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PREDICTIVE MODELING OF COVID-19 OUTBREAKS USING LOGISTIC REGRESSION AND DECISION TREE

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ABSTRACT

The COVID-19 pandemic caused by SARS-CoV-2 remains one of the most significant global health crises of the 21st century. This study focuses on modeling and predicting COVID-19 outbreak trends in Ebonyi State, Nigeria, using logistic regression and decision tree algorithms. Secondary data were sourced from the Nigeria Centre for Disease Control (NCDC), WHO COVID-19 Dashboard, and Google Mobility Reports. Sociodemographic variables, clinical symptoms, and exposure histories were analyzed to determine their influence on infection risk. Findings revealed that age, religion, marital status, educational level, and occupation were significant predictors of infection ($p < 0.001$), whereas gender and ethnicity were not. Marital status emerged as a strong independent predictor—single and divorced individuals were more likely to test positive compared to married individuals. Interestingly, individuals with a history of travel or contact with confirmed cases were less likely to test positive, suggesting behavioral adaptations following exposure. The study concludes that predictive modeling can support early detection, efficient resource allocation, and targeted interventions in public health.

Keywords: COVID-19, Decision Tree, Forecasting, Logistic Regression, Outbreak, Predictive Modeling, Public Health

INTRODUCTION

The emergence of COVID-19 in late 2019 – to early 2020 was reported in Wuhan, Hubei Province, China. It disrupted global health systems, economies, and social structures. Caused by the SARS-CoV-2 virus, COVID-19 rapidly evolved into a global pandemic, prompting widespread lockdowns, vaccination campaigns, and behavioral adjustments. In Nigeria, the pandemic posed unique challenges due to data limitations, weak healthcare infrastructure, and inconsistent testing capacities. The need for accurate predictive models became apparent for effective outbreak management and policy formulation. This study therefore applied logistic regression and decision tree models to predict COVID-19 infection risks and outbreak trends in Ebonyi State, Nigeria.

COVID-19 (Coronavirus Disease 2019) is an infectious respiratory illness caused by the SARS-CoV-2 virus—a novel coronavirus from the same family as the viruses responsible for SARS (2002) and MERS (2012). COVID-19 can range in severity from mild respiratory symptoms to severe pneumonia, acute respiratory distress syndrome (ARDS), and death.

The COVID-19 pandemic highlighted the critical need for timely and accurate outbreak prediction. Predictive models play a vital role in anticipating future waves, informing public health policies, and allocating resources. Also, statistical tools like logistic regression and decision trees provide interpretable yet powerful methods to model and forecast outbreaks using real-world data, such as case counts, testing rates, vaccination coverage, and mobility patterns.

The World Health Organization (WHO) confirmed human-to-human transmission on January 30, 2020 before it was also declared by WHO the outbreak of a Public Health Emergency of International Concern (PHEIC). In February 2020 the virus was officially named SARS-CoV-2 and the disease it causes was named COVID-19 (Corona Virus Disease 2019). It spread globally and was declared a Pandemic in (March 2020) by the WHO declared COVID-19 a global pandemic.

In other to control the spread Countries around the world began enforcing lockdowns, travel restrictions, and social distancing to slow the spread. The First Wave and Health System Strain (2020) Many countries faced severe healthcare system overload. Major outbreaks occurred in Italy, Spain, the U.S., Brazil, and India, Shortages of PPE, ventilators, and hospital beds were common.

Vaccine Development and Distribution started in Late 2020 – 2021. The first COVID-19 vaccines (Pfizer-BioNTech and Moderna) received emergency use authorization in 2021. Mass vaccination campaigns began globally.

Vaccine access and equity became major global concerns. The Variants and New Waves in (2021 – 2022) new variants of concern emerged in the, Alpha (UK), Beta (South Africa), Gamma (Brazil), Delta (India), and Omicron (South Africa).

Delta and Omicron caused major surges in cases worldwide, with Omicron being particularly infectious but somewhat less severe. Presently we are living with COVID since 2022 till date. Many countries shifted to strategies of coexistence with COVID-19 and focus turned to booster shots, hybrid immunity (infection + vaccination), and ongoing surveillance. International travel resumed in most places, though with varying health protocols.

