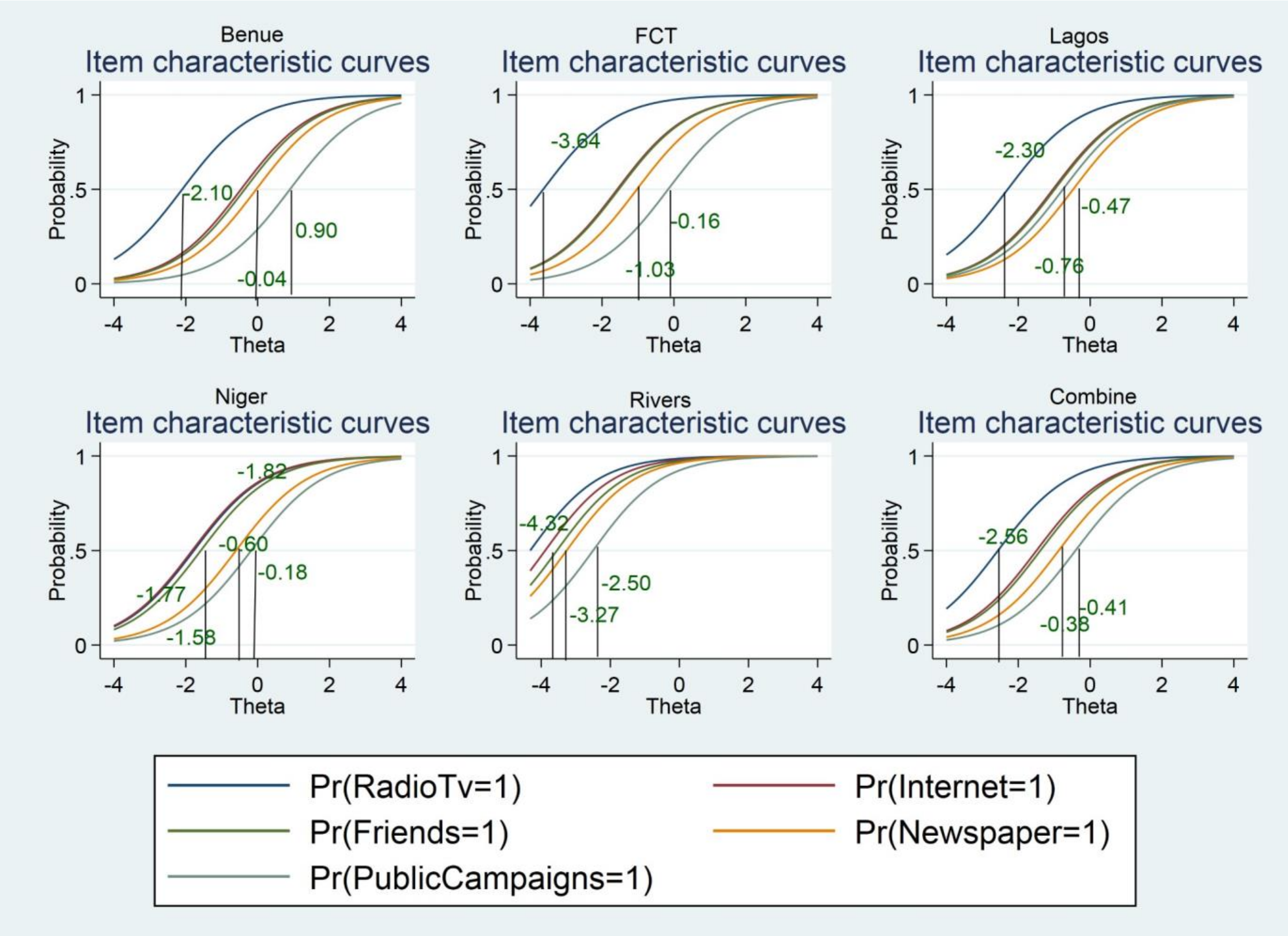

Figure 1: Sources of COVID-19 Information in Nigeria

On sources of information, Figure 1 graphically presented varied categories of respondents' traits (social status) who got COVID-19 information on horizontal *(x)* denoted as *Theta* (θ), and the probability of making their responses on vertical *(y)* axis in consonant with Table 1. Result from Benue attested to the fact that lower social status respondents most likely got information on COVID-19 pandemic from Radio/Television *(-2.10)*, internet *(-0.46)* and friends *(-0.36)* in that order. The parameter estimates in Table 1 for radio/television, internet and friends also agreed with graphical findings. Apart from these, at least only moderately social status respondents had assessed to COVID-19 pandemic information from Newspapers *(-0.04)*, and public campaigns *(0.90)* as the graph and Table 1 suggested. It is better to emphasize here that of all this sources, Radio/Television had done well. In addition, findings from FCT revealed that though at least, lower social status respondents received information on COVID-19 pandemic from radio/television *(-3.64)* most likely, internet *(-1.58)*, friends *(1.54)*, newspaper *(-1.03)*, and public campaigns *(-0.16)* in accordance to their social status as suggested by Figure 1 and supported by Table 1.

