# COVID-19 Guidelines: A Multimodal Video Analysis of Student Behavioral Compliance During Senior Secondary Certificate Examination

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**Abstract**

In order to address the economic pressure and the negative impact of school closure on students, Nigerian government approved the reopening of secondary schools for graduating classes starting from 4th August, 2020, with comprehensive guidelines and protocols. Regrettably, many students were reported to have tested positive to COVID-19, questioning their compliance towards the guidelines. This study therefore investigates students' behavioral compliance towards COVID-19 guidelines, and factors predicting such behavior. Participants involved 205 graduating secondary school students whose behavioral compliance towards the guidelines was observed over three examination days. Although coding large amounts of video data and identifying social actions from the data has become a huge challenge for many researchers, our study shows that observable behavior can be catalogued using multimodal approach to identify and characterize behavioral frames in rich video data. Three state Hidden Markov Models was estimated in R package on three observed and categorized behaviors: hand-washing, use of face mask, and social distancing. Based on probabilities of occurrence of these behaviors, three behavioral frames emerged: cautious, reluctant and defiant attitudes. Results show that defiant attitude was the most prevalent among the behavioral frames, with some level of alternation between reluctant and cautious frames. Our follow-up OLS model indicates that perceived health threat, perceived clarity of guidelines, obligation to obey rule, moral alignment, emotional state, and impulsivity significantly predict students' behavioral compliance towards COVID-19 guidelines. We recommend stringent measures and intensive awareness campaigns to mitigate students' offending behavior.

**Keywords:** *COVID-19; Guidelines, Behavioral compliance; Behavioral frames; Multimodal; Student*

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## Background to the Study

In order to contain the spread of COVID-19 pandemic which has claimed many lives globally,[1] authority across the globe have adopted strict measures aimed at protecting vulnerable individuals from contagion. These measures include enforcement of social distancing rules, total national lockdown, and ban on international flight, among others. According to recent estimates, complying with mitigation measures can save up to 20 million lives globally, and 38.7 million lives if the measures are adopted early (Walker et al., 2020). Closely related to this estimate is an excerpt of media briefing by WHO Director General on March 16, 2020:

"Social distancing measures can help to reduce transmission and enable health systems to cope…. Hand-washing and coughing into your elbow can reduce the risk for yourself and others…. But on their own, they are not enough to extinguish this pandemic. It's the combination that makes the difference…. Washing your hands will help to reduce your risk of infection. But it's also an act of solidarity because it reduces the risk you will infect others in your community and around the world. Do it for yourself, do it for others".[2]

Despite the huge success of these measures across many countries, implementing them, and ensuring that people maintain social distance and refrain from unnecessary outdoor activities in authoritarian and liberal societies for weeks result into ultimate human challenge (Rooij et al., 2020). This is consistent with Soper's (1919) editorial review following the 1918 pandemic that killed millions of people worldwide: "It does not lie in human nature for a man who thinks he has only a slight cold to shut himself up in rigid isolation as a means of protecting others on the bare chance that his cold may turn out to be a really dangerous infection" (p. 502).

Following the first phase of gradual ease of lockdown in Nigeria on 4th May, 2020, the Federal Government approved the reopening of secondary schools for graduating classes starting from 4th August, 2020, with comprehensive guidelines and protocols. This reluctant measure was adopted to address the economic pressures and the negative impact of school closure on girl-child education, children with disabilities, children at risk, and those that were cut-off by barriers in digital learning (Ministry of Education, 2020). Unfortunately, a confirmed report indicates that 20 secondary school students tested positive for COVID-19 (Premium Times, 2020), questioning their behavioral compliance on school guidelines and protocols. Following our presumptions on possible non-compliance across secondary schools nationwide, we investigated student behavioral compliance towards COVID-19 guidelines for schools and learning facilities, and factors that shape such compliance. To the best of our knowledge, there is no published empirical or theoretical evidence that examined people's compliance of COVID-19 guidelines in Nigeria, and factors that shape such compliance. However, related studies have been conducted to: track public perceptions towards the reality of the disease (Olapegba et al., 2020; Iorfa et al., 2020; Yusuf, Gusau and Maiyaki, 2020); examine its psychological distress and experiences (Olaseni, Akinsola, Agberotimi and Oguntayo, 2020); and forecast its spread (Joseph, Nweze, Sulaiman and Loko, 2020; Ibrahim and Oladipo, 2020), among others.