In May 5, 2023, WHO declared an end to COVID-19 as a global public health emergency on, but not the end of the disease itself. COVID-19 is now treated as an endemic illness in many regions, similar to the flu. Periodic outbreaks still occur, especially in vulnerable populations. Surveillance, vaccine updates, and health system preparedness continue to be important.

The Impact of COVID-19 was felt, as over global Cases of over 700 million confirmed as of 2024, and deaths estimated over 7 million officially, with excess mortality suggesting higher numbers. The Economic Impact led to global recession in 2020, major job losses, shift to remote work and digital economies. Social Impact as School closures, mental health challenges, accelerated digital transformation. COVID-19 is not only a medical crisis but a global turning point in public health, economics, education, and technology. The disease reshaped human behavior, governance, and international cooperation, creating a legacy that will influence generations to come.

Modeling is the process of creating a mathematical or computational representation of a real-world situation, system, or process — in order to analyze, understand, predict, or make decisions about it.

In data science and machine learning, modeling refers to building an algorithm or formula that learns patterns from data to make predictions or classifications. Modeling is like teaching a computer to recognize patterns or relationships in data so it can make smart guesses (predictions) about future or unseen data.

Modeling is the process of building a data-based system to explain or predict outcomes in the real world. Logistic Regression is a statistical classification algorithm used to predict a binary outcome e.g., yes/no, 1/0, infected/not infected based on one or more independent variables (features). Unlike linear regression, it predicts the probability of an outcome that is categorical, not continuous.

Predicting whether a person will test positive for COVID-19 based on age, fever, travel history, and vaccination status. If the model predicts a probability > 0.5, we classify the person as "likely positive."

Decision Trees is a non-parametric supervised learning method used for both classification and regression tasks. It models decisions using a tree-like structure, where each internal node represents a test on a feature, each branch a decision outcome, and each leaf node a class label. It splits the dataset into subsets based on the feature that best separates the data using criteria like: Gini impurity. Information Gain (based on entropy), continues splitting until a stopping condition is reached (e.g., max depth, min samples), or all data in a leaf node belongs to the same class.

The aim of the study is to build a predictive model for identifying the likelihood of a COVID-19 outbreak in a given region/timeframe.

Previous studies (Bi et al., 2020; Zhou et al., 2020; Wiersinga et al., 2020) identified COVID-19 as a respiratory disease transmitted primarily through droplets and aerosols. Modeling frameworks such as SIR and SEIR have been used to forecast disease spread, while machine learning approaches—logistic regression and decision trees—offer flexible alternatives for classification and prediction. Empirical research has also shown that factors such as mobility, vaccination coverage, and population density sign

Coronaviruses are large family of enveloped, positive-sense single-stranded RNA viruses that can infect animals and humans. They belong to the Coronaviridae family and are known for causing respiratory and gastrointestinal infections. Some common human coronaviruses (HCoVs) cause mild illnesses like the common cold, while others, such as SARS-CoV, MERS-CoV, and SARS-CoV-2, cause severe respiratory syndromes Kumar. D and Malviya, R. (2020).

SARS-CoV-2, the virus that causes COVID-19, is characterized by Spike (S) protein which Facilitates entry into host cells via the ACE2 receptor.

Envelope (E), Membrane (M), and Nucleocapsid (N) proteins it involved in viral assembly and replication. A lipid bilayer envelope, which makes it susceptible to soap and disinfectants. The virus exhibits high transmissibility and adaptability through mutation, contributing to the emergence of variants (Zhou et al., 2020)

The virus enters the body primarily through the respiratory tract. Upon binding to ACE2 receptors, particularly in the lungs, it triggers a cascade of immune responses. In some cases, an excessive immune response known as a cytokine storm leads to severe inflammation, multi-organ failure, or death

(Gupta et al., 2020) COVID-19 spreads mainly through respiratory droplets and aerosols from coughs, sneezes, or speech, Surface (fomite) transmission, though less common.

