Segmentation of African countries based on infection and death rates of COVID-19 before vaccination: A rigid population to source for workforce amidst the pandemic?

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A B S T R A C T

This study established segments among African countries to show the hierarchies of COVID-19 infection and death rates across the continent before the commencement of vaccination. Four clusters were extracted, each consisting of countries with a similar number of cumulative infections and deaths per 100 thousand population. When compared with the pre-vaccination figures from Europe, Americas, and Asia, it was observed that the African population exhibited a good level of rigidity and resilience to the pandemic, pre-vaccination. Majority of African countries - evaluating to 84% - were clustered into the segment with low infection and low death rates. Only 4% of the countries were clustered into the higher infection and highest death rates segment. This is an indication of the rigidity of a greater part of the African population to COVID-19 before vaccination. To forestall total business shutdown in the event of a similar pandemic in the future, multinational corporations could explore their workforce from the African population given the level of rigidity exhibited pre-vaccination.

Introduction

The first African countries where vaccination against COVID-19 commenced were Ghana and Ivory Coast, with COVAX doses, on 1st March 2021 [25]. Similarly, South Africa's first vaccine doses against the virus were from Johnson & Johnson, first received in the second quarter of 2021 [11]. Prior to the commencement of vaccination across Africa, the figures from the World Health Organization (WHO) COVID-19 weekly epidemiological update showed that as of 31 January 2021, a total of 2,570,474 persons had contracted the virus across the continent. Out of this figure, a total of 62,504 [2.4%] individuals had died from the infection [27]. The infections and deaths figures from Africa accounted for three percent each of the global infections and deaths before the commencement of vaccination. Figures from other continents/regions indicated that Americas accounted for 44% of global infections and 47% of global deaths, Europe accounted for 34% each of global infections and deaths, and South-East Asia accounted for 13% of global infections and nine percent of global deaths [27]. To contain

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the pandemic, several vaccines such as CoronaVac, Covaxin, Pfizer-BioNTech, Covishield, Johnson & Johnson, and AstraZenaca were developed and rolled out for vaccination [17].

Prior to the commencement of vaccination, the pandemic negatively affected businesses across the world including investment, sales, employment, production, and supply chains ([8,12]; International Labour Organization [15]). The negative effects on businesses were largely caused by the lockdown rules imposed by various authorities, the inability of some enterprises to operate remotely, and the health consequences of the pandemic on citizens. At the onset of the pandemic, several assertions were made to imply that the African continent was going to be badly affected more than other continents [1,4]. The predictions were premised on the weak healthcare systems and low standard of living in most parts of Africa. Despite these predictions, the COVID-19 situation report data which were reported daily by different sources proved otherwise. One of the comprehensive data sources on the morbidity of COVID-19 and its mortality is authored by WHO. The data consist of variables with vital information that could be modeled to examine how the African continent (vis-à-vis other continents) were affected before the commencement of vaccination.

Against this backdrop, the purpose of this study was to deploy cluster analysis to segment African countries based on COVID-19 epidemiology prior to vaccination. The research findings consist of hierarchical clusters that segment African countries into sub-groups that reflect similarity in the magnitude of morbidity and mortality. The segmentation reveals whether or not majority of the African population were rigid to the pandemic, pre-vaccination, compared to other continents. Since businesses were shut down mainly to control COVID-19 infection and death rates, human capital could be explored from a population that exhibits rigidity to avert business disruptions in the event of a future wave.

Related literature

Several studies have been reported in the literature concerning COVID-19 in Africa. One of these is the study by Orisakwe et al. [20] in which acclaimed remedies against COVID-19 adopted by some African countries were examined. The study held that due to weak and over-stretched orthodox healthcare facilities in most parts of Africa, some countries resorted to the use of plant leaves and natural spices to treat COVID-19. According to Orisakwe et al. [20], plants such as ginger, turmeric, garlic, pawpaw leaves, guava, and neem were found to be ready sources of home remedy against the disease. In another research, Gachohi et al. [10] examined the challenges faced by the efforts to curtail the spread of coronavirus in Africa. The authors attributed one of these challenges to the high number of people who use drugs (PWUDs) in sub-Saharan Africa. Government interventions against COVID-19 are usually targeted at the general population and frontline medical personnel while excluding key populations such as PWUDs. However, key populations act as transmission medium to the general population [10].