Likewise from Lagos, finding revealed that lower status respondents were informed of COVID-19 pandemic through radio/television *(-2.30)* first, followed by internet *(-1.03)*, friends *(-0.99)*, newspaper *(-0.47)*, and public campaign *(-0.76)*. In Niger, both radio/television *(-1.77)* and internet *(-1.82)* were discovered to have same profound impact in disseminating COVID-19 pandemic information on lower social status respondents than friends, newspaper, and public campaigns has shown in both Figure 1 and Table 1. On the other hand, results from Rivers suggested that mostly likely all these sources of information were geared towards sensitizing and impacting lower social status while radio/television *(-4.32)* performed exceptionally well. Internet *(-3.89)*, friends *(-3.55)*, newspaper *(-3.27)*, and public campaign *(-2.50)* were all taking cares of lower social status in our survey.

Our findings in Nigeria (combined) as a whole suggested that radio/television *(-2.56)* had more impact on at least lower social status respondents than other mediums, followed by internet *(-1.38)*, friends *(-1.38)*, newspaper *(-0.88)*, and public campaign (-0.41). Comparatively, radio/television was discovered to be more effective in disseminating information to lower social status individuals/citizenry in Rivers and FCT than any other areas. Public campaigns in Benue was not felt by lower social status respondents like other areas, however, government agencies in charge of public campaigns need to arise to their duties.

On COVID-19 testing centres, the findings presented in Table 1 revealed that none of the lower social status respondents acknowledge any testing centre. Few respondent who acknowledge testing centre were at least moderate social status respondents: Benue (0.74), FCT (0.32), Lagos (0.12), Niger (1.15), Rivers (0.43), and combined (0.55). This was the reason why it was impossible for lower social status respondents to list at least a COVID-19 testing centre in their domains. This has been set back for government efforts, only high social status respondents were able to list two COVID-19 testing centres. On vaccination centres, only in Lagos (-1.00) we have lower social status respondents who were able to admit the existence of COVID-19 vaccination centres while it took only moderate or more social status from Benue (1.33), FCT (0.38), Niger (0.85), Rivers (0.31) to acknowledge vaccination centre.

The resultant of this is that only in Lagos we had a lower social status respondents who were able to list a COVID-19 vaccination centres (Lagos =-0.85) whereas most respondents finding it difficult to name a COVID-19 vaccination centres not to talk of two in other locations. It must be emphasized here that only those on high social status were able to acknowledge and list at most one: Benue (1.26, 1.69), FCT (0.38, 1.72), Lagos (-0.85, 0.64), Niger (0.88, 2.31), Rivers (0.32, 6.87), and combined (0.40, 1.87). This means, it was mostly possible for respondents in Lagos and FCT to list two centres than respondent in Benue to list just a centre, and most likely impossible for anyone to list two centres from Rivers!

