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COVID-19 influence on commuters' attitude towards riding public buses for essential trips

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ABSTRACT

The key workers, required to continue to travel for essential works during the COVID-19 pandemic, are subjected to extreme health and psychological implications along with prevailing financial hardship. This paper applies the Bayesian regression analysis to determine the factors affecting the decision of key workers and other commuters on riding public buses for essential trips during the COVID-19 restrictions on movement. The key workers are staying out the bus routes with higher frequency of passenger boarding to avoid the COVID-19 transmission but other people were unable to avoid these busy routes because of poor accessibility to essential goods and services. The COVID-19 pandemic not only changes the travel behaviour of daily commuters and key workers but also aggravates the existing transportation problems at Lagos and Abuja cities in Nigeria.

1. Introduction

The public transport has the high-risk environment of COVID-19 transmission and is the hardest hit of revenue losses due to the limited operation following the government advice on using public transports. A research in an inner city General Practitioner surgery in Nottingham stated that the potential of developing influenza increased by six-fold for people travelling the public transports within five days of symptom onset (Troko et al., 2011). A study on the mobility restrictions at Wuhan city in China during the COVID-19 pandemic found that the movement restrictions reduced the inflows into Wuhan by 76.98 % and outflows from Wuhan by 56.31 % and within Wuhan by 55.91 % (Fang et al., 2020). The study also revealed that the risk of virus transmission would be 105.27 % higher among 347 cities outside of the Hubei province if the city were not isolated from 23rd January 2020 (Fang et al., 2020). However, the mobility restrictions are criticised for the adverse impacts on people’s life and economy (Mogaji, 2020). Huang et al. (2020) analysed the mobility data collected from Baidu Maps in China and stated that COVID-19 related restrictions significantly changed the mobility patterns and travel behaviour among daily commuter.

People are avoiding public transport by trading off between time, crowding, car ownership and active transport during COVID-19 pandemic. The public transport service providers are increasing the fares and reducing or cancelling the services to offset the higher operational costs due to low ridership, government regulations and passenger perception of COVID-19 risk (Gkiotsalitis & Cats, 2021). These cause adverse impacts on the key workers who are low paid and mostly below or near the poverty line (Rojas-Rueda & Morales-Zamora, 2021). Cities in developing countries, with higher number of key workers and vulnerable populace have public buses and trains the only transport activity of active transport network. The low frequency, disruptive public bus services and higher bus fares in the developing world cities made the mobility very difficult for the key workers.

The research question is: what are the factors affecting the essential trips during the COVID-19 lockdown in developing world cities? This paper applies the Bayesian regression analysis to assess the factors affecting the travel decision of key workers and other essential trips for choosing public buses during the COVID-19 lockdown at Lagos and Abuja cities in Nigeria. The paper is organised as follows. Section 2 reviews the studies on the impacts of COVID-19 restrictions on the transport system. Section 3 discusses different stages of COVID-19 restrictions by the Nigerian government and the impacts on the transport system in the case of Abuja and Lagos, the two largest cities in Nigeria.

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2. Literature review

The physical distancing has proven a key mitigation measure to control the COVID-19 transmission that severely affected the travel behaviour particularly riding on public transports. Major cities in China, the United States, the United Kingdom, Singapore, Netherlands, Iran, Hungary, Canada, France and other countries have experienced 60 %-95 % drop in ridership on public transports during the COVID-19 pandemic (Teixeira and Lopes, 2020; Buesky, 2020; de Haas et al., 2020; Gkiotsalitis & Cats, 2021). The change of public behaviour following government guidelines, safety concerns and scope of working from home are the main causes of this significant reduction in ridership (Gray, 2020; Nicola et al., 2020). Due to the novelty and variants of COVID-19 virus, the ongoing literature is struggling to address its implications on public transport operations and travel behaviour of road users with different socio-demographic characteristics (Gkiotsalitis & Cats, 2021).

Budd and Ison (2020) proposed a ‘responsible transport’ concept to support the transport policies in response to COVID-19 pandemic and to inform the effects of individual travel behaviour on others and local environment. Budd and Ison (2020) argued that the bottom-up approach by taking responsibility for own actions can encourage the government and international agencies to create the financial, political and physical infrastructure for sustainable transport behaviour. The proposal of a ‘responsible transport’ by Budd and Ison (2020) without indicating the quantifiable measures of success questions its applicability and effectiveness. Mogaji (2020) assessed the COVID-19 impacts on transport system, economy, and social and religious activities in Lagos, Nigeria using an online questionnaire survey and Pearson correlation coefficients. Mogaji (2020) stated that the disruption in transport system seriously affected the social, religious and economic activities in Lagos. The Pearson correlation coefficients of economic, social and religious activities with impact on transportation were 0.4, 0.3 and 0.27 that were not significant enough to justify the impacts of transport disruptions on these activities, respectively. In addition, a correlation matrix is insufficient to draw the relationship between the activities and transportation as the activities are related to travel and socio-economic characteristics of the trip makers and transport system. Gutiérrez et al. (2020) briefly illustrated the COVID-19 implications on the public transport due to the public perception as well as the challenges to provide safe and reliable public transport services. Molloy et al. (2021) examined the mobility behaviour of 1439 Swiss residents using the GPS tracking panel and online questionnaire survey during the COVID-19 lockdown. The car and train travels were declined by 60 % and 95 % among the respondents during the strict COVID-19 restriction period. The relaxation period of travel restriction observed the returning of cars particularly in morning and evening peak hours but the public transport ridership was low (20 % of pre-COVID levels). The mid-day off-peak traffic observed the higher car usages comparing to the pre-COVID levels suggesting that people are becoming more dependent on cars and avoiding public transport. This may cause additional traffic congestion and potential financial challenges for the operation of public transport (Molloy et al., 2021). However, Molloy et al. (2021) observed the increasing number of cycling urging for new temporary and permanent cycling infrastructure in larger cities in Switzerland. Beck and Hensher (2020) conducted a longitudinal travel survey in Australia when many state jurisdictions started to ease travel restrictions. The study observed that travellers were concerned of riding public transports and travelling mostly by private car for shopping, social and recreational purposes. The travel behaviour is changing with safety measures, vaccination and policy measures that significantly reduces the psychological concerns of riding public transports. In addition, the change of consumer preferences could influence travel behaviour towards those stores that were open, including the location of stores and duration of restriction period. The change of traveller’s preferences requires to be examined as they might prefer larger stores or more diverse clusters with more goods to reduce overall trips.

