Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
A modified UTAUT model for the acceptance and use of digital technology for tackling COVID-19

Boluwaju A. Akinnuwesi, Faith-Michael E. Uzoka, Stephen G. Fashoto, Elliot Mbunga, Adedoyin Odumobo, Oluwaseun O. Amusa, Moses Okpeku, Olumide Owolabi

A R T I C L E  I N F O

Keywords:
Acceptance and use of COVID-19 digital tackling technology
Nigeria, People's Behavioural Intention
UTAUT

A B S T R A C T

COVID-19 pandemic expedites the development of digital technologies to tackle the spread of the virus. Several digital interventions have been deployed to reduce the catastrophic impact of the pandemic and observe preventive measures. However, the adoption and utilization of these technologies by the affected populace has been a daunting task. Therefore, this study carried out exploratory investigation of the factors influencing the behavioural intention (BI) of people to accept COVID-19 digital tackling technologies (CDTT) using the UTAUT (Unified Theory of Acceptance and Use of Technology) framework. The study applied principal components analysis and multiple regression analysis for hypotheses testing. The study revealed that performance expectancy (PE), facilitating conditions (FC) and social influence (SI) are the best predictors of people's BI to accept CDTT. Also, organizational influence and benefit (OIB) and government expectation and benefits (GEB) influence the people's BI. However, variables such as age, gender and voluntariness to use CDTT have no significance to influence BI because the CDTT is still nascent and not easily accessible. The results show that the decision-makers and regulators should consider inciting variables such as PE, FC, SI, OIB and GEB, that motivate the acceptance and use of CDTT. Furthermore, the populace must be sensitized to the availability and use of CDTT in all communities. Also, the path diagram and hypothesis testing results for CDTT acceptance and use, will help government and private organizations in planning and responding to the digitalization of COVID-19 protective measures and hence revise the COVID-19 health protection regulation.

1. Introduction

The COVID-19 outbreak started in 2019 in Wuhan, which was caused by the new coronavirus SARS-COV-2 (Severe acute respiratory syndrome coronavirus 2) [1,2]. The World Health Organization (WHO) on 11th March 2020, declared it as a pandemic [1,3]. As of 15th July 2021, the total number of confirmed cases of COVID-19 globally was about 189 million; and over 4 million deaths were reported in 222 countries. Also, in Nigeria, there were about 168,000 confirmed COVID-19 cases and about 2000 deaths. The spread of the virus is astounded to the global society because of the fast rate of transmission and deaths. However, several conventional measures were adopted to prevent the spread and outbreak of the disease such as hand washing, face masking, social distancing and sanitizing. Similarly, COVID-19 digital tackling technologies have been developed for tracking and contact tracing, social distance monitoring, temperature screening, diagnosing and symptoms tracking. These technologies are developed to complement the conventional measures of preventing the spread of the disease. Therefore, such responses to COVID-19 highlight the importance and the accelerated development of CDTT in fostering inclusive, just and fair societies during the current pandemic.

Governments of countries enact laws and enforce COVID-19 regulations such that the populace (i.e. End-users) accept and use the available CDTT to prevent the disease from spreading. However, the adoption, acceptance and use of CDTT deployed to tackle COVID-19 has been severely challenged and ultimately affect their efficacy. This is exacerbated by factors including attitude (perceived need, risk and benefit),

https://doi.org/10.1016/j.susoc.2021.12.001
Received 28 September 2021; Received in revised form 19 November 2021; Accepted 3 December 2021
Available online 16 December 2021
2666-4127/© 2021 The Authors. Published by Elsevier B.V. on behalf of KeAi Communications Co., Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/)
data security and privacy, infrastructure, ease of use, digital literacy, level of education, the magnitude of public awareness programmes, and public trust [4]. Though there have been lots of research works reported on COVID-19 but there is very limited research on adoption, acceptance and use of CDTT developed for tackling COVID-19. Like other developing countries, Nigeria faces some challenges relating to infrastructure, electricity, literacy, belief and custom, internet connectivity, and low per capita income [5,6]. These impediments influence people’s behavioural intention (BI) to adopt, accept and use available digital technologies. Therefore, this study aimed at investigating the digital solutions deployed to tackle COVID-19 and also factors affecting the behavioural intention of the populace to use CDTT in Nigeria. This study was guided by the UTAUT model and sought to address the following research questions (RQ):

a RQ-1: What problems do people encounter in the use of digital tools to tackle COVID-19?
b RQ-2: What factors and moderating variables influence the behavioural intention of the populace to accept and use CDTT?
c RQ-3: What framework is suitable for acceptance and utilization of the CDTT?