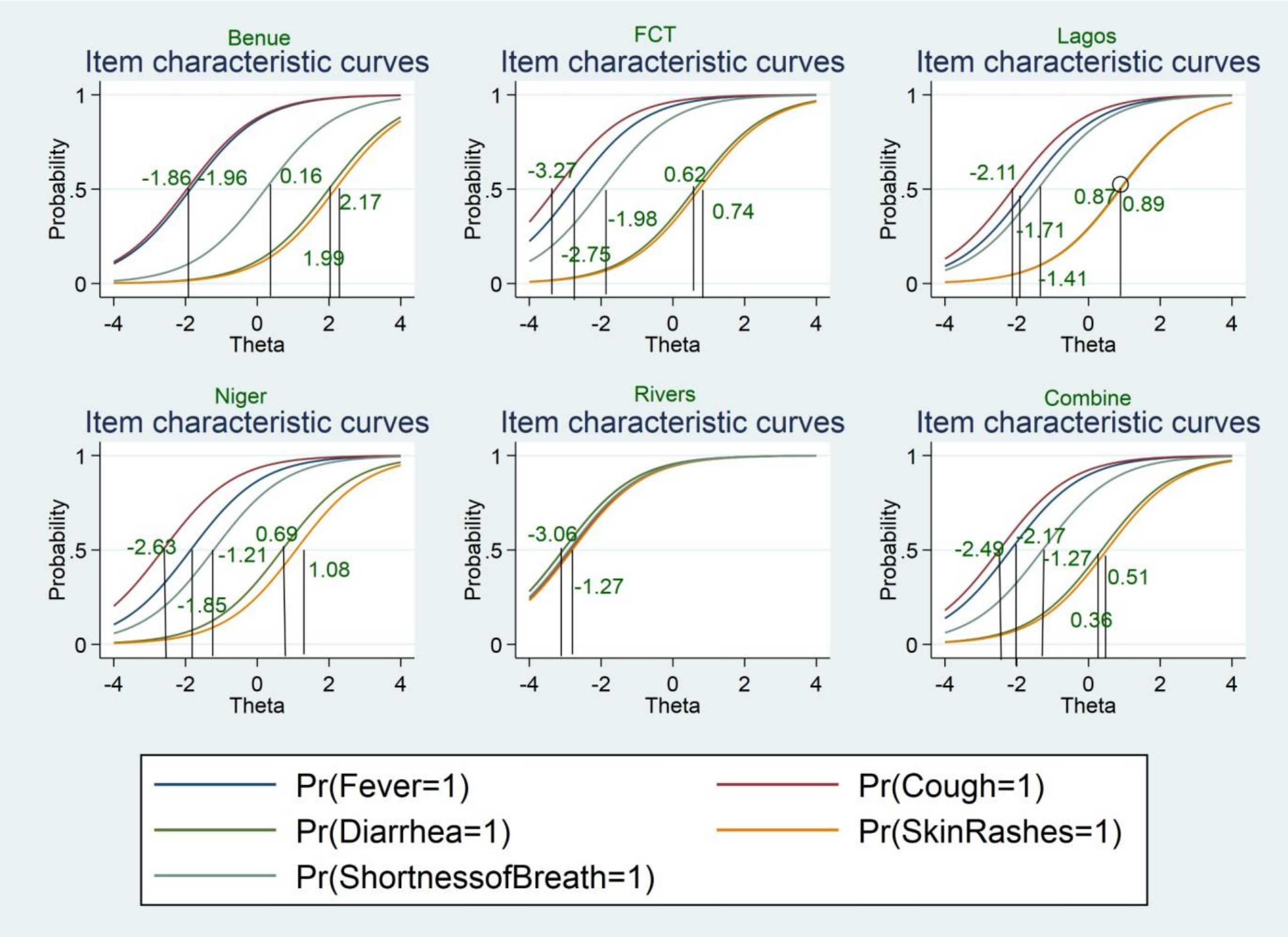

Figure 2: Some Symptoms of COVID-19 Acknowledged in Nigeria

5.2 On symptoms of COVID-19

The results in both Table 1 and Figure 2 show that at least lower social status respondents acknowledged different symptoms of COVID-19: Benue(-5.16), FCT(-4.68), Lagos(-3.10), Niger(-3.34), Rivers(3.55), combined (-3.69). A further breakdown of these symptoms revealed that at least lower social status respondents attested to Cough followed by Fever in Benue (-1.96,-1.86), FCT (-3.27, -2.76) , Lagos (-2.11, -1.71), Niger (-2.63, -1.85) Nigeria as a whole (-2.49, -2.16) Rivers (-3.06, -2.84). On the other-hand, only high social status respondents were able to acknowledge, diarrhoea, skin rashes/discolouration of the fingers and shortness of breath in Benue (2.17), FCT (0.74), Lagos (0.89) , Niger (1.08), except Rivers (-2.80). This call for more efforts to enable lower social status individuals to be aware of these symptoms.