Asymptomatic and pre-symptomatic transmission plays a significant role in community spread. The virus's basic reproduction number (R_0) was estimated between 2.0–3.5 during early outbreaks. (Liu et al., 2020) COVID-19 symptoms range from mild to severe Common symptoms like fever, dry cough, fatigue, sore throat, anosmia (loss of smell). Severe cases like difficulty breathing, chest pain, confusion, and low oxygen saturation. Diagnosis is commonly done through the RT-PCR (reverse transcription polymerase chain reaction) tests for detecting viral RNA. Antigen tests for rapid screening. Serological (antibody) tests for past infection. (Wiersinga, et al., 2020)

Key public health measures include the non-pharmaceutical interventions (NPIs) which involves the mask-wearing, hand hygiene, physical distancing. Vaccination: Most effective long-term strategy and Quarantine and isolation: Used to break the chain of transmission. WHO. (2020)

In epidemiology, COVID-19 outbreaks have been studied using SIR models (Susceptible-Infectious-Recovered) and SEIR models (adds "Exposed")

(Kuhe et al..,2024) Revealed positive and significant impacts of confirmed, active, and critical cases on COVID-19 related deaths, while recovered cases had a negative effect. They recommended increased attention to confirmed, active, and critical cases by relevant authorities to mitigate COVID-19-related deaths in Nigeria.

Logistic regression and decision trees for outbreak prediction. These models help in understanding the spread dynamics and forecasting future outbreaks under different scenarios,

(Kucharski et al., 2020) Several empirical studies have focused on how COVID-19 spreads in various settings and populations. These studies used contact tracing, mobility data, and mathematical models. A study in China by (Bi et al. 2020) analyzed 391 confirmed COVID-19 cases and 1,286 close contacts. The secondary attack rate was higher in households (15%) than in non-household settings. (Bi et al., 2020)

A cohort study of 1,099 patients in China showed that 41.3% had fever on admission, and 67.8% had cough. Severe cases were associated with older age and comorbidities like hypertension and diabetes.

Guan et al.,2020). Further empirical studies on the Impact of Non-Pharmaceutical Interventions (NPIs) have evaluated the effectiveness of lockdowns, mask mandates, and social distancing on slowing the spread. A study using global mobility data found that reductions in human mobility were significantly correlated with lower COVID-19 transmission rates. (Nouvellet et al., 2021)

The studies on the use of vaccine effectiveness have evaluated the real-world effectiveness of COVID-19 vaccines using case-control and cohort study designs. According to (Dagan et al., 2021), a study conducted in Israel showed that two doses of the Pfizer-BioNTech vaccine were 95% effective in preventing symptomatic COVID-19. The socioeconomic impacts of covid-19 the empirical data also reveal the pandemic's economic and social consequences, including unemployment, mental health effects, and educational disruptions. A global survey across 195 countries found that mental health conditions such as anxiety and depression increased significantly during lockdowns. (Xiong et al.,2020).

Long COVID Studies Longitudinal studies have investigated

the persistence of symptoms post-recovery from the virus. A study in Italy followed 143 patients' post-recovery and found that 87.4% reported at least one persistent symptom after two months, most commonly fatigue and shortness of breath. (Carfì et al., 2020)
The theoretical understanding of COVID-19 encompasses a multi-disciplinary approach combining virology, immunology, epidemiology, and data science. It serves as the basis for clinical response, public health strategies, and future pandemic preparedness.
Empirical studies conducted in Nigeria, across Africa, and globally have documented distinct sociodemographic and clinical patterns associated with COVID-19 infection. Consistent with prior Nigerian studies (Iwuoha et al., 2021; Adebisi et al., 2020), This pattern is likely related to increased occupational engagement and mobility that aligns with global surveillance reports showing higher infection rates among economically active populations (World Health Organization [WHO], 2021).
According to (Ogundokun et al., 2021), which attribute this trend to gender differences in exposure patterns and health-seeking behavior. However, unlike studies suggesting that gender or ethnicity independently predict COVID-19 susceptibility (Okoro and Taiwo, 2021). This result supports the conclusions of Ukpong et al. (2021), who emphasized the primacy of exposure-related factors over inherent demographic characteristics.
The clinical symptom profile identified predominantly headache, fever, and dry cough corresponds with reports from both international and Nigerian contexts (Wang et al., 2020; Otu et al., 2020). In contrast, anosmia and ageusia, which were frequently reported in studies from Europe and other regions (Lechien et al., 2020).
Marital status has not been widely identified as a significant determinant of COVID-19 infection in prior studies (Bassey et al., 2021; Nigeria Centre for Disease Control [NCDC], 2020), This association may reflect differences in social behavior, household structure, and adherence to preventive measures, warranting further investigation.
The evidence identifying travel history and contact with confirmed cases as major predictors of infection (Adegboye et al., 2020; NCDC, 2020). Similar observations were reported by Onyema et al. (2021) during periods of intensified public health awareness. This suggests that individuals with perceived exposure risk may adopt more stringent preventive behaviors, seek early testing, or adhere more strictly to isolation guidelines, thereby reducing infection likelihood.