Some studies have been conducted at the granular level of African countries with respect to COVID-19. For instance, Aronu et al. [3] modeled the survival rate of COVID-19 patients in Nigeria. The study deployed the autoregressive integrated moving average model on the COVID-19 data obtained from the Nigerian Centre for Disease Control. The results found the mean survival rate of patients to be 27.5%, while the median survival rate stood at 25.4% [3]. In another study, Sayedahmed et al. (2020) [29] investigated the level of knowledge, attitude, and safety practices regarding COVID-19 among Sudanese. The research data were obtained through self-administered online survey, and the results showed that a good percentage of the population had adequate knowledge about the disease, including its mode of transmission. However, it was discovered that only 48.5% of the sample population adopted safety practices against COVID-19 [29].

From the foregoing, it is apparent that various aspects of COVID-19 specific to Africa have been studied to some extent. However, a study that evaluates the hierarchies of the morbidity and mortality of the pandemic among African countries before the advent of vaccination appears to be missing. It is important to examine how rigid or susceptible the continent was to the pandemic before vaccination started compared to other continents. This stems from the fact that a population that exhibits rigidity to the virus could be explored by multinationals to complement their workforce. This will avert business interruptions in the event of a similar pandemic.

Materials and methods

COVID-19 data

The dataset for this study was obtained from the World Health Organization's COVID-19 weekly epidemiological update as of 31 January 2021 [27]. As of this time, vaccination had not yet commenced in any African country; and the data give a picture of the epidemiology before the vaccination era. The situation report on a total of 49 African countries/territories make up the experimental dataset consisting of the variables presented in Table 1.

Variable selection and data preprocessing

Table 1 presents the variables related to COVID-19 morbidity and mortality. The data values in each variable are per country. It should be pointed out that for the purpose of this study, only two variables, namely, *cum_cases_per_100k_population* and *cum_deaths_per_100k_population* were selected for experiments. The variable, *cum_cases_per_100k_population*, keeps

Table 1
Dataset variables on number of infections and deaths.

Variable	Description
new_cases_last_7_days	The number of confirmed COVID-19 cases reported in the last 7 days within the country.
cum_cases	Cumulative confirmed COVID-19 cases reported in the country since inception.
cum_cases_per_100k_population	Cumulative confirmed COVID-19 cases (since inception) per 100 thousand population of the country.
new_deaths_last_7_days	The number of COVID-19 deaths reported in the last 7 days within the country.
cum_deaths	Cumulative COVID-19 deaths reported in the country since inception.
cum_deaths_per_100k_population	Cumulative COVID-19 deaths (since inception) per 100 thousand population of the country.

track of the infection rate in each country in terms of the number of persons infected out of every 100 thousand citizens. Similarly, *cum_deaths_per_100k_population* keeps track of the death rate; that is, the number of persons killed by the pandemic out of every 100 thousand citizens. The other variables were eliminated during data preprocessing.

As part of the data preparation process, the experimental dataset was normalized to a uniform scale prior to cluster analysis. Countries such as South Africa and Eswatini had very high infection and death rate values, while Tanzania and Burundi had extremely low values. If these extreme values were not scaled to the same range, the outliers would have had negative effects on the clustering results. Consequently, the original values of the dataset were normalized and scaled to the range [0, 1] using min-max normalization [9]. Furthermore, the optimal number of clusters to extract were evaluated on the dataset using two methods, namely, the average silhouette [6] and the gap statistic [24]. The average silhouette method, shown in Fig. 1(a), suggested two clusters as the optimal, while the gap statistic method suggested five clusters – see Fig. 1(b). Given the different number of clusters suggested by the two methods, the authors computed the average ($[2 + 5] \div 2 = 3.5 \approx 4$) and then settled for four as the optimal number of clusters.
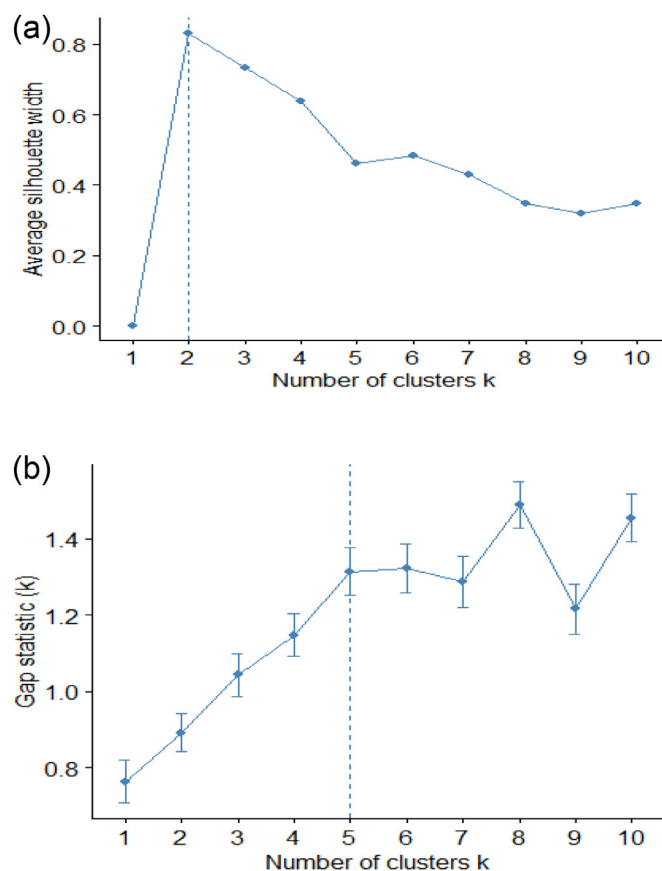