The overall aim and contribution of this study is the development of a modified UTAUT model for CDTT adoption in developing country context through the extension of the original UTAUT framework that was presented in [7]. The original UTAUT model was modified using the factors that we established to be significant predictors of people’s BI to accept CDTT based on the results of our data analysis. To the best of our knowledge, this is the first study on the development of an acceptance and use of the technology model for COVID-19 digital tackling technologies in the Nigerian context. The proposed CDTT acceptance model serves as a guide to policy makers on COVID-19 protective measures in private and government organizations in developing economies.

The paper is organized as follows: Section 2 presents the literature review. In Section 3, the methodology is presented. Section 4 presents the discussion of results while the conclusion is presented in Section 5.

2. Literature review

We are in the revolutionary age of digital technology and this led to the development of lots of digital solutions for real-life problems and people are meant to accept and use them accordingly [8]. The outbreak of SARS-CoV-2 is giving birth to several digital solutions to tackle the spread of COVID-19 and the solutions help to complement the clinical tools that are currently being used as Personal Protective Equipment (PPE). The CDTT developed for tackling COVID-19 can be presented under the following categories: Tracking and Contact tracing; Social distancing; Temperature screening; Prognosis; Diagnosis and Treatment. These technologies are developed and they function properly based on the following concepts: Internet of Things (IoT), Geographical Information System (GIS), Artificial Intelligence, Big Data, Internet of Medical Things (IoMT), Cellular Technology and Smart Application, Virtual Reality and Blockchain [2].

A lot of studies on COVID-19 emphasized the following:

a Prediction/Projections of COVID-19 cases [9–11].
b Legislative response to COVID-19 emergencies vis-à-vis the impact on human right protection [12,13].
c Public opinions on early preventive measures for COVID-19 [14].
d Psychological impacts of COVID-19 pandemic on people [15,16].
e Spatial analysis of the spread of the COVID-19 [17–20].
f Risk assessment / Risk of transmission [21,22].
g COVID-19 dataset structuring [23]; Symptom profiling e.g. [24].
h Genetic characterization/variation [25,26].
i Testing / Detection [27,28]; Analysis of risk factors [29].
j Transmission dynamics [30]; and Differential diagnosis [31].

In addition, studies on some emerging technologies to better the lives of people in this period of the COVID-19 pandemic have been reported. For example, the use of teledmedicine and virtual software to treat patients during COVID-19 was considered in [32] and the findings of the author suggested that the use of these applications to remotely treat patients helped to reduce the congestion of patients in hospital, protect the healthcare facilities and minimize the spread of COVID-19.

Hernández-Orallo et al. in [33] evaluated the effectiveness of Bluetooth based smartphone applications for contact tracing for COVID-19. The authors did the study with the view to model the system performance based on precision, utilization, tracing speed and implementation. Their results showed that smartphone contact tracing applications worked effectively when combined with measures such as social distancing and that a centralized implementation model was more effective. Similarly, a review was done in [34] to capture the digital innovations in response to COVID-19 globally. The authors identified that digital innovations complement the conventional medical measures in the following areas: population surveillance, case identification, and contact tracing.

However, safety and privacy remain major concerns that are raised against these technologies [35–37]. Moreover, data collected in Israel about the use of technologies to fight against the spread of COVID-19 also affirmed privacy concerns and the need to provide safeguards needed to minimize the risk of civil human rights [38]. The interview report presented in [39] also established the need to strike a balance between protecting public health and safeguarding civil rights. In the same light, Maalseen and Dowling in [40] affirmed that privacy and potential discrimination should be critically approached in this era of accelerated technology adoption due to crises of COVID-19.

In [41,42], the authors identified and described digital solutions and technologies for COVID-19 diagnosis, prevention and surveillance. The fast growth of digital technologies was attributed to the need for good digital healthcare measures that would complement the conventional medical measures employed to tackle COVID-19.