Similar studies had been conducted in country-specific settings, employing different analytic methods. For example, Folmer et al. (2020), investigated the level of compliance and adherence to social distancing measures in the Netherlands, with a view to understanding the processes that sustained citizens' compliance; how their compliance with mitigation measures developed; and how resources that sustained their compliance developed throughout the study period. Using two waves of online surveys administered on 2087 nationally representative samples between 7-10 (first wave; n = 1064) and 21-23 (second wave; n = 1023) July, 2020, the authors reported increase in compliance as opposed to decline in their previous study between May-June. Overall, they found important predictors of compliance, including capacity to comply, perceived health threat, and support for mitigation measures. Similarly, Rooij et al (2020), examined the level of compliance with COVID-19 mitigation measures in the United States. Using an online survey administered to 570 participants across 35 states that adopted such measures, the authors found that while perceptual deterrence was not associated with compliance, the later does depend on people's capacity to obey rules, opportunity to break rules, self-control, moral support and social norms.

Earlier studies conducted at the beginning of mitigation measures across countries (e.g. Gadarian, Goodman and Pepinsky, 2020; Maekelae et al., 2020) also examined the level of people's support/resistance to the measures, their perceived efficacy of the measures, and what influence such support. These studies found that people support COVID-19 mitigation measures at first few weeks, but displayed extreme resistance towards the mitigation in the subsequent weeks. In addition, Zettler et al (2020), examined factors affecting acceptance of personal restriction due to COVID-19 guidelines and protocols. Their study indicates that socioeconomic status, perceived health threat, and age are the strongest demographic profiles affecting acceptance of personal restriction. Despite the comprehensive nature of these studies, unfortunately, compliance was based on self-reported measures rather than observed behavior. While self-reported measures are widely used when measuring aspects of human behavior, the authenticity of such measures is difficult to determine (Gram, 2010; Brill and Schwab, 2019), and in many cases, could be subject to response bias (Folmer et al., 2020). In this regard, Creswell (2014), emphasized that observing participants' behavior during specific situations provides more reliable data. Based on this argument, we chose to analyze multimodality of students' behavioral compliance using rich video data collected at a three-day interval. In what follows, the study was guided by three empirical questions:

1. What are the prevalent observed behaviors of students towards COVID-19 guidelines?
2. What behavioral frames (i.e. clusters of behavior) can emerge from these observed behaviors?
3. What factors significantly predict the identified behavioral frames?

**Methodology**

**Data and Participants**

Inspired by advancement of digital media as a tool to translate visual illustration into meaningful ideas, we delved into multimodality of student behavioral compliance towards COVID-19 guidelines and protocols enforced by the Federal Ministry of Education for safe reopening of schools and learning facilities. Multimodality in the context of this study refers to diverse modes employed by people to communicate beyond language (Antoniadou, 2017). These modes play significant roles in mediating contemporary meaning-making processes from text, image, video, sound, gesture, posture, and spatial cognition (Bezemer and Jewitt, 2010; Bezemer and Mavers, 2011). Meaning derived from these data sources is multimodal and needs to be investigated holistically (Hackling, Murcia, Ibrahim-Didi, and Hill, 2014). Multimodal approach has been applied in a number studies, including those that focus on behavioral analysis (Andrade, Delandshere and Danish, 2016; Banos et al., 2016), image enabled-communication (Snyder, 2010; Ademilokun and Olateju, 2015) and self-injury (Seko, 2013; Seko and Lewis, 2016).