Fig. 1. (a) Optimal number of clusters by the average silhouette method. This method suggested two clusters as the optimal to be extracted from the COVID-19 data.
(b). Optimal number of clusters by the gap statistic method. This method suggested five clusters as the optimal to be extracted from the COVID-19 data.

Hierarchical cluster analysis

Hierarchical clustering is a modeling [7] technique that constructs a hierarchically organized sequence of clusters for a set of data objects [18]. The technique subgroups the dataset,X into Q partitions $\{P_1,...,P_Q\}$. If clusters C_i and C_j satisfy $C_i \in P_n, C_j \in P_m$ and $n > m$, then either $C_i \subset C_j$ or $C_i \cap C_j = \emptyset \; \forall i \neq j$, and $n, m = 1, ..., Q$ [2]. What this means is that for any two clusters of a hierarchical partition, either one cluster is a subset of the other or the two clusters are disjoint completely. The clustering algorithm uses a distance measure to evaluate the (dis)similarity between pairs of observations and then places the most similar observations into the same cluster [18,28]. A variant of hierarchical clustering is the agglomerative clustering where each observation is considered as a cluster in the first step [16]. In the subsequent steps, two or more clusters that are most similar are joined together to form a bigger cluster. The process continues until all clusters have been joined into a single cluster. In practice, a hierarchical clustering structure is represented by a dendrogram [5,18].

One of the important steps in hierarchical clustering is the evaluation of the (dis)similarities among each pair of clusters. This is achieved by a distance measure, such as the Euclidean, and clusters that are most similar are linked together [21,28]. The commonly used linkage methods include complete, single, average, and Ward's linkage [5,16,28]. The linkage method that is suitable for the structure of an experimental dataset is evaluated prior to cluster extraction. The suitability is determined by the linkage method that produced the highest cophenetic coefficient on the dataset [21].

In this study, the four linkage methods produced the following cophenetic coefficients on the COVID-19 dataset: Ward [0.9806], complete [0.9666], average [0.9516], and single [0.9181]. It should be noted that the Ward linkage method identified the best clustering structure, and it was therefore selected for the experiments.

Results and discussion

The R statistical computing software was deployed for agglomerative hierarchical cluster analysis of the COVID-19 dataset using the Ward's linkage method. The clustering function was invoked on the dataset and the analysis produced the dendrogram shown in Fig. 2.

Fig. 2 shows the hierarchies of infection and death rates among the 49 African countries in the dataset. Four optimal clusters identified during preprocessing were extracted and the distribution of countries across the clusters is shown in Table 2. The clustering implies that countries within the same cluster experienced a similar magnitude of infection and death rates.

Validation of clustering results

Clustering validation is an important aspect of cluster analysis that evaluates the goodness of clustering results [5]. A validation method, known as cluster separation, was evaluated to examine to what extent objects in one cluster are dissimilar to objects in another cluster [14]. The bar chart in Fig. 3 is a plot of the final cluster means for each variable in each of the clusters. It should be noted that the cluster means for each variable are different across all the clusters. This is an indication that inter-cluster dissimilarity has been maximized among data samples of different clusters [5].