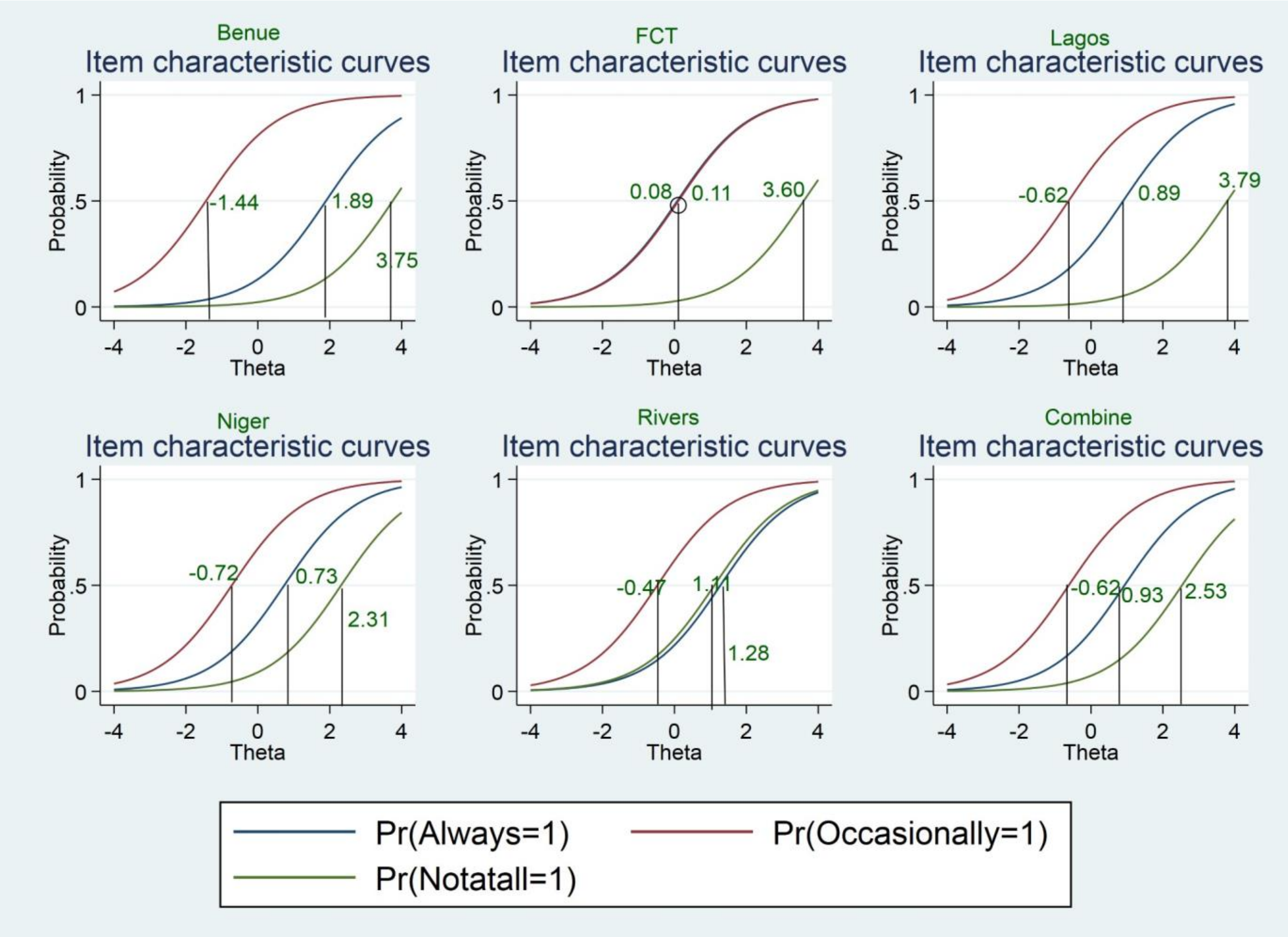

Figure 3: Usage of Face Mask in Nigeria

5.3 On the use of face mask

Our findings here show that most likely lower social status respondents aligned with the use of this non-pharmaceutical protocols (wearing of face mask): Benue (-3.15), FCT (-3.44), Lagos (-2.28), Niger (-2.10), Rivers (-3.19), and combined (-2.74) as fully displayed in Table 1. Unbundle wearing of face mask, we discovered that lower social status respondents occasionally wear face mask in public place as suggested in Figure 3, moderate social status respondents were always wearing face mask, and high social status respondents wear face mask not at all as non-pharmaceutical protocols in curbing transmission of COVID-19 pandemic.