Unlike most of the European countries, Sweden took relatively liberal approach to COVID-19 restriction and the government and public agencies recommended telework and virtual meeting. Hiselius and Arnulfalk (2021) examined the effects of recommendations on the meeting and travel behaviour of employees in five public agencies in Sweden. Hiselius and Arnulfalk (2021) stated that the work trips were reduced significantly due to the recommendations but expected the prospect of digital tools for employee's communication and collaboration.

The literature on travel restrictions using online survey data and time-series travel data examined the COVID-19 impact on the traffic volume. Hadjidemetriou et al. (2020) used the real-time data on driving, walking and transit to examine the relationship between COVID-19 restrictions and human mobility. Hadjidemetriou et al. (2020) observed that the announcement of the COVID-19 Emergency Bill by the UK government had a direct impact on people’s travel behaviour. During the period of national lockdown, the travel by cars, public transports and walking were reduced by 60 %, 80 % and 60 % comparing to the same period of previous year, respectively. Oum and Wang (2020) applied the urban traffic congestion economic model to analyse the private and socially optimal travel restrictions to contain the transmissible diseases. Individuals do not internalise the external cost of infection risk on others when participating in the social activities. Oum and Wang (2020) advocated that the government should implement socially optimal lockdown period and travel restrictions to contain the COVID-19 pandemic and the socially optimal length of travel restrictions and monetary penalty should be higher in higher population density areas and larger cities. Oum and Wang (2020) assumed the same utility and infection risk/cost functions for the uniformly distributed population in the quadratic utility function that simplified the trip utility function. The trip utility function is different for different transport modes and is the function of travel costs, travel time and characteristics of transport mode users. Pullano et al. (2020) analysed the mobile phone trajectories in 1436 administrative areas of mainland France to compare the traffic flow before and during the COVID-19 lockdown at both local and country levels. Pullano et al. (2020) estimated that a 65 % travel reduction in the countrywide during the lockdown affecting mostly the short-distance work trips during the peak-hour and long-distance non-work trips. The connectivity of major cities in the mainland France was reduced to short-distance commuting, however the mobility reduction was unevenly distributed across regions (Pullano et al., 2020). The study also observed that the regions with higher proportion of active sectors and population in the most active age range (24–59 years) were the most affected areas in mobility reduction during the lockdown.

Parady et al. (2020) conducted an online survey among the key workers working at the groceries, shopping centres, restaurant and leisure centres in the Kanto region of Japan to determine the factors affecting the discrete travel behaviour during the COVID-19 self-restriction request of the Japanese government. Parady et al. (2020) determined that the groceries and shopping were less vulnerable while the eating-out and leisure activities were more vulnerable to the social effects of self-restriction. Parady et al. (2020) quantified the qualitative variables in different measurement scales such as social anxiety, trait anxiety, risk perception, perception of degree of going-out self-restriction, social expectations regarding going-out self-restriction behaviour and subjective well-being. The use of different point scales for quantifying these variables is questionable in terms of their standard values and applicability in discrete choice models. Shamshiripour et al. (2020) examined the impacts of COVID-19 pandemic on the people’s mobility styles and travel behaviour in the Chicago region of the United States. Shamshiripour et al. (2020) applied the stated preference survey including individual travel behaviours, habits, perception before and during the COVID-19 pandemic and the expectation on the mobility.
Shamshiripour et al. (2020) observed that the potential of these mobility styles and travel behaviour being persistent or changed after the pandemic in Chicago. The study revealed that working from home had a high potential towards sustainable future if the home-office provides comfortable and energetic workspace, restful breaks and minimum disruptions. Shamshiripour et al. (2020) also observed the shift from shared mobility options towards walking, bicycling, using scooters and personal vehicles. Truong and Truong (2021) explored the relationship between the daily trips by distance and the COVID-19 infections in the United States using the daily travel data from the Bureau of Transportation Statistics and the COVID-19 data from the Centers for Disease Control and Prevention. Truong and Truong (2021) identified a negative correlation between the residents’ daily trips longer than 3 miles and the daily COVID-19 associated death in the United States but the relationship was insignificant in case of new infection cases. The study also observed a closed loop scenario between residents’ travel behaviour and COVID-19 infections in the United States as the residents started short trips to stores, works, beaches, visiting friends and families and other activities with a decrease of reported new infection cases and deaths.

It is obvious that the COVID-19 pandemic has changed the travel behaviour particularly towards the public transports. The question is: what are the factors influencing the travel behaviour towards public transport? Cho and Park (2021) used a random parameter mixed logit model on two different datasets from stated preference survey for quantitatively measuring the crowding impedance of public transit passengers before and during the COVID-19 pandemic. The study used six levels of crowd multiplier with crowd loading from 0 % to >180 % and the sitting probability from 100 % to 17 %. Cho and Park (2021) estimated that the crowd multipliers during COVID-19 pandemic were 1.04 to 1.23 times higher than that of before pandemic context and the subway passengers are more concerns of infection transmission than the bus passengers. The study did not consider the socioeconomic characteristics of public transit passengers.