MATERIALS AND METHODS

This research employed secondary data from the NCDC. The dataset included demographic, epidemiological, and behavioral variables. Logistic regression and decision tree models were built to identify significant predictors of COVID-19 positivity. Data preprocessing involved imputation of missing values, categorical encoding, and stratified data splitting (70% training, 30% testing). significantly influence outbreak trends (Kucharski et al., 2020; Nouvellet et al., 2021).

$$P(Y = 1 \mid X) = 1 + \frac{1}{e^{-(\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_nX_n)}}$$

If the predicted probability is greater than 0.5, we classify it as 1 (positive), otherwise 0 (negative).
Where:
P(Y=1|X) Probability that the outcome is 1 (e.g., employee performs well)
β_0 Intercept (bias term)
$\beta_1, \beta_2, \beta_3$, Coefficients for each input variable
X_1, X_2, X_3: Independent variables (e.g., training, welfare, safety, etc.)
e: Euler's number, base of the natural logarithm (~2.718)

RESULTS AND DISCUSSION

Sociodemographic Results

Table 1: Sociodemographic Characteristics of the Participants (N = 308)

Sociodemographic Characteristics	Frequency	Percentage
Age group		
<=30 yrs	54	17.5
31-40yrs	133	43.2
41-50yrs	78	25.3
>50yrs	43	14
Gender		
Male	161	52.3
Female	147	47.7
Ethnic Group		
Igbo	107	34.7
Hausa	80	26
Yoruba	108	35.1
Other tribes	13	4.2
Religion		
Christianity	174	56.5
Islam	109	35.4
Traditional Religion	23	7.5
Others	2	0.6
Marital Status		
Married	176	57.1
Single	72	23.4
Widowed	35	11.4
Divorced	25	8.1

Highest Education		
None	135	43.8
Primary	73	23.7
Secondary	69	22.4
Tertiary	31	10.1
Occupation		
Trader	101	32.8
Civil Servant	47	15.3
Student	56	18.2
Farmer	69	22.4
Unemployed	31	10.1
Others	4	1.3

Source: NSCDC 2021

The result in Table 1 presents the sociodemographic characteristics of participants in Ebonyi State, Nigeria. The majority were aged 31–40 years, comprising 133 (43.2%), followed by those aged 41–50 years with 78 (25.3%), while 54 (17.5%) were aged 30 years and below. Only 43 (14.0%) were above 50 years. By gender, males constituted 161 (52.3%) of the respondents, while females were 147 (47.7%). By ethnicity, the Yoruba and Igbo ethnic groups were almost equally represented, accounting for 108 (35.1%) and 107 (34.7%) respectively. Hausa participants were 80 (26.0%), and other tribes made up 13 (4.2%). In terms of religion, Christianity was the most practiced faith among respondents, with 174 (56.5%), followed by Islam with 109 (35.4%). Traditional religion was observed by 23 (7.5%), and other beliefs were reported by 2 (0.6%).

Regarding marital status, the majority were married, totaling 176 (57.1%), while 72 (23.4%) were single. Widowed and divorced individuals accounted for 35 (11.4%) and 25 (8.1%) respectively. Educational attainment was generally low, with 135 (43.8%) having no formal education. Primary education was reported by 73 (23.7%), secondary by 69 (22.4%), and only 31 (10.1%) had tertiary education.