Similarly, the cluster plot in Fig. 4 shows that cluster separation was achieved as there is no overlapping among any two clusters. Cluster separation is an indication that only similar samples are contained within a given cluster [13]. That is, each of the four segments consists of only the countries with similar COVID-19 infection and death rates.

It is instructive to note that there is sufficient evidence to show that the clusters extracted from the COVID-19 dataset on Africa are valid and meaningful. In the next section, the practical implications of the clusters are discussed.
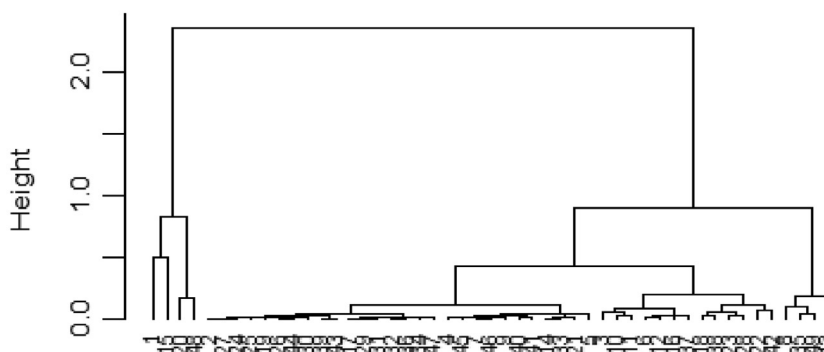

Fig. 2. Dendrogram.

Table 2
List of countries by cluster.

Cluster 1: Higher infection rate and highest death rate				
	Eswatini	South Africa		

Cluster 2: Low infection rate and low death rate

Tanzania	Burundi	Eritrea	Benin	South Sudan
Burkina Faso	Côte d'Ivoire	Guinea	Niger	Chad
DR Congo	Uganda	Mauritius	Nigeria	Togo
Sierra Leone	Madagascar	Mozambique	Central African Republic	Ghana
Angola	Rwanda	Mali	Liberia	Cameroon
Ethiopia	Congo	Guinea-Bissau	Gabon	Kenya
Malawi	Senegal	Zambia	Gambia	Equatorial Guinea
Algeria	Lesotho	Sao Tome and Principe	Zimbabwe	Mauritania
Comoros				