Participants involved final year students writing senior secondary certificate examination (SSCE) across five purposely selected secondary schools[3] in Sokoto State. In order to monitor students' behavioral compliance, we video-recorded the students in each school for three examination days[4], with emphasis on three exhaustive behaviors: hand-washing, use of face mask, and social distancing. These behaviors are exhaustive because there are no other rules concerning students in the guidelines. Although many students were captured in the video, we exclusively focused on fewer students who appeared in all the videos recorded within the three examination days in each school. We had two reasons for doing this. First, to examine whether there are changes in behavioral compliance/resistance over time; and second, to easily identify the students for a follow-up survey with the aim of estimating factors predicting their behavior. Overall, a smaller sample size of 205 students matched our selection criteria, with research evidence suggesting that numerical standard for sample size in qualitative research is not available (Marshall, and Rossman, 2010). However, several authors have proposed 'saturation' to achieve sample size adequacy (Charmaz, 2006; Morse, 1991, Marshall and Rossman, 2010).

**Procedure**

We obtained ethical approval for this study from the Ministry of Basic and Secondary Education, Sokoto State, with the agreement that: (1) pictures and videos emerged during the research would be kept unpublished; and (2) locations of data collection must exclude the classroom environment. These measures were taken for a number of ethical reasons, including identity protection of schools and students, and prevention of potential examination malpractice. All principals of the schools provided their consent prior to data collection. Upon approval, we embarked on covert video-recording of the students at five strategic locations: hand-washing centers, libraries, cafeterias, playgrounds, and tree shades. Although researchers posit that all observational studies should sit along a continuum of participant consent to avoid invasion of privacy, however, studies examining deviant behaviors are only possible through substantially covert participant observation (see Roulet, Gill and Stenger, 2016). In each location, the video recording lasted for 30 minutes as a means of identifying our target participants easily across the three examination days and as a means of observing change in behavior over time.

**Analysis**

While recognizing the power of technology to identify behavioral features by means of computer vision and machine learning, we manually analyzed these features based on multilevel coded behaviors. The coding began with identification of participants across the three examination days, and then proceeded with observation of multimodalities of the behavioral features across different time points. Our approach to coding involved assigning numerical weights to observed categories across the three behavioral features. In the first behavior (*hand-washing*), three categories were formed to include: 1 = no hand-washing; 2 = < 20 seconds hand-washing; and 3 = 20 seconds and above. The second behavior (*use of face mask*) was represented by four categories: 1 = no face mask; 2 = covering nose and mouth; 3 = covering mouth only; and 4 = lowering below mouth. In the third behavior (*social distance*), three categories were formed: 1 = very close; 2 = one meter apart; and 3 = two meters and above. Every category in each behavior is mutually exclusive of the other. For example, if a student lowered his mask below his mouth, he cannot cover his mouth at the same point in time. Because these behavioral features are likely to change over time for each participant, we examined behavioral transition using a 3 minutes interval across the three examination days. This interval was considered to be sufficient enough to contain information about the transition due to lengthy nature of behavioral change from our participants. Although time interval coding may lack the precision of recording onset and offset events, Bakeman and Gottman (1997), argued that it is a suitable approach to synchronize simultaneous streams of behaviors.

These behaviors, observed at different time points, are represented in the form of time-series data, and followed a multimodal distribution. Andrade et al (2016) recommend the use of statistical models that deal with multivariate, time-dependent, and multimodal distributions to estimate probabilities associated with occurrence of time-varying behavior. The resulting data contains 2460 observations and nine variables (Day, Time, Participants ID, gender, school ownership type, school location, and the three observed behaviors). Because our observation was time dependent, we employed Hidden Markov Model (HMM) in the R package to estimate the probability of behavioral occurrence and the number of latent classes (also known as epistemological frames; see Andrade et al., 2020) that are likely to produce such behaviors. HMM is a family of statistical analysis designed to analyze time-series data. The model assumes that data is generated from a set of finite observations with different latent classes that predict observable behaviors (Visser and Speekenbrink, 2010).