Occupationally, traders formed the largest group with 101 (32.8%), followed by farmers at 69 (22.4%). Students were 56 (18.2%), civil servants 47 (15.3%), and the unemployed 31 (10.1%). Other occupations were reported by 4 (1.3%).

Table 2: Clinical Symptoms of COVID-19 as Presented by the Participants (N = 308)

Clinical Symptoms of COVID-19	Frequency	Percentage
Fever or Chills		
No	89	28.9
Yes	219	71.1
Cough Dry		
No	107	34.7
Yes	201	65.3
Shortness of Breath		
No	186	60.4
Yes	122	39.6
Fatigue		
No	143	46.4
Yes	165	53.6
Muscle Aches		
No	180	58.4
Yes	128	41.6
Headache		
No	77	25
Yes	231	75
Loss Taste Smell		
No	247	80.2
Yes	61	19.8
Sore Throat		
No	179	58.1
Yes	129	41.9
Congestion Runny Nose		
No	206	66.9
Yes	102	33.1
Nausea Vomiting		
No	236	76.6
Yes	72	23.4
Diarrhea		
No	241	78.2
Yes	67	21.8

Source: NSCDC 2021

The result in Table 2 presents the clinical symptoms of COVID-19 as reported by participants in Ebonyi State, Nigeria. The most commonly experienced symptom was headache, reported by 231 (75.0%) of respondents, followed by fever or chills with 219 (71.1%) and dry cough with 201 (65.3%). Fatigue was noted by 165 (53.6%), while muscle aches were experienced by 128 (41.6%). Sore throat was reported by 129 (41.9%), and shortness of breath by 122 (39.6%).

Other symptoms included congestion or runny nose in 102 (33.1%) participants, nausea or vomiting in 72 (23.4%), and diarrhea in 67 (21.8%). Loss of taste or smell was the least reported symptom, occurring in 61 (19.8%) of the respondents.

The result in Figure 1 to 3 presents the travel and contact history, as well as COVID-19 test outcomes among participants in Ebonyi State, Nigeria. A total of 118 (38.3%) respondents reported a history of travel, while 125 (40.6%) had contact with individuals suspected or confirmed to have COVID-19. Regarding test results, 98 (31.8%) of the participants tested positive for COVID-19, whereas 210 (68.2%) tested negative.