Kopidas et al. (2021) conducted an online questionnaire survey to determine the factors affecting the post-pandemic travel behaviour of the Athens public transport riders in Greece using both a clustering algorithm and a discrete duration model. The cluster model demonstrated that the students and frequent passengers would like to use public transport for a long period after the COVID-19 pandemic. The low-income and infrequent passengers as well as people at 46–65 age group demonstrated the high value of their recovery time. The discrete duration model identified that the socio-demographic and psychological factors were the most significant factors for public transport recovery time. Kopidas et al. (2021) stated that people owning private car, at 46–65 age group and used the protection gear in a public transport would less likely use public transport for their daily trips. However, the sample size of online questionnaire survey was small and biased to private car ownership that led to favouring alternative transport mode instead of public transport.

Politis et al. (2021) investigated the effects of socioeconomic factors on the travel behaviour of Greek citizens during the 42 days long countrywide lockdown. Politis et al. (2021) concluded that female traveller were more reluctant to travel due to anxiety. Elderly travellers (over 65 years old) adjusted their mobility needs to avoid congestion in shops and services. Dingil and Esztergár-Kiss (2021) analysed the socio-demographic and travel characteristics of passengers during the pre-pandemic and pandemic time based on the international survey. Dingil and Esztergár-Kiss (2021) stated that the income and education level of transport users and the travel distance were the major determining factors in the pandemic modal shift; however they believed that the modal change during the pandemic was not permanent.

The literature on the effects of COVID-19 pandemic on transportation focused on the policy implications, change of travel behaviour, public transport ridership and the factors affecting travel behaviour during and before the pandemic. Many governments had taken strict travel restrictions to avoid the transmission of virus only allowing the essential trips. The key workers and travellers with low-income level in developing countries are dependent on public transport for commuting. These groups are the hardest hit of the strict travel restrictions that is not addressed in the previous studies. This study analyses the effects of socio-demographic, travel, psychological, policy and the public transport operational characteristics of the key workers and other essential trip-makers on riding public buses.

3. Case study

The World Health Organization categorised Nigeria along with other thirteen African countries as high-risk locations for the infection rate of COVID-19 on 31st January 2020 (Onyebuchi & Martins, 2020). Nigeria, the most populous country in Africa, has had 256,958 confirmed COVID-19 cases and 3144 deaths as of 29 June January 2022, according to Johns Hopkins University data. The Nigerian government had enforced three phases of lockdown to reduce the COVID-19 cases and deaths during the period of 27th April 2020 to 27th July 2020 (Ibrahim et al., 2020). The first phase, starting from 27th April 2020 to 1st June 2020, observed the lockdown of Abuja, Federal Capital Territory (FCT) and Lagos along with nationwide curfew from 8 pm to 6 am (Ibrahim et al., 2020). During the next four weeks (from 2nd June 2020 to 29th June 2020), government gradually eased the lockdown by changing the nationwide curfew from 10 pm to 4 am daily, resuming work in banks and government offices from 9 am to 2 pm on Monday to Friday, resuming worshipping in religious places and exempting the interstate transport for essential services, agricultural products, manufacturing goods and petroleum products (Ibrahim et al., 2020). The airports were reopened for local flights, schools were resumed for returning secondary students and the interstate travel ban was lifted during the phase three period (Ibrahim et al., 2020). Other measures included travel restrictions to thirteen countries with high COVID-19 cases, temporary suspension of Visa on arrival policy, ban gatherings of over 50 people, closure of public and private schools at Lagos, closure of international airports in Abuja and Lagos, closure of all shops except food stores in Abuja and mandatory facemask in public places.

The government restrictions and measures to mitigate the COVID-19 transmission significantly influenced the travel behaviour of people at major cities in Nigeria. The transport system of major cities in Nigeria like Abuja and Lagos are dependent on the informal and privately owned buses, minivans, taxis and commercial motorcycles. Abuja and Lagos have high traffic congestions and accidents with limited road capacity, higher transport costs, excessive demand for parking, poor bus services and lack of national transportation policy (Adanikin & Oyedepo, 2017; Onokala & Olajide, 2020; Solanke, 2013). The prevailing transportation problems coupled with COVID-19 pandemic had exacerbated the daily commuting of key workers and other commuters at Abuja and Lagos.

4. Methodology

An online questionnaire survey was conducted among commuters of Area 1 (Abuja), Berger (Abuja), Mainland (Lagos) and Island (Lagos) bus routes from 15th October 2020 to 11th November 2020 when the lockdown was enforced on these two cities. The survey was conducted during the lockdown period to understand the travel behaviour of key workers and other essential trip makers. To follow the government COVID-19 guidelines, the passengers were provided the online survey link rather than face-to-face questionnaire survey. A total of 2075 passengers were requested to participate in the online survey at the selected four routes. A total of 393 passengers (56 % male and 44 % female) responded the online survey of which 46, 70, 209 and 68 passengers were from Area 1, Berger, Mainland and Island bus routes, respectively.

This study categorises the factors of choosing public buses during COVID-19 lockdown into three parameters: demographic characteristics, passenger boarding frequency at selected bus routes and concerns on COVID-19 impacts (Fig. 1). The demographic characteristics include
the gender, age, monthly income, possession of a driving license, employment status, household size and marital status of essential trip makers. The commuters' concerns on COVID-19 impacts were defined by how COVID-19 pandemic affected the respondent's decision on choosing the transport mode. The commuters' concerns include the psychological, operation and policy effects on modal choice and willingness to share ride.

The sample size is very small comparing to the population of Lagos and Abuja that are 22.58 million and 3.28 million, respectively (Lagos BRTData, 2020; World Population Review, 2020). The small size of dataset affects the uncertainty of regression parameters. To overcome the limitation of small dataset the probability distribution of the model parameters require to be determined rather than the values of parameters. This study applies the Bayesian linear regression to generate the decision on choosing public bus from a Gaussian distribution and determines the posterior distribution for model parameters. The Bayesian regression analysis formulates the linear regression between the choice of riding buses and the independent variables (Fig. 1) using probability distributions rather than point estimates offsetting the drawbacks of small sample size.