Over the years, HMMs have been applied in several disciplines, including sociology, psychology, economics, genetics, speech recognition, and engineering. Prior to our analysis, a transition matrix was estimated to provide us with information about the sequence of the latent classes and possible change in behavior. In order to extract the number of latent classes that are likely to produce the observed behavior, we employed the Bayesian Information Criterion (BIC) as baseline comparison, with lower BIC considered to fit the data better (Andrade et al., 2020). The number of extracted latent classes along with probabilities of occurrence of the observed behavior helped us to frame clusters of behavior (known as behavioral frames) using numerical coding. It should be noted that this method is unsupervised because the algorithm does not employ *a priori* classification. For example, it is possible to frame clusters of behavior that share similar characteristics (e.g. clusters of face mask use) without any priori classification. We employed unsupervised algorithm due to lack of training set[5] which is used to infer relevant latent classes in the supervised algorithm. These coded behavioral frames were rated by two raters, yielding 86% absolute agreement (for more on behavior framing, see Russ, Lee and Sherin, 2012; Andrade et al 2016).

**Follow-up Study**

Our study would be incomplete if we only focused on students' behavioral compliance alongside probabilities of occurrence of such behaviors. For this reason, we embarked on a follow-up study to estimate the factors predicting these behaviors. The follow-up study involved a closed-ended survey, comprising eight constructs: (1) knowledge of the guidelines, (2) perceived clarity of the guidelines, (3) perceived health threat of the disease, (4) emotional state concerning the disease, (5) obligation to obey rules, (6) moral alignment with rules, (7) deterrence, and (8) impulsivity (self-control). These constructs have been used in a number of studies (see Folmer et al., 2020; van Rooij et al., 2020).

Knowledge of the guidelines was measured using one item in the survey. We asked the participants to indicate their level of knowledge concerning the guidelines. Responses involved five-point Likert scale format (1 = no knowledge; 5 = high knowledge). Perceived clarity of the guidelines was measured using one item. Participants were asked to indicate the extent to which the guidelines are clear to them (1 = extremely not clear; 5 = extremely clear). Perceived health threat was also measured by one item. We asked participants to indicate their perceived health threat of COVID-19 to the general public (1 = Strongly disagree; 5 = Strongly agree). Emotional state was measured by two items to examine how participants feel about COVID-19 with regards to its adverse effect (1 = Not bothered; 5 = scared). Obligation to obey rule was examined using three Likert scale items (1 = strongly disagree; 5 = Strongly agree). Participants were asked to submit their response concerning their obligation to obey rules when: (1) they hear of any rules from the government, (2) they are not supportive of the rules, and (3) they don't understand the reasons behind the rules.

Participants' moral alignment was measured by one item; they were asked to submit if they have a moral belief that people should always obey laws (1 = Strongly disagree; 5 = Strongly agree). Deterrence was measured by two items, requesting participants to submit whether school authorities will: (1) find out or (2) punish them if they don't comply with COVID-19 guidelines (1 = very improbable; 5 = very probable). Lastly, impulsivity (self-control) was measured using three items taken from 8-item impulse control subscale in the Weinberger Adjustment Inventory (WAI; Weinberger & Schwartz, 1990). We asked the participants to submit whether they: (1) do things without giving them enough thought; (2) get carried away and go too far when doing something fun; and (3) do things that suit them without thinking about their consequences (1 = Strongly disagree; 5 = Strongly agree).

To estimate whether these constructs predict students' behavioral compliance, we employed ordinary least square (OLS) regression analysis, in which coded behavioral frames were regressed upon these constructs (for a similar approach, see Folmer et al., 2020; van Rooij et al., 2020). Prior to OLS estimation, preliminary assumption tests were conducted to check for normality, stationarity, collinearity, and hetreoskedasticity, with no violations noted.

**Results and Discussion**

Five Hidden Markov Models starting from two latent states were estimated to decide the one that best fit the data. Based on values of the BIC, three latent state model was selected because it fits the data well (3-state BIC = 3216). Table 1 below presents the average prevalent behaviors towards COVID-19 guidelines across the three examination days. For example, it is apparent from the observed behavior that "no hand-washing (64.4%)", "no face mask (62.4%)", and "no social distancing (72.7%)" were the prevalent behavior displayed by the participants. Note that this prevalence involved instances in which the behaviors occur across the three days. These observed behaviors were statistically proportioned across the three latent states to give the actual probability of occurrence of the behaviors. Based on these proportions of behavior across the latent states, we framed students' behavior as cautious, reluctant and defiant attitudes (see table 2). It should be noted that the overall combination of these behaviors produced the behavioral frames, not just individual behavior. The first frame represents cautious attitude: hand-washing >20 seconds (0.59); covering nose and mouth (0.47); and maintaining distance of 2 meters (0.53). The second frame represents reluctant attitude: hand-washing <20 seconds (0.53); covering mouth only (0.54); and maintaining distance of 1 meter (0.51). The third frame indicates defiant attitude: no hand-washing (0.67); no face mask (0.68); and no social distance (0.71).