In [43], the authors presented an analysis of behavioural intention to adopt social media technology as a tool for Small and medium-size enterprises (SME) to advertise their products. It was noted that the spread of COVID-19 paralyzed most of the SMEs and therefore the need arose for alternative virtual means of carrying out business activities. The results indicated that there is much awareness of- and high intention to adopt social media tools available for SMEs that were affected by the COVID-19 pandemic. Moreover, the authors noted that organizational context, technological context, environmental context, and social media awareness, significantly influence the intention to adopt social media tools. Therefore the authors suggested that the government should provide supports for SMEs in a crisis like COVID-19 and similar studies were also reported in [44,45].

The authors in [46] sampled the opinions of visitors to public hospitals in Singapore to study their awareness, acceptance and adoption of the national digital contact tracing tool for COVID-19. They noted that a large percentage of the people were aware of the technology and are willing to adopt, accept and use it. Similarly in [47], an integrated expectation confirmation and health belief model (ECHBM) was developed in Thailand to explain the adoption and continuance intention of people to use contactless digital technologies in COVID-19 crises. The authors identified that perceived susceptibility, perceived usefulness, satisfaction and perceived seriousness had a significant impact on the intention to use contactless payment systems. Perceived usefulness and confirmation were also identified to be significant determinants of consumer satisfaction. Public opinion on the adoption of social distancing was also analysed and presented in [14]. The results showed that situational awareness has a significant influence on social distancing. Therefore increasing situational awareness in periods of pandemics through formal sources of information can result in a significant increase in the adoption of protective health behavior and hence minimize the spread of diseases.
Factors influencing the acceptance of work from home (WFH) technologies in the period of COVID-19 was studied in [48] using the extended UTAUT model and employing environmental concern and 57.4% acceptance was predicted for WFH technology. In [49], the adoption of digital contact tracing in the period of COVID-19 was studied. The authors conceptualized the relationship between governance approaches and contextual societal factors that could influence digital contact tracing adoption. The results showed how to monitor contacts with the view to achieving the desired health, economic, and societal benefits during a pandemic period such as COVID-19. Adoption of digital technologies in the period of COVID-19 has helped government and private organizations in planning and responding to emergencies [50].

A good number of studies were reported on factors influencing the adoption of digital technologies in teaching and learning in time of crises such as COVID-19. For example, Ezzat in [51] explored the factors affecting the teaching staff in the public universities in Egypt to accept and use social media tools for teaching in the period of the COVID-19 crises. Technology Acceptance Model (TAM) was adopted and the following significant internal factors were identified by the author: perceived ease of use and perceived usefulness, while infrastructure and device access were considered partially as external factors. Similarly, TAM was used in [52] to study students’ acceptance of technology-mediated teaching during COVID-19 in four German universities. The authors extended the model with the following variables (i.e. time flexibility, learning flexibility and social isolation) that influenced perceived usefulness. Also in [53], the influence of culture and individual characteristics in the adoption of computer-based collaborative learning during the pandemic such as COVID-19 was carried out. Structural Equation Modelling (SEM) was used to assess the relationship among the construct. The results showed that students’ perception of computer-based collaborative learning positively associated with the student’s personality and cultural beliefs.

The importance of users’ participation has been reported by several scholars in various studies including the application of digital technologies to prevent COVID-19 [1,2]. Among these applications, users’ health data have been used for risk assessment of COVID-19 outbreaks [21]; prediction of mortality risk [54,55]; differential diagnosis [56–58]; analysis of opportunities and challenges of integrating COVID-19 based digital technologies [2,3,59]; comparison of COVID-19 detection methods [60]; treatment guidelines [61].

Our study indicates that there is significant progress in the development of digital tools to tackle COVID-19 and we noted the following merits: forecasting COVID-19 cases and mortality rates become easier and faster; tracking COVID-19 infected patients and contact persons is easier and faster; there is an interconnection of medical equipment, smart health applications and smart sensors for COVID-19 monitoring and detection; improvement in health care delivery system with the view to respond to COVID-19 emergencies using smart applications and smart wearable devices; provision of good guide for healthcare professionals to administer COVID-19 cases; mapping of COVID-19 hotspots areas become easier and faster; and creation of awareness on COVID-19 by frequently sending notifications on contact persons, signs and symptoms and location. Despite the aforementioned merits, there is no study known to the authors at the time of this study on adoption, acceptance and use of CDTT considering the predictors of people’s BI in the context of developing countries such as Nigeria. Therefore, the objective of this study is to investigate the acceptance and use of the digital technologies deployed to tackle COVID-19 in developing country context using Nigeria as case country. The UTAUT model was applied as a theoretical framework to guide the study.