The Bayesian linear regression to choose public bus for essential trips by key workers and other commuters is shown in Eq. (1).

\[ Y_i = \beta_0 + \sum_{j=1}^{K} \beta_j (x_{ij} - \bar{x}_j) + \varepsilon_i, \]  
(1)

where \( Y_i \) is the choice of \( i \) respondents to ride public bus for \( r \) essential trip; \( x_{ij} \) and \( \bar{x}_j \) are the values and mean of independent variables \( j \) assigned by \( i \) respondents; \( \beta_j \) is the correlation coefficient of independent variables \( j \); \( \varepsilon \) is the error term that is independent and identically normal; \( \beta_0 \) is the mean of \( Y_0 \) when \( x_0 \) equals to \( \bar{x} \). The independent variables are the factors of choosing public buses during COVID-19 lockdown (Fig. 1).

The prior distributions of \( \varepsilon \) and \( \beta \) need to be determined for Bayesian inference assuming that \( \varepsilon_i \) and \( \beta_j \) follow the normal and multivariate normal distributions, respectively. The Bayesian inference initialises a prior belief for an unknown quantity, collect data through a likelihood function and combines the likelihood and prior for an update on the unknown quantity (Albert & Hu, 2020). The Bayesian inference requires conjugacy for exact analytical solution and simulation. The normal prior is a conjugate as \( \beta \) and normal sampling density are from the same family of normal distribution with unknown mean \( (\beta_0) \) and variance \( (\sigma^2) \). If a normal prior for the unknown \( \beta_0 \) and known \( \sigma^2 \) is specified, we can achieve a normal posterior for mean with updated parameters \( \beta_0 \) and \( \sigma^2 \) (Albert & Hu, 2020). For the Bayesian inference of \( \sigma^2 \) in a normal model, we used the Gamma prior on the inverse of variance. The shape and rate of inverse-gamma distribution are used as prior density (Vijayaraghunathan & Strimivas, 2021). If the value of \( \gamma \) prior is 1, the prior is given the same weight as sample and the prior is 1/\( \beta_0 \) important of the sample for a \( \beta_0 \) value of g-prior (Wetzels et al., 2012). The hierarchical model (Eq. (2)), including the inverse Gamma distribution to variance \( (\sigma^2) \), provides the multivariate Normal-Gamma conjugate family, with hyperparameters \( b_0, b_0 \), \( \gamma \), \( v_0 \) and \( \sigma^2 \) (Clyde et al., 2020). The normal prior distribution is shared among the means of all groups in a hierarchical model and the hyperparameters provide information on the means (Albert & Hu, 2020). The conjugate priors reduce the Bayesian updating of hyperparameters rather than computing integrals.

\[
\begin{align*}
\beta_0, \beta_j | \sigma^2 &\sim \text{Normal} (\beta_0, b_0)^T, \sigma^2 \Sigma_j, \\
\sigma^2 &\sim \text{Gamma} (v_0, v_0 \sigma^2_0 / 2) \\
\end{align*}
\]  
(2)

The prediction ability of Bayesian inference depends on the observed data model variance and the posterior variance. The observed data model variance measures the variability within the groups. The posterior variance measures the variability in the measurements between the groups. As the data size in this study is small, the variability in the Bayesian inference is large. The Zellner’s g-prior was used for Bayesian test of two-factor ANalysis Of Variance (ANOVA) designs where one factor was within variability and other was between variability. The hypothesis is that there is a main effect of both factors. This main effect hypothesis is compared against the null hypothesis. The null hypothesis \( (M_0) \) is that the selected factors of choosing public buses during COVID-19 lockdown (Fig. 1) do not affect the Bayesian model. The full model
(M2) states that the factors affect the dependent variable i.e. choice to ride a bus. The Bayes factor for the full model (M2) to the null (M0) model is given in Eq. (3), where R is the coefficient of determination of M1 (Wetzels et al., 2012). The R^2 is a measurement to explain the variability of one factor caused by its relationship to another factor. The Beta distribution, a conjugate prior for the binomial distribution, was used for the Bayesian inference of regression coefficients.

\[ BF[M_2 : M_0] = (1 + g)^{(n_j - 1)/2} \left[ 1 + g \left( 1 - R^2 \right) \right]^{-(n_j - 1)/2} \]  \hspace{1cm} (3)

### 5. Data analysis

Majority of the respondents were within the age groups of 15–24 years (42 %) and 25–34 years (53 %) since they have access to internet services. More than half of the respondents had small household size (2–4) and low monthly income (<100,000 Naira). Only 7 % of the respondents were key workers of whom 40 % possessed a driving license and 36 % of non-key workers had a driving license. A total of 75 % trips were made for essential purposes. The most commonly cited COVID-19 impacts on daily commuting are higher transport costs (64 %), physical distancing (15 %) and inadequate public bus services (13 %). The low frequency and disruptive public bus services during the COVID-19 lockdown reduced the operational revenues. The public bus services in Nigeria are provided by the private operators and the operators increased the bus fares to adjust the operational costs resulting in higher transport costs.

The trip and demographic characteristics of travellers are important attributes in choosing transport modes (Tsai et al., 2012; Ye et al., 2007). Ortúzar and Willumsen (2011) stated that access to or ownership of a car, possession of a driving license, income, household size and residential density were major factors of choosing transport modes. Chowdhury and Ceder (2016) reviewed studies on integrated public transport system and determined that psychological, operational and policy modal choice were the most significant factors influencing the commuters’ willingness to use an integrated public transport system. In addition, safety awareness, satisfaction and perception of the quality of service are the important attributes of modal choice (Abiodun, 2010; Olawole & Aloba, 2014; Wang et al., 2020).

Female travellers are ranked 1 as they are more reluctant to ride bus during the COVID-19 pandemic comparing to male travellers (Politis et al., 2021). This study identifies that the highest number of bus riders in the selected four routes are within the age group of 25–34 years (52 %) followed by 15–24 years (42 %), 35–44 years (5 %) and over 45 years (1 %). The lowest-income group are more frequent travellers on public buses than other income group.