Of the three behavioral frames, defiant attitude was the prevalent attitude displayed by the participant (63.4%), suggesting non-compliance of COVID-19 guidelines among students. It should be noted that the proportion of the observed behaviors adds to one in each frame. For example, the proportion of hand-washing behaviors – no hand-washing (0.14), < 20 seconds (0.27), and 20 seconds above (0.59) – adds to one within the cautious behavioral frame. This represents a property of our statistical model, and therefore, higher probabilities carry more weight in defining the behavioral frames. Although these behavioral frames are idiosyncratic for each student, they occur consistently regardless of gender and school location (see table 3). Put differently, no significant association in the behavioral frames was observed between male and female students ($X^2$=5.31; p=0.32) and between urban and rural schools ($X^2$=4.58; p=0.82). However, significant association was observed on school ownership type, with students from federal-owned schools displaying more cautious and less defiant attitude compared to their counterparts from private and state-owned schools who displayed more of defiant attitude ($X^2$=32.76; p=0.01).

**Table 1:** Average Prevalent Behavior of Student

| Behavior | Sub-Category | Frequency | Percent |
|---|---|---|---|
| Hand-washing | No Hand-washing | 1584 | 64.4 |
| | < 20 seconds | 516 | 21.0 |
| | 20 seconds above | 360 | 14.6 |
| | Total | 2460 | 100.0 |
| Face Mask Use | No face mask | 1536 | 62.4 |
| | Lowering below mouth | 456 | 18.5 |
| | Covering mouth only | 324 | 13.2 |
| | Covering mouth and nose | 144 | 5.9 |
| | Total | 2460 | 100.0 |
| Social distancing | Very close | 1788 | 72.7 |
| | 1 meter apart | 504 | 20.5 |
| | 2 meters and above | 168 | 6.8 |
| | Total | 2460 | 100.0 |

**Table 2:** Probability of Occurrence of Behavior Across Behavioral Frames

| Behaviors | Cautious Attitude N = 384 (15.6%) | Reluctant Attitude N = 516 (21.0%) | Defiant Attitude N = 1560 (63.4%) |
|---|---|---|---|
| Hand-washing | | | |
| No Hand-washing | 0.14 | 0.32 | 0.67 |
| < 20 seconds | 0.27 | 0.53 | 0.28 |
| 20 seconds above | 0.59 | 0.15 | 0.05 |
| Face Mask Use | | | |
| No face mask | 0.03 | 0.16 | 0.68 |
| Lowering below mouth | 0.18 | 0.26 | 0.21 |
| Covering mouth only | 0.32 | 0.54 | 0.07 |
| Covering mouth and nose | 0.47 | 0.04 | 0.04 |
| Social Distancing | | | |
| Very close | 0.15 | 0.28 | 0.71 |
| 1 meter apart | 0.32 | 0.51 | 0.26 |
| 2 meters and above | 0.53 | 0.21 | 0.03 |

**Table 3:** Difference in Behavioral Frames

| Variables | Cautious Attitude (n=384) | Reluctant Attitude (n=516) | Defiant Attitude (n=1560) | $X^2$ (p-value) |
|---|---|---|---|---|
| Gender | | | | |
| Male | 204 (53.1%) | 265 (51.4%) | 774 (49.6%) | 5.31 (0.321) |
| Female | 180 (46.9%) | 251 (48.6%) | 786 (50.4%) | |
| School Ownership Type | | | | |
| State | 90 (23.4%) | 177 (34.3%) | 747 (47.9%) | 32.76 (0.01) |
| Federal | 189 (49.2%) | 169 (32.8%) | 294 (18.9%) | |
| Private | 105 (27.4%) | 170 (32.9%) | 519 (33.2%) | |
| School Location | | | | |
| Urban | 196 (51.0%) | 264 (51.2%) | 765 (49.0%) | 4.58 (0.82) |
| Rural | 188 (48.9%) | 252 (48.8%) | 795 (51.0%) | |