3. Methods

3.1. Unified Theory Of Acceptance and Use of Technology (UTAUT) model

Fig. 1 presents the UTAUT model that is adopted in this study as the theoretical framework for finding and examining the factors that influence the users’ behavioural intentions to accept and use the digital tools developed to tackle COVID-19. Though there are other acceptance models such as Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Theory of Planned Behaviour (TPB), Combined model of TAM and TPB (C-TAM-TPB), Motivational Model (MM), model of Personal Computer Utilization (MPCU), Social Cognitive Theory (SCT) and Innovation Diffusion Theory (IDT); but Venkatesh et al. in [7,62] established that UTAUT outperformed these models by explaining as much as 70 percent of the variance in behavioural intention and 50% in technology use. The results of the empirical examination carried out on UTAUT by Dwivedi in [63] confirmed the findings of Venkatesh et al. in [7,62]. Age, gender, experience and voluntariness are the moderators identified in UTAUT to enhance its predictive power and make UTAUT different from the other acceptance models [63]. Moreover, UTAUT has been extensively used to explain technology acceptance.

UTAUT model recognizes the technology acceptance influencing variables under four different constructs that serve as direct determinants of acceptance and usage behavior of users [7]: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Condition (FC). The key moderators for the constructs are Gender, Age, Voluntariness and Experience.

Performance expectancy describes the degree of belief of an individual that the use of technology will assist him/her to improve in his/her job performance [7]. The factors contained in PE are: perceived usefulness [64], extrinsic motivation [65], job-fit [66], relative advantage [67], outcome expectation [68]. The influence of PE on technology acceptance is moderated by gender and age [69].

Effort expectancy describes the degree of ease that is associated with the use of a technology [7]. The factors that are composed in EE are perceived ease of use [70], complexity [66] and ease of use [67]. The moderating variables are gender, age and experience [69].

Social influence defines the degree of importance perceived by an individual on the belief of other people for him or her to use a new technology [7]. It is composed of these factors: subjective norm [71], social factors [66] and image [67]. The variables defined to moderate the influence of SI are gender, age, voluntariness and experience [7].

Facilitating condition defines the extent of the belief of an individual that the existence of organizational and technical infrastructure supports the use of technology. It is composed of perceived behavioural control [72], facilitating condition [66], and compatibility [67]. The moderating variables defined for FC are age and experience [7].

3.2. Data collection

We used questionnaires for data collection in this study. We got participants from the six states of the South-West geopolitical zone of Nigeria (i.e. Ogun, Ekiti, Osun, Lagos, Oyo, and Ondo states). Participants were from the following job sectors: healthcare centers (e.g. hospitals, clinics, medical laboratories), academic institutions, corporations (e.g. banks, insurance companies etc.), IT firms, market places (e.g. general open markets in communities, shopping malls, supermarkets), Law enforcement agencies (e.g. police, army, immigration, civil defense, customs) and farm settlements in rural areas. We received responses from organizations in each of the job sectors. We distributed the questionnaires via e-mail and face-to-face to the respondents. Respondents also completed some of the questionnaires online using the online version developed using the SurveyMonkey application. A total of eight hundred (800) questionnaires were administered face-to-face, via email and online. We received 650 (81.25%) questionnaires that were correctly completed and were used for our analysis. The respondents were mostly from the healthcare sector, government establishment, academic institutions, corporations and IT firms and they are more knowledgeable about the COVID-19 pandemic and its major concerns while the respondents we got at various farms settlements and market places have shallow knowledge about COVID-19 and its safeguard measures.

There are three sections in the questionnaire. The first section contains the following demographic information: age of respondents, gen-
nder, education background of the respondent, job sector of the respondent, position in the organization, size of the organization, age of the organization, the extent of usage of digital tools, and the voluntariness to use digital tools. The second section contains questions that allow us to measure the extent to which respondents make use of safeguard tools against COVID-19. The third section focuses on questions that help us to measure the perception of the people about the acceptance and use of CDTT. Analysis of the respondents’ responses to the questions in the third section of the questionnaire helps us to identify the factors that influence the behavioural intention of people to accept and use digital tools for tackling COVID-19 and hence propose an acceptance and utilization framework for CDTT. The factor variables were measured using the 5-point Likert-type scale.