The ‘driving licence and employment status’ variable was ranked based on the proportion of key workers, participating in this survey, had the driving license. For example, 4 is assigned for non-key workers without driving license (57 % of total respondents), 3 for non-key workers with driving license (36 %), 2 for key workers with driving license and 1 for key workers without driving license.

The selected four bus routes were ranked based on the frequency of passenger boarding on buses, for instance, 1 and 4 were assigned to the lowest and highest passenger boarding, respectively. The online survey shows that 53 % of total respondents are travelling at Lagos-Mainland bus route, while 18 % respondents at Lagos-Island and Abuja-Berger and 11 % respondents at Abuja-Area 1 bus routes, respectively.

The ‘psychological effect on modal choice’ observes the reason for subconsciously changing the commuter’s decision on choosing public buses. For example, 53 % of total respondents were strongly affected by the knowledge of COVID-19 severity, while 9 % of total respondents strongly disagreed that the knowledge of pandemic influenced their decision on riding buses.

The ‘operational effect on modal choice’ states that the health concerns and potential infection risk of COVID-19 influence the modal choice. Most of the frequent bus commuters on the selected bus routes were within the low-income group and had no alternative arrangement for commuting. Despite the health concerns and infection risk, a significant proportion of respondents (63 % of total respondents) strongly disagreed the ‘operational effect on transfer’, while only 8 % respondents agreed with the ‘operational effect on transfer’.

The Nigerian government introduced three phases of COVID-19 related movement restrictions to contain the virus. Ibrahim et al. (2020) questioned the practicality of the phases as the COVID-19 cases were persistently increased in each phase. The ‘policy effect on modal choice’ defines the effects of strict restrictions towards easing lockdown during the three phase on riding buses for essential trips. Majority of the respondents (88 % of total respondents) either agreed (42 % of total respondents) or neutral (46 %) on the influence of government’s lockdown policies on riding the public bus. The willingness to share rides describes the perception of passengers sharing the rides during pandemic. Similar proportion of respondents (29 %) agreed as well as disagreed that the government’s lockdown policies influenced their decision riding public buses.

The correlation matrix (Pearson correlation coefficient, r) of selected variables shows that the independent variables of choosing public buses are not significantly correlated (<0.3) reducing the multicollinearity effects in regression modelling (Table 1). Higher correlations only observed among the ‘policy and operation effects’ and ‘employment status and driving license’ and ‘key workers’ (Table 1). Similarly, the variance-covariance (cov(xjy)) matrix didn’t observe any significant orthogonality among the regressors that might affect the estimation of regression parameters (Table 1).

### 6. Results

#### 6.1. Modelling fitness

The fitness of Bayesian models of choosing public buses for essential trips by key workers and other people are examined using the variance of error terms for log likelihood function (intercept), prior distribution and posterior distribution; Bayes factor; R-square; standard errors and ANOVA tests. The error variance measures the variability produced by insignificant factors such as measurement inaccuracy and is not attributable to the independent variables. Error variance of Bayesian models shows the posterior mean of 0.002 and 0.181 for essential trips by key workers (ETKW) and other people (ETOP) with 95 % credible intervals of 0.002 and 0.003, and 0.157 and 0.209, respectively (Table 2 and Fig. 2). There is no significant difference between the posterior mean and the population mean (Fig. 2). Therefore, the unexplained variations that exist in these models are minimal confirming the fitness and compatibility of the models.

The Bayes factor illustrates similar meaning of p-value in classical statistics that is the likelihood ratio of alternative (M2) and null (M0) models (Penny et al., 2007). However, the Bayes factor is sensitive to prior distribution as the marginal likelihood could be large or very small if the prior distribution places lot or little of probability mass where the likelihood distribution peaks, respectively (Kruschke, 2015). Raftery (1995) categorised the Bayes factors into four groups, for instance, 1–3, 3–20, 20–150 and ≥150 represent the weak, positive, strong and very strong evidence that the observed results occur under the alternative model (M2), respectively. The Bayes factors for both models in Table 3 show the strong evidence in favour of alternative model (M2) stating that the selected factors influenced riding public buses for essential trips. The null hypothesis (M0) states that factors have no influence on riding buses for essential trips. The R-square values of Bayesian models represent the strong relationship between Bayesian models and choosing public buses for essential trips (Table 3). Table 3 shows that 98 % and 69 % explanation of all variability of the response data around the mean by the Bayesian models for ETKW and ETOP, respectively. The lower adjusted R-square values comparing to R-square values justifies that the independent variables improve both of the models (Table 3). The smaller
### Table 1
Correlation and variance-covariance matrix.