The major aim of frame analysis is to identify transition instances of behavioral frames across time points (Andrade et al., 2016). For this reason, we employed Optimal Matching (OM) algorithm to identify how the behavioral frames alternate over five minutes interval across three days (Halpin, 2010; Gabadinho, Ritschard, Mueller and studer, 2011). OM algorithm is widely used in sequence analysis for computing "pairwise dissimilarity values based on the number of transformations required to make two sequences identical" (Andrade et al., 2016: p.299). Results of the OM algorithm (see table 4) revealed three behavioral frame transitions: (1) from reluctant to defiant; (2) from defiant to reluctant; and (3) from cautious to defiant. For example, some participants who lowered their face mask below their mouth and stayed one meter away from others later decided to remove their masks and stayed very close with others. While the first and second transition occurred frequently, the third transition occurred sparingly, with research evidence suggesting that people's compliance with COVID-19 mitigation measures continue to be eroding (Folmer et al., 2020).

**Table 4:** Average Behavioral Frame Transition

| Onset (mins) | Offset (mins) | Hand-washing | Face mask use | Social distancing | Frame |
|---|---|---|---|---|---|
| 00:00 | 03:00 | No | No | No | Defiant |
| 03:00 | 06:00 | No | No | No | Defiant |
| 06:00 | 09:00 | <20 mins | Below mouth | No | Reluctant |
| 09:00 | 12:00 | No | No | No | Defiant |
| 12:00 | 15:00 | No | Nose | 1 meter | Reluctant |
| 15:00 | 18:00 | No | No | No | Defiant |
| 18:00 | 21:00 | No | Mouth only | 1 meter | Reluctant |
| 21:00 | 24:00 | >20 mins | Mouth & Nose | 2 meters | Cautious |
| 24:00 | 27:00 | No | No | No | Defiant |
| 27:00 | 30:00 | No | No | No | Defiant |

Our follow-up study shows the mean scores of the 8 constructs (see table 5). Perceived knowledge of the guidelines had a mean score of 4.31, suggesting that the participants had adequate knowledge of the guidelines. Perceived clarity of the guidelines had a mean score of 1.95, implying that the guidelines are not clear to the students. In addition, perceived health threat of the disease had a mean score of 2.12. This implies that the participants had a strong belief that COVID-19 poses no health threat to the general public. It was also gathered that the participants are not bothered (M = 1.32) whenever the disease is mentioned or whenever they heard of new cases and deaths as a result of COVID-19. The mean value of obligation to obey rule is 3.31, suggesting that the participants have a moral obligation to comply with rules. Participants' moral alignment with rules had a mean value of 4.62, depicting that they have moral belief that people should always obey rules. Deterrence had a mean value of 2.21. This suggests that the participants disagreed that school authorities will always find out and punish them if they don't comply with COVID-19 guidelines. Lastly, participants' impulsivity is 4.24, indicating a low self-control.

**Table 5:** Descriptive statistics of Constructs

| Construct | Mean | Std. Deviation | Interpretation |
|---|---|---|---|
| Knowledge of guidelines | 3.61 | 0.47 | Adequate knowledge |
| Perceive clarity of guidelines | 1.95 | 0.28 | Not clear |
| Perceived health threat | 2.12 | 0.16 | No threat |
| Emotional state | 1.32 | 0.24 | Not bothered |
| Obligation to obey rule | 3.31 | 0.37 | Obligation to comply |
| Moral alignment | 3.78 | 0.72 | Morally inclined |
| Deterrence | 2.21 | 0.18 | Low deterrence |
| Impulsivity | 4.24 | 0.52 | Highly impulsive |