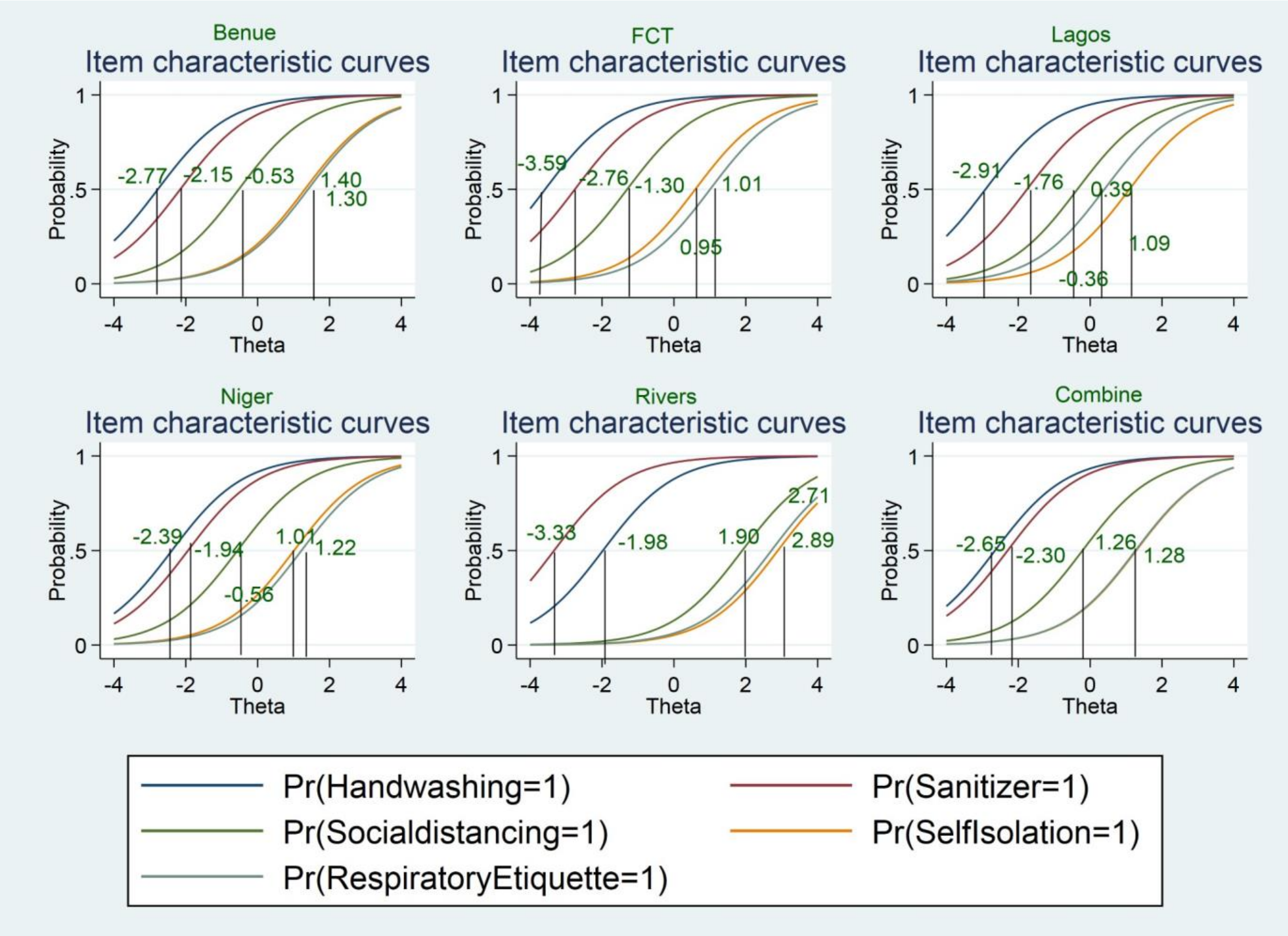

Figure 4: Practice of Non-Pharmaceutical Protocols in Nigeria

5.4 On the Practice of Non-pharmaceutical Protocols of COVID-19

The study discovered that lower social status segment of the respondents aligned with hand washing, sanitizer, and social distancing in that order. The scientific evidence abound as Benue (-2.78, -2.15 , -0.53), FCT (-3.59, -2.76, -1.30), Lagos (-2.91, -1.76, -0.36), Niger (-2.39,-1.94, -0.56), Rivers (-1.98 , -3.33, -1.90), Combine (-2.65, -2.30, -0.21); however, high social status respondents practised self-isolation, and respiratory etiquette as presented and displayed in Table 1 and Figure 4 respectively. On the other hand, scientific evidences also show that moderate, high, and higher social status respondents took first, second, and booster doses of the COVID-19 vaccines. Inferentially, lower social status respondents were less likely to take COVID-19 vaccine.

6 Conclusion

If awareness of COVID-19 testing, and vaccination centres together with vaccine acceptability were properly done among the lower social status individuals, it would be a key public strategy to reduce overall diseases burden due to COVID-19. Our study provides a retrospective insight into the COVID19 awareness, symptoms, and vaccination; with results indicating that most likely lower social status may be willing to receive first, second, and booster doses of the vaccine if and only if there were much awareness of testing, and vaccination centres. The findings further revealed that vaccine acceptability differs on the basis of social status. There was vaccine acceptability among the high social status individuals; rather, greater work would be needed among lower status individuals to accept first, second, and booster doses of COVID-19 vaccine. These findings can help guide the planning, and development of future efforts to increase awareness of pharmaceutical intervention of COVID-19 vaccine.

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