| Parameter | Gender | Age | Location | Marital status | HH | Driving License | Employ. & driving license | Monthly income | Psychology | Operation | Policy | Ride share | Trip |
|-----------|--------|-----|----------|----------------|----|-----------------|--------------------------|----------------|------------|-----------|--------|------------|------|
| Gender    | r      | 1   | 0.08     | 0.07           | 0.03| 0.103           | -0.137                   | -0.05          | 0.00       | 0.03      | 0.02   | 0.06       | -0.04|
|           | cov(x,y)|    |          |                |     |                 |                          |                |            |           |        |            |      |
| Age       | r      | 0.08| -0.02    | -0.07          | 0.00| 0.103           | -0.137                   | 0.00           | 0.146      | 0.109     | -0.184 | 0.00       | -0.186|
|           | cov(x,y)|    |          |                |     |                 |                          |                |            |           |        |            |      |
| Location  | r      | 0.07| -0.02    | -0.11          | 0.05| 0.00            | 0.02                     | 0.05           | 0.00       | 0.07      | -0.15  | 0.00       | -0.07|
|           | cov(x,y)|    |          |                |     |                 |                          |                |            |           |        |            |      |
| Marital status | r | 0.03 | -0.239 | -0.131 | 0.1 | -0.149 | -0.174 | -0.136 | 0.02 | -0.139 | -0.138 | -0.03 | 0.00 | 0.107 | -0.05 |
|           | cov(x,y)|    |          |                |     |                 |                          |                |            |           |        |            |      |
| HH        | r      | 0.103| 0.102    | 0.03           | 0.00| 0.103           | -0.03                    | 0.00           | 0.100      | 0.09      | -0.09  | 0.109      | 0.00 |
|           | cov(x,y)|    |          |                |     |                 |                          |                |            |           |        |            |      |
| Driving License | r | 0.271| 0.00 | -0.131 | -0.174 | 0.10 | 0.10 | -0.641 | -0.128 | 0.07 | -0.01 | -0.08 | 0.00 | -0.04 |
|           | cov(x,y)|    |          |                |     |                 |                          |                |            |           |        |            |      |
| Keyworker | r      | 0.07 | -0.146  | -0.107         | 0.10| 0.103           | 0.10                     | 0.10           | 0.086      | -0.124   | 0.09   | 0.03       | 0.02 |
|           | cov(x,y)|    |          |                |     |                 |                          |                |            |           |        |            |      |
| Employment | r     | -0.137| -0.109  | 0.02           | 0.02| 0.091           | -0.64                    | 0.88           | 0.100      | 0.00      | 0.03   | 0.03       | 0.08 |
| & driving license | r | -0.05 | 0.05 | 0.02 | 0.00 | -0.04 | -0.21 | 0.12 | 0.46 | 0.00 | 0.01 | 0.04 | 0.03 |
|           | cov(x,y)|    |          |                |     |                 |                          |                |            |           |        |            |      |
| Monthly income | r | -0.05 | -0.184 | 0.07 | -0.139 | -0.09 | -0.128 | -0.124 | 0.00 | 0.1 | -0.09 | 0.149 | 0.01 | 0.01 | -0.09 |
|           | cov(x,y)|    |          |                |     |                 |                          |                |            |           |        |            |      |
| Psychological effect | r | 0.00 | 0.00 | -0.05 | -0.138 | -0.109 | 0.07 | 0.09 | 0.03 | -0.09 | 1 | 0.06 | 1.00 | 0.25 |
|           | cov(x,y)|    |          |                |     |                 |                          |                |            |           |        |            |      |
| Operational effect | r | 0.03 | -0.168 | -0.01 | -0.03 | 0.06 | -0.01 | 0.03 | 0.03 | 0.149 | 0.06 | 1 | 3.24 | 2.26 | 0.01 |
|           | cov(x,y)|    |          |                |     |                 |                          |                |            |           |        |            |      |
| Policy effect | r | 0.02 | 0.02 | -0.01 | -0.00 | -0.05 | -0.08 | 0.02 | 0.08 | 0.01 | 0.190 | 0.324 | 1 | 0.314 | -0.01 |
|           | cov(x,y)|    |          |                |     |                 |                          |                |            |           |        |            |      |
| Share ride | r      | 0.06 | 0.06 | 0.02 | -0.107 | -0.104 | 0.00 | 0.07 | 0.06 | 0.01 | 0.125 | 0.226 | 0.314 | 1 | -0.149 |
|           | cov(x,y)|    |          |                |     |                 |                          |                |            |           |        |            |      |
| Essential trip | r | -0.04 | 0.07 | 0.00 | -0.05 | -0.156 | -0.04 | -0.05 | -0.01 | -0.09 | 0.01 | 0.01 | -0.01 | -0.01 | 1.00 |
|           | cov(x,y)|    |          |                |     |                 |                          |                |            |           |        |            |      |

### Table 2
Bayes estimate of error variance for essential trips.

| Parameter | Posterior Mode | Posterior Mean | Posterior Variance | 95% Credible Interval Lower Bound | 95% Credible Interval Upper Bound |
|-----------|----------------|----------------|-------------------|----------------------------------|----------------------------------|
| Error variance | 0.002 | 0.179 | 0.002 | 0.181 | 0.000 | 0.000 | 0.002 | 0.157 | 0.003 | 0.209 |
standard error of the estimates also support the more accurate prediction ability of the Bayesian models (Table 3).

The ANOVA test determines the overall significance of estimated models and fitness of the independent variables with corresponding dependent variable. The overall significance of the Bayesian models in the ANOVA results is defined by the F-statistics and significance level. Table 4 shows that the F-value of Bayesian model for choosing public buses by key workers is 778.52 with significance level of 0.0001 suggesting that the selected independent variables reliably predicted the decision to choose public buses by key workers during the COVID-19 pandemic. The F-value for Bayesian model of choosing public buses by other people is 2.0153 with the significance level 0.01 implying that the Bayesian model is reliable only at 10% significance level (Table 4).

6.2. Factors affecting the choice of riding public buses for essential trips

The posterior mean of independent variables in Bayesian linear regression determines the viability of the estimated variables within the credible interval. The posterior mean of ‘psychological effect of key workers is −0.0033 with the credible interval of −0.0112 and 0.0045 for choosing public buses (Table 5). This states that an increase in the ‘psychological effect of modal choice’ due to the risk of COVID-19 adversely affect the decision of key workers riding public buses. The posterior mean of ‘operational effect on transfer’s is 0.0039 with credible interval of −0.0045 and 0.01246 reveals that the concerns of potential risk of COVID-19 infection among key workers influence their decision on choosing public buses (Table 5). The Nigerian government’s COVID-19 restriction on movement inversely related to keyworker’s decision on riding public buses. The posterior mean of the ‘policy effect on modal

Table 3
Bayes factor model summary for ETKW and ETOP.