In order to estimate the factors that significantly predict the identified behavioral frames, we estimated three OLS regression models, in which each behavioral frame was pooled as dependent variable in each model (see table 6). Results from OLS regression models indicate that cautious attitude is significantly predicted by obligation to obey rules and moral alignment. On the other hand, defiant attitude was predicted by perceived clarity of guidelines, perceived health threat, emotional state, and impulsivity. However, reluctant attitude was not significantly predicted by any variable. An inspection of the share of variability of the regressors indicates that they shared 32.1% of variability in cautious attitude and 46.3% in defiant attitude. This suggests that other variables could still account for the rest of the variability in the three behavioral frames. In consistent with our findings, recent studies that examined factors predicting COVID-19 compliance revealed a number of factors, including capacity to comply, self-control, perceived health threat, and support for mitigation measures (Folmer et al., 2020; van Rooij et al., 2020).

**Table 6:** OLS models on Behavioral Frames

| Constructs | Cautious Attitude | Reluctant Attitude | Defiant Attitude |
|---|---|---|---|
| Knowledge of guidelines | 0.06<br>[0.02] | -0.24<br>[0.01] | -0.23<br>[0.02] |
| Perceive clarity of guidelines | 0.31<br>[0.12] | -0.07<br>[0.03] | 0.54***<br>[0.01] |
| Perceived health threat | 0.57<br>[0.03] | 0.36<br>[0.02] | 0.19**<br>[0.03] |
| Emotional state | 0.12<br>[0.01] | 0.04<br>[0.02] | 0.37**<br>[0.04] |
| Obligation to obey rule | 0.34***<br>[0.02] | -0.21<br>[0.01] | -0.26<br>[0.01] |
| Moral alignment | 0.21**<br>[0.01] | 0.08<br>[0.01] | 0.12<br>[0.03] |
| Deterrence | 0.26<br>[0.04] | 0.23<br>[0.02] | 0.25<br>[0.04] |
| Impulsivity | 0.32<br>[0.03] | -0.12<br>[0.02] | -0.41***<br>[0.03] |
| R-squared | 0.321 | 0.256 | 0.463 |
| F-statistics | 0.000 | 0.000 | 0.000 |

**p<0.05, ***p<0.01

**Note:** Standard error appear in brackets

A number of explanations can be offered as to why these factors predict the behavioral frames. For example, the positive effect of perceived clarity of guidelines on defiant attitude could be due to insufficient explanation of the guidelines to the students. Thus, students are less likely to comply if the mitigation measures are unclear. The positive effect of perceived health threat and emotional state on defiant attitude could be due to the fact that the participants did not see COVID-19 as a public health threat and the fact that they are not bothered with the disease. In our previous study, we observed that people hold negative view about COVID-19, and strongly affirmed that it was never a life threatening disease (Yusuf et al., 2020). Individuals with such mindset are less likely to comply with COVID-19 guidelines and protocols. The negative effect of impulsivity on defiant attitude could be explained by the fact that self-control largely determines people's behavior towards an event. For example, people who are highly impulsive are less likely to comply with mitigation measures. This is consistent with studies that examined the impact of self-control on offending behavior (Pratt and Cullen, 2005; Vazsony, Mikuska and Kelley, 2017; van Rooij et al., 2020).

On the other hand, the positive effect of moral obligation to obey rules and moral alignment on cautious attitude could be due to nurtured behaviors in the students within their social environment. This is to say that people's moral obligation and alignment are a function of their social environment, and these variables are the ultimate virtue that helps one to comply with rules. Thus, people are more likely to obey rules when they are morally inclined to do so. As expected, deterrence did not significantly predict any of the behavioral frames. There is inconclusive research evidence on whether stricter punishment can deter offending behavior, with several authors arguing that knowledge, certainty and severity of punishment are what matters most in preventing offending behavior (Wright, 2010; Nagin, 2013; Simpson et al., 2014). However, van Rooij et al (2020) posit that "achieving minimum certainty of detection and punishment for violating COVID-19 mitigation measures would be challenging" (p.26).