3.3. Data analysis and results

Fig. 2 illustrates the general analysis and results framework used in this study. The seven stages of the framework are shown in the boxes and the brief descriptions of the stages are shown to the left and the specific methodology applied in each stage is shown to the right. A detailed description of the stages and the results are presented in subsections 3.3.1–3.3.7. We used Statistical Package for Social Sciences (SPSS) to analyze the data collected. We analyzed the demographic data based on descriptive statistics whereas Kaiser-Meyer-Olkin (KMO), Bartlett’s Test of Sphericity and test of significance were carried out to confirm the sampling adequacy for factor analysis. The significant measured variables that could influence the acceptance and use of CDTT, were extracted by using principal component analysis. The analysis was carried out in three stages: generate the correlation matrix for all the variables; extract the factors from the correlation matrix, and rotate the extracted factors to maximize the relationship between the variables and some factors. Internal consistency was measured using Cronbach’s alpha. Regression analysis was carried out to identify the degree of influence of the factor variables on CDTT. We equally used regression analysis to determine the causal impacts of the moderating factors (i.e. age, gender, experience and voluntariness of use).

3.3.1. Stage I: demographic distribution of the respondents

Sample Distribution and Descriptive Statistics

Table 1 presents a summary of the demographic distribution of the respondents. The respondents were mostly male (55.2%). Also, almost all the respondents (84.6%) are adults that are over 20 years old. They have different levels of education with 64.9% of them having Bachelor’s or higher degrees and hence the majority of the respondents are literate and also came from different job sectors. We had most respondents from the government establishments (19.7%), healthcare sector (15.5%), academic institutions (14.9%) and corporations (14.2%). We have 91.4% of the respondents that are working with organizations that are (0 - 30) years old. Also, the organizations are mostly small scale (42.0%) and medium scale (32.0%). All levels of management were represented in our study sample. It is interesting to know that 89.4% of the respondents indicated their voluntariness to use digital tools made available for them to discharge their duties. Moreover, 79.8% of the respondents are experienced in the extent to which they have used digital technologies. It is implied from our results that the majority of the respondents are educated, knowledgeable, mature and experienced. The extent of their familiarity with digital technologies and the voluntariness to use them implies that they would be willing to use digital tools to tackle COVID-19 if the tools are available, affordable and accessible.

Use of safeguard measures to tackle COVID-19

We asked some questions in Section B of the questionnaire to measure the extent to which people adhere to and use the safeguard measures available for tackling COVID-19. It is an assessment of the compliance of the respondents with the COVID-19 safeguard measures. Component analyses of the safeguard measures are presented in Table 2. We classify the safeguard measures into two: (1) traditional safeguard measures whereby digital devices are not employed and (2) digital safeguard measures whereby digital technology is employed. Each of the safeguard measures identified in this study was assigned usage score (US) or aggregate score (AS). The usage score is defined in Eq. (1) as presented in [73]:

\[
Usage\ Score\ (US)\ or\ Aggregate\ Score\ (AS) = \sum_{i=1}^{n} w_i P_i
\]

where \(w_i (i = 1,2,3,4,5)\) is weight (i.e. \(w = 0,1,2,3,4\)) assigned to \(i^{th}\) grouping (i.e. \(0\%\rightarrow (w_1 = 0);\ [1-25\%] \rightarrow (w_2 = 1);\ [26-50\%] \rightarrow (w_3 = 2);\ [51-75\%] \rightarrow (w_4 = 3);\ [76-100\%] \rightarrow (w_5 = 4)\) of percent usage of a given measured variable. While \(P\) is the aggregate percent of respondents that use the measured variable according to the percentage of the times specified. The maximum obtainable usage score is 400 (i.e. 100% respondents utilizing a given measured variable [76 –100%] of the time). The assignment of usage score or aggregate score to the val-
Table 1
Sample distribution and descriptive statistics.