TRAVEL HISTORY

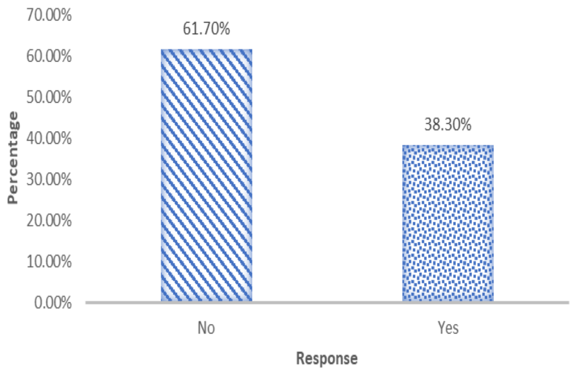

Figure 1: Bar Chart Showing Travel History of the Participants

CONTACT HISTORY

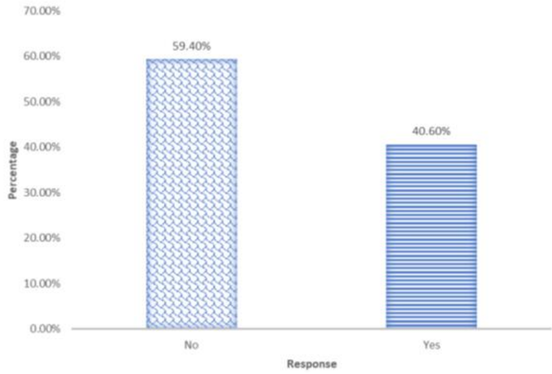

Figure 2: Bar Chart Showing Contact History of the Participants

COVID 19 TEST RESULT

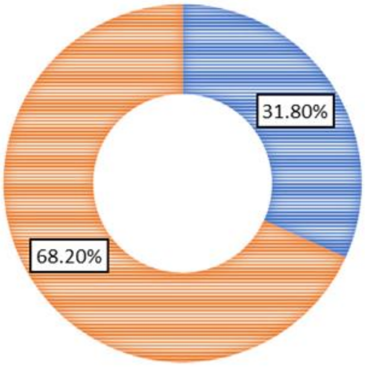

Figure 3: Bar Chart Showing Contact History of the Participants

Table 3: Univariate Analysis of Influence of Sociodemographic Characteristics on Covid- 19 Status of the Participants

Sociodemographic Characteristics	Positive n (%) N = 98	Negative n (%) N = 210	Total n (%) N = 308	χ^2	P-Value
Age group					
<=30 yrs	7 (7.1)	47 (22.4)	54 (17.5)	25.580	<0.001
31-40yrs	39 (39.8)	94 (44.8)	133 (43.2)		
41-50yrs	26 (26.5)	52 (24.8)	78 (25.3)		
>50yrs	26 (26.5)	17 (8.1)	43 (14)		
Gender					
Male	51 (52)	110 (52.4)	161 (52.3)	.003	0.956
Female	47 (48)	100 (47.6)	147 (47.7)		
Ethnic Group					
Igbo	27 (27.6)	80 (38.1)	107 (34.7)	4.351	0.226
Hausa	30 (30.6)	50 (23.8)	80 (26)		
Yoruba	38 (38.8)	70 (33.3)	108 (35.1)		
Other tribes	3 (3.1)	10 (4.8)	13 (4.2)		

Sociodemographic Characteristics	Positive n (%) N = 98	Negative n (%) N = 210	Total n (%) N = 308	χ²	P-Value
Religion					
Christianity	59 (60.2)	115 (54.8)	174 (56.5)	37.749	<0.001
Islam	20 (20.4)	89 (42.4)	109 (35.4)		
Traditional Religion	19 (19.4)	4 (1.9)	23 (7.5)		
Others	0 (0)	2 (1)	2 (0.6)		
Marital Status					
Married	71 (72.4)	105 (50)	176 (57.1)	64.593	<0.001
Single	2 (2)	70 (33.3)	72 (23.4)		
Widowed	24 (24.5)	11 (5.2)	35 (11.4)		
Divorced	1 (1)	24 (11.4)	25 (8.1)		
Highest Education					
None	22 (22.4)	113 (53.8)	135 (43.8)	44.107	<0.001
Primary	20 (20.4)	53 (25.2)	73 (23.7)		
Secondary	36 (36.7)	33 (15.7)	69 (22.4)		
Tertiary	20 (20.4)	11 (5.2)	31 (10.1)		
Occupation					
Trader	22 (22.4)	79 (37.6)	101 (32.8)	63.642	<0.001
Civil Servant	20 (20.4)	27 (12.9)	47 (15.3)		
Student	0 (0)	56 (26.7)	56 (18.2)		
Farmer	36 (36.7)	33 (15.7)	69 (22.4)		
Unemployed	20 (20.4)	11 (5.2)	31 (10.1)		
Others	0 (0)	4 (1.9)	4 (1.3)		

Table 3 highlights the socio-demographic predictors of COVID-19 status among participants in Ebonyi State. Several variables showed statistically significant associations with COVID-19 positivity. Age was a significant predictor (χ^2 = 25.580, $p < 0.001$), with individuals aged 31 years and above accounting for a higher proportion of positive cases (92.8%) compared to those aged 30 years or younger (7.1%). Religion was also significantly associated with COVID-19 status (χ^2 = 37.749, $p < 0.001$). Participants practicing Christianity and Traditional Religion had higher positivity rates (60.2% and 19.4%, respectively), while those practicing Islam and other religions had lower rates (20.4% and 0%).