Although our descriptive analysis showed that the participants have adequate knowledge of the guidelines, surprisingly, it does not significantly predict any of the behavioral frames. It appears that negative belief concerning the reality of the disease in Nigeria (as found in our previous study) could suppress the power of knowledge. While this is not statistically proven in our study, a number of authors, in epistemological and ontological point of view, argued that belief is a necessary condition for knowledge even though they are distinct concepts (Bell, Halligan and Ellis, 2006). Thus, people can have adequate knowledge about some rules but fail to comply because they don't believe in the existence of the scenarios that precipitated such rules.

On the basis of these findings, we conclude that behavioral compliance towards COVID-19 guidelines among students is not a free choice, but a function of external factors. Put differently, the ability to comply with COVID-19 guidelines is largely a function of moral inclination which is intrinsically driven within the social context. Conversely, the ability to defy the rules is largely a function of belief, self-control and emotional state.

## Conclusion and Recommendations

One of the challenges faced by behavioral analysts is the rigorous and tedious task of coding large amounts of rich video data while consistently identifying frames of behavior. However, as argued by Andrade et al (2016), it is easier to frame behaviors from observed behavioral clusters and then examine how these clusters alternate over time. Based on this argument, we examined students' behavioral compliance towards COVID-19 guidelines using multimodal video analysis. Although multimodal analysis had been applied in different disciplines, to the best of our knowledge, there is no published empirical study that examined COVID-19 behavioral compliance using the approach, as most studies largely rely on self-reported measures. Our findings suggest that "no hand-washing", "no face mask", and "no social distancing" were the prevalent behavior displayed by the participants. These observed behaviors were catalogued into three behavioral frames: cautious, reluctant and defiant attitude, with defiant attitude found to be the prevalent frame. These frames occurred consistently across the observation periods regardless of gender and school location. However, school ownership type was significantly associated with behavioral frames, with students in federal-owned schools displaying more cautious attitude compared to their counterparts in private and state-owned schools who displayed more defiant attitude. Optimal Matching algorithm revealed three behavioral frame transitions: (1) from reluctant to defiant; (2) from defiant to reluctant; and (3) from cautious to defiant.

Our follow-up survey shows that that cautious attitude is significantly predicted by obligation to obey rule and moral alignment. In addition, defiant attitude was predicted by perceived clarity of guidelines, perceived health threat, emotional state, and impulsivity. Overall, we conclude that the ability to comply with COVID-19 guidelines is largely a function of moral inclination which is intrinsically driven. On the other hand, the ability to defy the rules is largely a function of belief, self-control and emotional state. Based on these findings, we recommend that stringent measures should be adopted to ensure that students comply with the guidelines. Before adopting these measures, we strongly recommend that the students need to be highly sensitized on the dangers of the pandemic and the potential benefits of compliance with the guidelines. Their mindset also needs to be modified through awareness programmes that are effective in changing offending behavior.

## Limitations

We were challenged by a number of limitations that were beyond our control. First, it would be inappropriate to generalize our findings to Nigerian student population using only five schools in one state. We quite understood that observing sampled schools across the 36 states would be almost impossible, considering time and cost involved. However, our methodological approach to behavioral framing using rich video data could be employed by other authors to understand the level compliance to COVID-19 mitigation measures in other settings. Second, we limited our observations to only students who appeared frequently in our video recording across the three examination days, leaving out those who appeared sparingly and whose behavior might significantly contribute to our study. However, our sole motive was to identify change in behavior over time, as it would be inconclusive to report behaviors that were observed at one instance.

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1. Mortality rate as at 28th August, 2020 is 827, 246; see WHO weekly operation update on COVID-19 https://www.who.int/docs/default-source/coronaviruse/situation-reports/wou-28-august-approved.pdf?sfvrsn=d9e49c20_2

2. See https://www.who.int/dg/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-COVID-19---16-march-2020
3. The five schools were selected across: school ownership type: state-owned (2), federal-owned (2) and private-owned (1); school location: urban (3), rural (2); school type: boys school (2), girls school (2), mixed (1).

4. Examination days were selected based on when general papers were taken e.g. English, Mathematics and Biology

5. A training set is used to build statistical model and to evaluate the performance of a model. See James, G. An introduction to statistical learning: With application in R. 2013