| Criteria                  | Characteristics                  | Prefer not to answer |
|---------------------------|----------------------------------|----------------------|
| **Gender**                | Male.                            | Female.              |                      |
|                           | 55.2%                            | 44.8%                | 0.0%                 |
| **Age**                   | Below 20 Years                   | 15.4%                | 27.4%                | 33.1% | 24.1% |
|                           | 20 – 30 Years                    |                      |                      |       |       |
|                           | 31 – 50 Years                    |                      |                      |       |       |
|                           | Above 50 Years                   |                      |                      |       |       |
| **Education**             | Primary or Basic Education       | 5.1%                 | 3.5%                 | 15.5% | 64.9% | 5.5%  | 5.5%  |
|                           | Secondary                        |                      |                      |       |       |
|                           | Diploma                          |                      |                      |       |       |
|                           | Graduate or postgraduate          |                      |                      |       |       |
|                           | Informal Education               |                      |                      |       |       |
|                           | Others                           |                      |                      |       |       |
| **Job Position**          | Top Management                   | 2.9%                 | 25.4%                | 13.7% | 50.9% | 7.1%  |
|                           | Middle Management                |                      |                      |       |       |
|                           | Technical Staff                  |                      |                      |       |       |
|                           | Operational Staff                |                      |                      |       |       |
|                           | Others                           |                      |                      |       |       |
| **Job Sector**            | Corporations                     | 14.2%                | 19.7%                | 9.8%  | 15.5% | 8.3%  | 8.2%  | 14.9% | 9.4%  |
|                           | Government Establishment          |                      |                      |       |       |
|                           | Law Enforcement Agencies         |                      |                      |       |       |
|                           | Healthcare Sector                |                      |                      |       |       |
|                           | IT Firms                         |                      |                      |       |       |
|                           | Agricultural Farms               |                      |                      |       |       |
|                           | Academic Institutions            |                      |                      |       |       |
|                           | Markets                          |                      |                      |       |       |
| **Size of Organization** | Small Scale                      | 42.0%                | 32.0%                |       |       |
|                           | Medium Scale                     |                      |                      |       |       |
|                           | Large Scale                      | 26.0%                |                      |       |       |
| **Year of Organization** | Less than 5 years                | 22.2%                | 43.5%                | 25.7% | 8.6%  |
|                           | 5 – 15 years                     |                      |                      |       |       |
|                           | 16 – 30 years                    |                      |                      |       |       |
|                           | Above 30 years                   |                      |                      |       |       |
| **Respondent’s voluntariness to use digital technologies** | 0%                               | 1% - 25%             | 26% - 50%            | 51% - 75% | 76% - 100% |
|                           | 2.9%                             | 4.5%                 | 3.2%                 | 62.0% | 27.4% |
| **Extent of respondent’s use of digital technologies** | 0%                               | 1% - 25%             | 26% - 50%            | 51% - 75% | 76% - 100% |
|                           | 8.2%                             | 4.8%                 | 7.2%                 | 60.5% | 19.3% |
ues helps us to aggregate the responses and hence identify the measured variables that are of much concern to people in the use of CDTT.

Nose masking is one of the most emphasized safeguard measures against contracting COVID-19 however the results presented in Table 2 reflect that there is poor compliance (US = 174.8) to the use of nose masks. There is no full compliance as our results show that 72.6% of the population sampled have between (0.0% - 50%) compliance while 27.3% have compliance between (51.0% - 100%) to the use of nose masks. The respondents complained about the difficulty in breathing with the use of most of the nose masks that are available and hence people avoid the use of the nose mask except when they are within the premises of corporate companies or institutions where nose masking is strictly required. Similarly, there are concerns about hand washing. Full compliance to hand washing is not established from our results (US = 139.4). Our results show that 24.9% of the population did not practice hand washing particularly in general marketplaces and crowded government agencies (e.g. airports, immigration etc.). Very few organizations make this compulsory to their customers but hand sanitizing is compulsory and all organizations have hand sanitizing facilities and this is evidenced in our results that show that 84.3% of the population have (51% - 100%) degree of compliance and US = 323.7. Though about 15.7% of the population that works mostly in open market places have poor compliance to hand sanitizing. Also, social distancing (US = 115.5) is not fully complied with in places such as open markets where crowd control becomes difficult; public transport where the buses or cars are loaded with passengers in full capacity; and agencies

---

**Fig. 2.** Data analysis and results framework.
The aggregate score implies the following:

a. The implementation of CDTT will be based on: provision of adequate training (AS = 313.6); support from the management of the organizations (AS = 305); assurance of data privacy and security (AS = 300.9) and assurance of adequate protection against contraction of COVID-19 (AS = 351.4). The majority of the people (i.e. 83.5%) agreed that cost (with very low AS = 83.2) would not be an indicator to motivate the implementation of the technologies. Digital devices may not be less expensive however they could be affordable by those that desire to buy them.