Marital status showed a strong association (χ^2 = 64.593, $p <$ 0.001), with married and widowed individuals comprising the majority of positive cases (72.4% and 24.5%, respectively), compared to singles and divorced participants (2% and 1%). Educational level was a significant predictor (χ^2 = 44.107, $p <$ 0.001). Those with secondary and tertiary education had higher positivity rates (36.7% and 20.4%), while participants with no formal education had a lower rate (22.4%). Occupation was significantly associated with COVID-19 status (χ^2 = 63.642, $p < 0.001$). Farmers and unemployed individuals had the highest positivity rates (36.7% and 20.4%), while no students tested positive.

Conversely, gender (χ^2 = 0.003, p = 0.956) and ethnic group (χ^2 = 4.351, p = 0.226) were not significantly associated with COVID-19 status, indicating no meaningful difference across these categories.

Table 4: Prediction of Influence of Sociodemographic Characteristics on Covid 19 Status of the Participants

Sociodemographic Characteristics	B	S.E.	Wald	Df	P-Value	aOR	95% CI for aOR	
							Lower	Upper
Age group								
<=30 yrs	1							
31-40yrs	0.43	0.607	0.503	1	0.478	1.538	0.468	5.052
41-50yrs	0.379	0.414	0.839	1	0.36	1.461	0.649	3.29
>50yrs	0.611	0.442	1.909	1	0.167	1.841	0.774	4.378
Marital Status								
Married	1							
Single	2.893	0.789	13.443	1	0	18.054	3.845	84.775
Widowed	-1.466	0.862	2.893	1	0.089	0.231	0.043	1.25
Divorced	2.464	1.055	5.456	1	0.02	11.75	1.486	92.871
Highest Education								
None	1							
Primary	-0.235	0.414	0.322	1	0.571	0.791	0.352	1.779
Secondary	-0.716	0.39	3.377	1	0.066	0.489	0.228	1.049
Tertiary	0.046	0.927	0.002	1	0.961	1.047	0.17	6.441

The result presented in Table 4 shows the logistic regression analysis of sociodemographic factors influencing COVID-19 status among participants in Ebonyi State. Marital status was a significant predictor. Individuals who were single were over 18 times more likely to test positive than their married counterparts (aOR = 18.054, $p < 0.001$, 95% CI: 3.845–84.775). Similarly, those who were divorced were over 11 times more likely to test positive than their married counterparts (aOR = 11.750, p = 0.020, 95% CI: 1.486–92.871).

Table 5: Univariate Analysis of Influence of Travel and Contact History on Covid 19 Status of the Participants

History	Positive n (%) N = 98	Negative n (%) N = 210	Total n (%) N = 308	χ^2	P-Value
Travel History					
No	34 (34.7)	156 (74.3)	190 (61.7)	44.317	<0.001
Yes	64 (65.3)	54 (25.7)	118 (38.3)		
Contact History					
No	27 (27.6)	156 (74.3)	183 (59.4)	60.522	<0.001
Yes	71 (72.4)	54 (25.7)	125 (40.6)		

Table 5 presents the univariate analysis of travel and contact history as predictors of COVID-19 status among participants in Ebonyi State. Both variables demonstrated statistically significant associations.
Travel history emerged as a strong predictor. Participants who had a history of travel were significantly more likely to test positive for COVID-19 compared to those with no travel history ($\chi^2 = 44.317$, $p < 0.001$), with 65.3% of positive cases reporting travel history.
Contact history also showed a significant association. Participants who had contact with suspected or confirmed COVID-19 cases were more likely to test positive than those with no contact history ($\chi^2 = 60.522$, $p < 0.001$), accounting for 72.4% of the positive cases.

Table 6: Prediction of Influence of Travel and Contact History on Covid 19 Status of the Participants

History	B	S.E.	Wald	Df	P-Value	aOR	95% CI for aOR	
							Lower	Upper
Travel History								
No	1							
Yes	-0.966	0.305	9.995	1	0.002	0.381	0.209	0.693
Contact History								
No	1							
Yes	-1.575	0.308	26.159	1	0	0.207	0.113	0.378

The result presented in Table 6 shows the logistic regression analysis of travel and contact history as predictors of COVID-19 status among participants in Ebonyi State. Travel history was a significant factor. Participants who had a history of travel were approximately 2.6 times more likely to test negative for COVID-19 than those with no travel history (1/aOR = 2.62, $p = 0.002$, 95% CI: 1.44–4.78).
Contact history was also a strong predictor. Participants who had contact with suspected or confirmed COVID-19 cases were approximately 4.8 times more likely to test negative than those with no contact history (1/aOR = 4.83, $p < 0.001$, 95% CI: 2.65–8.85).