Cluster 3: Medium infection rate and low death rate

Botswana	Réunion	Seychelles	Namibia

Cluster 4: Highest infection rate and higher death rate

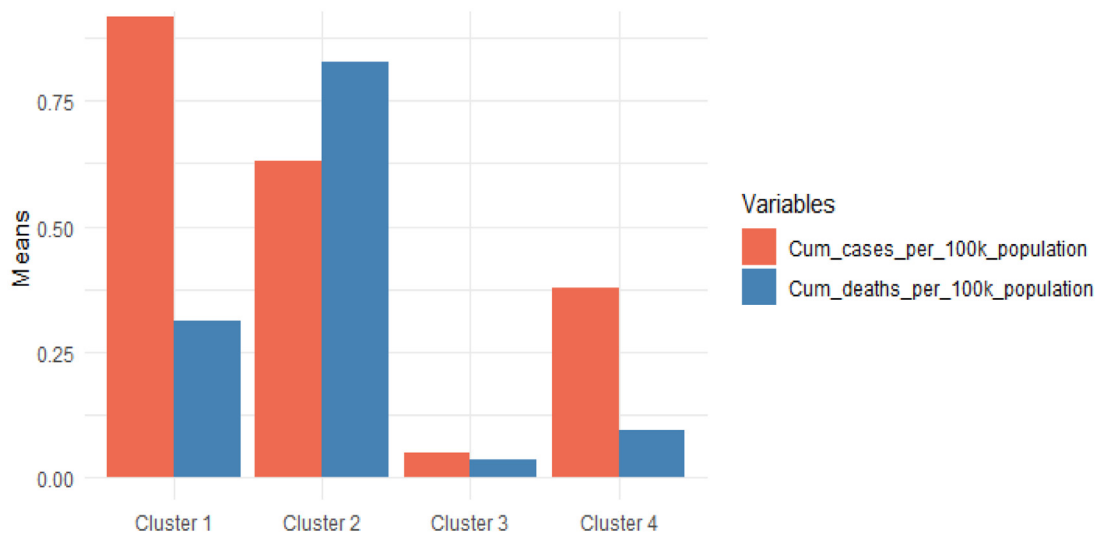|	Cabo Verde	Mayotte

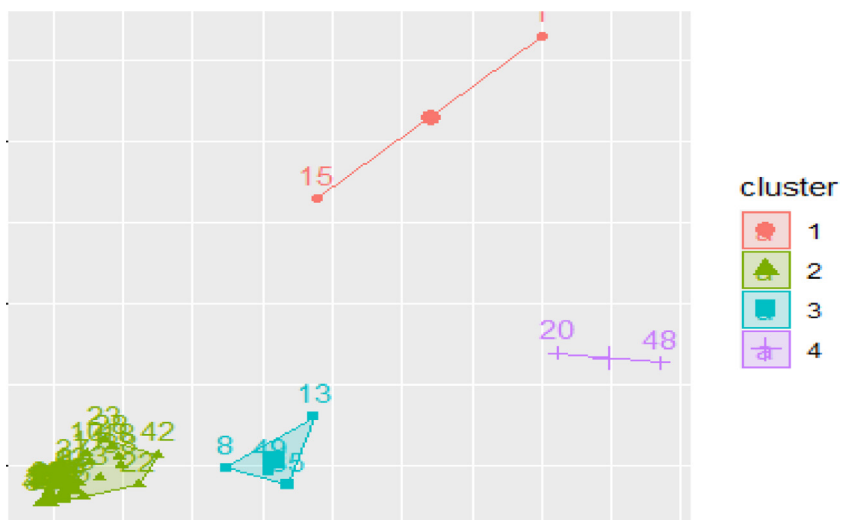
Fig. 3. Bar chart of final cluster means.
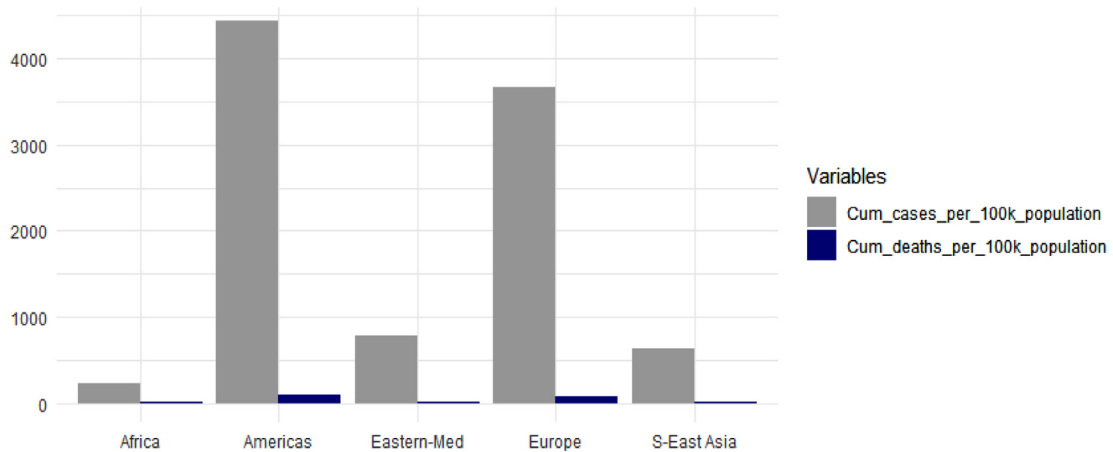

Fig. 4. Cluster plot.

Fig. 5. COVID-19 infection and death rates per WHO Regions. A comparison of the figures as of 31 January 2021 show that Africa was the least affected, pre-vaccination, according to [27]. Infection and death figures are reported out of every 100 thousand citizens.

Implications of extracted clusters

As noted from Table 2, the cluster analysis implies there are four hierarchies among African countries with respect to COVID-19 epidemiology. The infection and death rates are separately categorized into four as highest, higher, medium, and low. These hierarchies are discussed below.

Cluster 1 - higher infection rates and highest death rates countries. This cluster consists of countries/territories with higher rates of infection and highest death rates compared to other countries on the continent. The infection rates among these countries range from 1350 to 2444 persons per 100 thousand population, while death rates range from 48 to 74 persons per 100 thousand population – see Table 2 for list of countries within this cluster.

Cluster 2 - low infection rates and low death rates countries. These are the least-affected countries in both infection and death rates, compared to other African countries. The cluster is made up of countries which infection rates span one to 573 persons per 100 thousand population, with death rates ranging from 0 to 14 persons per 100 thousand population. The majority of countries, evaluating to 84%, belong to this cluster – see Table 2.