b. The problems associated with the implementation of CDTT are: poor and unstable internet connectivity (AS = 352.8); device authentication failure (AS = 313.3); electric power failure (AS = 315.1); and non-availability of the digital devices (AS = 331.3). In addition, many agreed that CDTT is expensive (AS = 300.9) for people to buy in a developing economy like Nigeria with a minimum wage of workers less than $100.00 per month. Also, all the respondents (100.0%) agreed that users’ identification is not of concern and not an indicator to motivate the implementation of CDTT. Similarly, technology malfunctioning (AS = 191.1) is partially considered to be a problem, though 47.7% of the respondents disagreed with this while 36.0% agreed and 16.3% were not sure.

c. Almost all the respondents agreed that the occurrence of problems in the implementation and use of digital technologies is inevitable, hence AS = 330.6 and 340.2 for regular occurrences of problems when using CDTT.

### 3.3.2. Stage II: confirmation of sampling adequacy

The Kaiser-Meyer-Olkin (KMO) value in our results is 0.834 and the significance (p) value is 0.000 (See Table 4). The KMO result falls in the “meritorious” range as defined by Kaiser & Rice in [74] [i.e. “marvelous in the 0.90s”; “meritorious in the 0.80s”; “middling in the 0.70s”; “mediocre in the 0.60”; “miserable in the 0.50 s; “miserable in below the 05s”] and it also aligns with the threshold value of KMO = 0.60 “for good factor analysis” that was defined by Tabachnick and Fidell in [75]. Moreover test of significance (at p < 0.001) [76]. Thus these results indicate that our sample size is adequate and it is appropriate to conduct PCA on the correlation matrix.

### 3.3.3. Stage III: Factors extraction, classification and retention

Exploratory factor analysis was carried out using principal component analysis (PCA) with the view to extract the significant variables that could influence the behavioural intention of users to accept and use CDTT.

---

**Table 2** Safeguard measures against COVID-19.

| Use of Traditional Measures | Use of Digital Measures | Percentage of the extent of usage and compliance | Percentage of the extent of usage and compliance |
|-----------------------------|-------------------------|-------------------------------------------------|-------------------------------------------------|
| **0% Compliance**          | **5% - 25% Compliance** | **50% - 100% Compliance**                       | **50% - 100% Compliance**                       |
| **Frequency**              | **Frequency**           | **Frequency**                                   | **Frequency**                                   |
| 97                         | 179                     | 109                                             | 12                                              |
| 14.9%                      | 30.8%                   | 40.0%                                           | 3.5%                                            |
| 24.9%                      | 40.0%                   | 21.3%                                           | 6.5%                                            |
| 20.0%                      | 60.0%                   | 23.3%                                           | 5.0%                                            |
| 15.7%                      | 40.7%                   | 25.5%                                           | 5.0%                                            |
| 15.5%                      | 25.5%                   | 25.5%                                           | 5.0%                                            |

of government where officials find it difficult to organize the crowd at the peak periods of their services. However, in a few corporate companies (e.g. banks, supermarkets, tertiary institutions), social distancing is strictly adhered to hence we have 20.4% complying to the extent of 51%–100%.

The digital tackling measures are not pronounced among the sample population. Our results showed that only the digital thermometer (US = 334) is widely used by people (93.0%) for temperature check to (51% - 100%) degree of usage or compliance but there is poor use and compliance to the utilization of the other digital devices and hence have very low usage scores (i.e. US = 37.5; 31.6; 12.1; and 9.6). The low usage could be attributed to some factors such as (see Table 3): high cost (AS = 282.3); non-availability of the digital tools (AS = 331.3); unavailability of internet (AS = 352.8); and electric power failure (AS = 331.5).

Measure of the basis for implementing digital systems to tackle COVID-19 and problems encountered

**Table 3** presents the component analysis of the basis for the implementation of digital systems for tackling COVID-19, problems encountered and the rate of occurrences of problems in the course of using the digital tools. The results presented in **Table 3** provide the answer to **RQ-1**: *What problems do people encounter in the use of digital tools to tackle COVID-19?*

The aggregate score implies the following:

a. The implementation of CDTT will be based on: provision of adequate training (AS = 313.6); support from the management of the organizations (AS = 305); assurance of data privacy and security (AS = 300.9) and assurance of adequate protection against contraction of COVID-19 (AS = 351.4). The majority of the people (i.e. 83.5%) agreed that cost (with very low AS = 83.2) would not be an indicator to motivate the implementation of the technologies. Digital devices may not be less expensive however they could be affordable by those that desire to buy them.