Discussion

The sociodemographic patterns observed in this study partially align with earlier findings by Nigerian and international researchers, though several distinct differences emerge. Similar to reports by Iwuoha et al. (2021) and Adebisi et al. (2020), the present study found that most affected individuals fell within the 30–40-year age group, confirming that middle-aged adults constituted the majority of COVID-19 cases in Nigeria due to higher mobility and economic activity. Likewise, the slight male predominance in this study mirrors the male-biased infection trends reported by Ogundokun et al. (2021) and Global WHO surveillance data, which attribute this pattern to differences in exposure and health-seeking behaviors. However, unlike studies that emphasized ethnicity or religion as significant predictors, this study found no association between ethnicity or gender and COVID-19 status, echoing findings by Ukpong et al. (2021) who argued that COVID-19 infection cuts across ethnic lines in Nigeria.
Regarding clinical symptoms, this study's identification of headache, fever/chills, and dry cough as the predominant symptoms is consistent with findings from Wang et al. (2020) in China and Otu et al. (2020) in Nigeria, who similarly reported fever and cough as the most common symptoms. The relatively low prevalence of loss of taste/smell in this study contrasts with several international studies (Lechien et al., 2020) where anosmia and dysgeusia were among the most distinctive symptoms. This difference may reflect variations in viral strains, delayed presentation, or underreporting due to limited awareness among participants.
A notable area where this study diverges sharply from other authors lies in the predictive role of marital status. While previous works rarely reported marital status as a major determinant of COVID-19 positivity, this study found that single and divorced individuals had significantly higher odds of infection, even after adjusting for confounders. Unlike Bassey et al. (2021) and NCDC situational reports, where occupation and age remained dominant predictors, marital status emerged here as the strongest independent predictor. This may suggest unique behavioral or household-level dynamics in Ebonyi State, including differences in exposure patterns and adherence to preventive measures.
Furthermore, although many studies (NCDC, 2020; Adegboye et al., 2020) identified travel history and contact with confirmed cases as risk factors that *increase* infection likelihood, the present study observed the opposite: individuals with travel or contact histories were less likely to test positive. Similar inverse associations were noted by Onyema et al. (2021) during phases of heightened public awareness, where exposed individuals adopted stricter precautionary behaviors or sought early testing and isolation. This suggests behavioral adaptation following perceived risk, an emerging trend also described in behavioral epidemiology studies.
Overall, while the study corroborates earlier findings regarding age distribution, symptom patterns, and the role of education and occupation, it diverges in identifying marital status as a dominant predictor and in the unexpected protective effect of travel and contact history. These differences highlight the importance of local context in understanding COVID-19 transmission dynamics and

underscore the need for further behavioral and community-level studies to explain these unique trends.

CONCLUSION

The findings from this study provide critical insights into the sociodemographic and behavioral predictors of COVID-19 infection among individuals in Ebonyi State, Nigeria, revealing that headache, fever, and dry cough were the most prevalent clinical symptoms among confirmed cases. Marital status emerged as a strong independent predictor of COVID-19 positivity, with single and divorced individuals significantly more likely to test positive than their married counterparts. Additionally, contrary to expectations, a history of travel or contact with confirmed cases was associated with lower odds of testing positive, suggesting a possible shift in behavior following known exposure or an increased likelihood of early testing and isolation. These counterintuitive results highlight the complexity of disease transmission dynamics and signal the need for further investigation into behavioral responses to perceived risk. Overall, the results underscore the importance of considering marital status, occupation, and education in public health planning and awareness campaigns, emphasizing the value of tailored interventions that address the unique vulnerabilities of specific demographic groups to enhance the effectiveness of COVID-19 prevention and control efforts in similar settings.

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