Cluster 3 - medium infection rates and low death rates countries. Countries within this cluster suffer moderate infection and death rates compared to other countries of Africa. Infection rates among these countries range from 906 to 1331 persons per 100 thousand population, with death rates spanning zero to 14 persons per 100 thousand population – see Table 2.

Cluster 4 - highest infection rates and higher death rates countries. The membership of this cluster includes countries with the highest infection rates and higher death rates compared to other African countries. The infection rates among these countries range from 2515 to 3017 persons per 100 thousand population, with death rates spanning 22 to 24 persons per 100 thousand population - see Table 2.

These results have practical implications regarding what could be described as the rigidity and resilience of a greater part of the African population to the pandemic. For instance, the cluster consisting of countries worst hit by the pandemic (cluster 4) has only two countries, Cabo Verde and Mayotte, as cluster members. As noted, the infection rates for the countries within this cluster range from 2515 to 3017 persons per 100 thousand population, with death rates ranging from 22 to 24 persons per 100 thousand population. During the same pre-vaccination era, the United States of America had an infection rate of 7757.2 persons per 100 thousand population with a death rate of 130.9 persons per 100 thousand population. Further, the United Kingdom had an infection rate of 5591.9 persons per 100 thousand population and a death rate of 155.5 persons per 100 thousand population. Furthermore, cluster 1 which consists of countries in the second hierarchy of worst-hit countries has only two member countries, South Africa and Eswatini, with infection rates ranging from 1350 to 2444 persons per 100 thousand population, and death rates ranging from 48 to 74 persons per 100 thousand population. Majority of African countries are distributed among clusters 2 and 3 where infection and death rates were very low even before vaccination commenced.

There were several predictions that the African continent was going to be affected by the pandemic more than other parts of the world [1,4]. It turned out that the continent was not badly affected as predicted even before the vaccination era. When the figures from Europe, Americas, and Asia are compared with those of Africa, it is evident that the African population exhibited a good level of rigidity and resilience to the pandemic – see Fig. 5.

Some studies have examined several factors which accounted for the low infection and death rates in most of the African countries. These factors include a younger age demographic structure, lack of long-term care facilities (such as old people's homes), protection acquired through previous exposures to coronaviruses especially from bats found in Africa, favorable climate, and early response by most African countries at the onset of the pandemic [19,22,23,26]. While some school of

thought attribute the low infection and death rates figures reported in Africa to the lack of testing facilities, others argue that there is no evidence that a large number of COVID-19 deaths have been unreported or concealed [22]. Since mass COVID-19 deaths were not concealed across Africa [22], it is logical to infer that majority of the population was not exposed to the virus, was exposed but not infected, or was infected but recovered soon after. These are indications of a population rigid to the pandemic.

The resilience and rigidity exhibited by majority of the African population to the COVID-19 pandemic is a positive sign to explore the human capital prospects of the continent, both during and after the pandemic. This stems from the fact that COVID-19 lockdown rules which disrupted businesses were imposed basically to control infections and deaths. Multinational corporations in various sectors could take advantage of this rigid population to complement their workforce. This would ensure continuity of operations in the event of another wave of the pandemic or a similar situation.

Conclusion

The results of the cluster analysis conducted in this study show that 84% of African countries were rigid to COVID-19 pandemic even before vaccination commenced. Out of the four clusters extracted, two consist of a total of four countries where infection and death rates were high. Majority of African countries are grouped into two clusters where COVID-19 epidemiology was relatively low compared to the rest of the world. Cluster memberships were determined using the values of cumulative infections and deaths per 100 thousand population of a country. Though Africa is generally considered as a developing continent with a largely weak healthcare system, the impact of the pandemic was relatively low during the peak of the disaster. The low impact has been attributed to a younger age demographic structure, lack of long-term care facilities (such as old people's homes), protection acquired through previous exposures to other forms of coronaviruses, favorable climate, and early response by most African countries when the pandemic started [4,19]. Since businesses were shut down during the peak of the pandemic to control infection and death rates, it is logical to hold that a workforce rigid to the virus will not require such disruptions. Human capital could be explored from the rigid African population by multinationals to complement all aspects of their workforce. This has the potential to avert business disruptions in the event of a future wave. The segmentation conducted in the present study and the conclusions relied on COVID-19 data before commencement of vaccination in Africa. Another study should be conducted using data obtained post-vaccination to compare the outcomes.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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