| Bayes Factor | R | R-Square | Adjusted R-Square | Std. Error of the Estimate |
|-------------|---|----------|-------------------|---------------------------|
| ETKW        | 57.21 | 0.982 | 0.964 | 0.963 | 0.05 |
| ETOP        | 26.37 | 0.73 | 0.69 | 0.63 | 0.14 |

Table 4
ANOVA model summary.

| Source | Sum of Squares | df | Mean Square | F-value | Significance level |
|--------|----------------|----|-------------|---------|-------------------|
| Regression | 25.07 | 4,724 | 13 | 1.928 | 0.363 | 778.522 | 2.015 | 0.0001 |
| Residual | 0.94 | 68.335 | 379 | 0.002 | 0.180 | 0.976 | 0.997 | 0.008 |
| Total | 26.01 | 73.059 | 392 | | | | | |

Table 5
Bayes coefficient estimates for key workers.

| Parameter | Posterior | 95% Interval |
|-----------|-----------|--------------|
| (Intercept) | −0.424 | −0.424 | 0.001 | −0.492 | −0.355 |
| Female trip maker | 0.001 | 0.001 | 0.000 | −0.009 | 0.012 |
| Possess a driving license | −0.476 | −0.476 | 0.000 | −0.491 | −0.462 |
| Age | 0.005 | 0.005 | 0.000 | −0.004 | 0.013 |
| Marital status | −0.008 | −0.008 | 0.000 | −0.026 | 0.010 |
| Household size | −0.007 | −0.007 | 0.000 | −0.015 | 0.002 |
| Employment status and driving license | 0.481 | 0.481 | 0.000 | 0.472 | 0.491 |
| Monthly income | 0.002 | 0.002 | 0.000 | −0.004 | 0.004 |
| Psychological effect on modal choice | −0.003 | −0.003 | 0.000 | −0.011 | 0.005 |
| Operational effect on modal choice | 0.004 | 0.004 | 0.000 | −0.005 | 0.012 |
| Policy effect on modal choice | −0.005 | −0.005 | 0.000 | −0.014 | 0.003 |
| Willingness to share rides | −0.003 | −0.003 | 0.000 | −0.010 | 0.004 |
| COVID19 impact on daily commuting | −0.001 | −0.001 | 0.000 | −0.006 | 0.004 |
| Frequently boarded bus route | −0.003 | −0.003 | 0.000 | −0.008 | 0.002 |
choice’ for key workers is −0.0054 with a credible interval of −0.0136 and 0.0028 (Table 5). The willingness to share rides among key workers also influenced their decision to ride public buses with a posterior mean of −0.0025 within the credible interval of −0.0096 and 0.0036 (Table 5). The respondents ranked the higher transportation costs as the most important COVID-19 impacts on their commuting followed by the physical distancing in public buses, traffic congestion and lack or reduction of transport services. The posterior mean of −0.0011 for ‘COVID-19 impacts on daily commuting’ with a credible interval of −0.0059 and 0.0036 shows that the traffic congestion and lack of transport vehicles were more important factors to the key workers for choosing public buses comparing to physical distancing and transport costs (Table 5). Major cities in Nigeria, including Abuja and Lagos, have the worst traffic congestions in the world despite several measures were undertaken by the government agencies. Therefore, the traffic congestions and lack of transport were the most important factors among key workers for choosing public buses during the lockdown. However, key workers were avoiding the bus routes with higher passenger boarding frequency to avoid the COVID-19 infection. The posterior mean of −0.0038 with the credible interval of −0.008 and 0.002 for the ‘frequently boarded bus routes’ justifies this argument (Table 5).

The demographic characteristics show that young, single and female key workers with low monthly income are more likely to choose the public buses (Table 5). However, key workers, who have large family and are possessing driving license, are reluctant to ride public buses because of car ownership or access to private vehicles (Table 5).

Similar to the Bayesian model for key workers, the ‘psychological effect on modal choice’ has inverse effect on choosing the public buses for essential trips by other people. The posterior mean of psychological effect is −0.001 with the credible interval of −0.069 and 0.067 for choosing public buses for essential trips (Table 6). The operational and policy effects have positive relationship in choosing the public buses for essential trips. The ‘operational effect on modal choice’ has a posterior mean of 0.043 with the credible interval of −0.029 and 0.115 (Table 6). The policy effect on transfer has a posterior mean of 0.019 with the credible interval of −0.052 and 0.089 (Table 6). The government policy of COVID-19 restrictions on movement adversely affected the trips of key workers but positively affected the essential trips by other people.

The willingness to share rides for essential trips also adversely influence the decision to choose public buses with a posterior mean of −0.086 within the credible interval of −0.146 and −0.026 (Table 6). Similar to key workers, people prioritised traffic congestions and availability of transport services instead of physical distancing for their essential trips during the COVID-19 lockdown (Table 6). However, people used the frequently boarded bus routes for their essential trips as most of the essential services are within the proximity to bus routes. The posterior mean of frequently boarded bus routes is 0.002 with the credible interval of −0.038 and 0.043 for the essential trips (Table 6). The demographic characteristics of travellers for essential trips show that young, single and female travellers with low monthly income are more likely to choose the public buses (Table 6). Similar to the key workers, people who have large family and are possessing driving license, are reluctant to ride the public buses (Table 6).

### Table 6

| Parameter | Posterior Mean | 95% Credible Interval |
|-----------|----------------|-----------------------|
| (Intercept) | 0.664 | 0.664 – 0.664 | 0.089 | 0.079 – 1.250 |
| Female commuter | 0.034 | 0.034 – 0.034 | 0.002 | 0.002 – 0.124 |
| Does not possess a driving license | 0.089 | 0.089 – 0.089 | 0.004 | 0.000 – 0.211 |
| Age of commuters | 0.056 | 0.056 – 0.056 | 0.001 | 0.001 – 0.129 |
| Marital status | −0.050 | −0.050 – 0.050 | 0.006 | −0.052 – 0.102 |
| Household size | 0.096 | 0.096 – 0.096 | 0.001 | 0.001 – 0.171 |
| Employment status and driving license | −0.061 | −0.061 – 0.061 | 0.002 | −0.145 – 0.023 |
| Monthly income | −0.028 | −0.028 – 0.028 | 0.000 | −0.064 – 0.007 |
| Psychological effect on modal choice | −0.001 | −0.001 – 0.001 | 0.001 | −0.069 – 0.067 |
| Operational effect on modal choice | 0.043 | 0.043 – 0.043 | 0.001 | −0.029 – 0.115 |
| Policy effect on modal choice | 0.019 | 0.019 – 0.019 | 0.001 | −0.052 – 0.089 |
| Willingness to share rides | −0.086 | −0.086 – 0.086 | 0.001 | −0.146 – −0.026 |
| COVID-19 impact on daily commuting | −0.002 | −0.002 – 0.002 | 0.000 | −0.043 – 0.039 |
| Frequently boarded bus routes | 0.002 | 0.002 – 0.002 | 0.000 | −0.038 – 0.043 |

7. Discussion

The importance of psychological, policy and operational effects of COVID-19 along with the prevailing traffic congestions and demographic characteristics of the commuters urges the local governments to undertake the following strategies for improving the traffic congestion and choosing the public and active transport for essential trips during the unprecedented challenges of pandemic:

- **Neighbourhood redesign for accessible basic goods and services:** the COVID-19 uncertainty shows how different socio-economic segments of the society are adjusting to the pandemic situation (Shamshiripour et al., 2020). Tables 5 and 6 show that low income people are most frequent trip makers despite the psychological effects of COVID-19 pandemic. The low-income people are one of the most adversely affected segments of our society and facing difficulties to attain the basic needs and services during the pandemic situation. Several studies examined the impact of recent epidemics on different parts of urban transportation system such as commuters, tourists, transit, shared mobility and personal mobility (De Vos, 2020; Kim et al., 2017; Shamshiripour et al., 2020; Wen et al., 2005). De Vos (2020) argued that physical distancing and stay-at-home caused limited physical activities and social interaction threatening the subjective well-being of individuals especially the older people who often trip to groceries and service sites as a part of social interaction. Although De Vos (2020) suggested the active transport as the potential solution for the individual’s well-being, he was unable to link the active transport with trips to activities and service sites for vulnerable people with pre-existing health conditions. Shamshiripour et al. (2020) pointed out the current transition of modal choices from the shared mobility options to active transport during the COVID-19 pandemic as an opportunity for promoting active transports and micromobility that can play substantial roles in planning towards more sustainable and resilient cities. Kim et al. (2017) found that land price, location of Middle East Respiratory Syndrome (MERS) hotspots, number of businesses, older population, and number of restaurants significantly influenced the transit ridership during the MERS outbreak in Seoul. The demand for walkable and bikeable communities with convenient access to basic goods and services has regenerated the interest in concept of the 15-min city with all essential amenities based within a fifteen minute walk or bicycle ride of people’s homes (Kendall & Niblett, 2021). The 15-min city will not only reduce the transmission of COVID-19 but also support all parts of the society during the COVID-19 restrictions.

- **Long-term plan for reducing traffic congestion:** the respondents ranked the higher transportation costs as the most important COVID-19 impacts on their commuting followed by the physical distancing in public buses, traffic congestion and lack or reduction of transport services (Tables 5 and 6). The government can coordinate with local authorities to examine the applicability and effectiveness of controlling the geographical sprawling, promoting polycentric cities and compact development are required to reduce the traffic congestion at

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larger cities in Nigeria. There is evidence of compact cities with more traffic congestion and polycentric cities with more sub-centres have less traffic congestion (Li et al., 2019). The impact of compactness and polycentricity on the traffic congestion is ambiguous and depends on the relative strength of the travel distance and concentration of origin-destination pairs (Ewing et al., 2018; Li et al., 2019). There is a common belief that the public transit investment and subsidisation of ride hailing can reduce the traffic congestion in larger cities. Some studies (Duranton & Turner, 2011; Rubin & Mansour, 2013; Stopher, 2004) were sceptical about the efficiency of public transit investment on traffic congestion, while Anderson (2014), Litman (2014) and Beaudoin et al. (2015) were advocating for the public transit.

**COVID-19 guidelines using public transport: the government should coordinate their planning and actions with transport providers for risk assessment, provision of adequate personal protective equipment at public transport, support transport workers and providing clear approach to physical distancing for all transport workers and passengers.** This will reduce the psychological, policy and operational effects of COVID-19 pandemic and other infectious diseases and boosting confidence in the safety of public transports.

8. Conclusions

This paper applies the Bayesian regression analysis to assess the factors affecting the bus riding decision by key workers and other essential trips during the COVID-19 lockdown at Abuja and Lagos cities in Nigeria. This study identifies that the psychological, policy and operational effects of COVID-19 pandemic along with the prevailing traffic congestions, transport costs and demographic characteristics of the commuters are the major factors of choosing public buses for essential trips during the government restrictions on movement.

The findings of this study urge the Nigerian government to invest in public transit services and infrastructure improving the operational efficiency of buses and journey time so that the key workers and low-income commuters can afford the transport costs. The government may coordinate with local agencies and private sectors to enable the commuters travelling at different peak times to offset the conglomerated problems of traffic congestions and COVID-19 pandemic effects in major cities. The online survey at social media platforms with small sample size during the lockdown at Abuja and Lagos cities is the major drawback of this study. The online survey validated by face-to-face survey can improve the average quality and outliers of the tested samples more accurately. The unprecedented effects of COVID-19 on mobility and travel behaviour are interactive and inconclusive as the heterogeneity and disparities of COVID-19 effects are not only limited to socio-demographic, economic, and psychological attributes. An unassailable holistic approach is required to ascertain the effect of variables on a specific mode choice during a global pandemic.

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