b. The problems associated with the implementation of CDTT are: poor and unstable internet connectivity (AS = 352.8); device authentication failure (AS = 313.3); electric power failure (AS = 315.1); and non-availability of the digital devices (AS = 331.3). In addition, many agreed that CDTT is expensive (AS = 300.9) for people to buy in a developing economy like Nigeria with a minimum wage of workers less than $100.00 per month. Also, all the respondents (100.0%) agreed that users’ identification is not of concern and not an indicator to motivate the implementation of CDTT. Similarly, technology malfunctioning (AS = 191.1) is partially considered to be a problem, though 47.7% of the respondents disagreed with this while 36.0% agreed and 16.3% were not sure.

c. Almost all the respondents agreed that the occurrence of problems in the implementation and use of digital technologies is inevitable, hence AS = 330.6 and 340.2 for regular occurrences of problems when using CDTT.
Table 3
Basis for implementing CDTT, problems and rate of problems occurrences.

| Concerns                                      | Variables                        | Percentage Measures | Aggregate Score (AS) |
|-----------------------------------------------|----------------------------------|---------------------|----------------------|
| What is the Basis for COVID-19 Digital tool implementation | Adequate Training               | 9                   | 1.4% 7.5% 4.2% 33.8%| 27 4.2% 35 5.4% 7 1.1% 225 34.6% 356 54.8% 330.6 |
|                                              | Cost effective                   | 370                 | 56.9% 26.6% 10.6% 3.8% | 247 38.0% 349 53.7% 340.2 |
|                                              | Supported by management           | 6                   | 0.9% 5.1% 10.7% 15.7%| 9 1.4% 10 1.5% 63 |
|                                              | Data privacy & security           | 4                   | 0.6% 7.8% 14.2% 24.9%| 203 31.2% 340.2 |
|                                              | Ensure adequate protection        | 20                  | 3.1% 0.0% 2.5% 3.2%  | 313.6 315.1 351.4 |
| What are the problem types anticipated/encountered in the use of COVID-19 digital tools | Unstable internet connection     | 430                 | 66.2% 33.8% 3.1% 0%  | 375 57.7% 352.8 |
|                                              | Identification problem           | 11                  | 1.7% 6.5% 3.1% 0%  | 127 19.5% 246.3 |
|                                              | Authentication failure            | 6                   | 0.9% 11.7% 2.5% 41.2%| 106 16.3% 191.1 |
|                                              | Electric power failure            | 60                  | 9.2% 17.4% 4.8% 49.1%| 102 15.7% 233.3 |
|                                              | Originality of product            | 62                  | 9.5% 38.2% 16.3% 23.7%| 284 43.7% 315.1 |
|                                              | Technology malfunction            | 9                   | 1.4% 1.1% 0% 60.2%  | 248 37.4% 331.3 |
|                                              | Non availability of digital tool  | 40                  | 6.2% 10.8% 10.0% 22.3%| 330 50.8% 300.9 |
|                                              | COVID-19 digital tackling tools are expensive | 300                     | 46.2% 50.2% 0.3% 1.8%  | 10 1.5% 62.2 |
| Rate of Problem Occurrence                   | Measures of Agreement            |                      |                      |                      |
|                                              | Strongly Disagree                |                      |                      |                      |
|                                              | Disagree                        |                      |                      |                      |
|                                              | Not Sure                        |                      |                      |                      |
|                                              | Agree                           |                      |                      |                      |
|                                              | Strongly Agree                  |                      |                      |                      |
| What is the extent of problem encountered during COVID-19 digital tool implementation | Most Regularly                 | 27                  | 4.2% 5.4% 1.1% | 225 34.6% 356 54.8% 330.6 |
|                                              | Regularly                       | 10                  | 1.5% 2.2% 4.6% 38.0%| 247 38.0% 349 53.7% 340.2 |
|                                              | Rarely                          | 314                 | 48.3% 44.8% 4.0% 1.4%| 9 1.4% 10 1.5% 63 |
|                                              | Never                           | 300                 | 46.2% 50.2% 0.3% 1.8%| 10 1.5% 62.2 |
We included 51 measured variables in our analysis. Fourteen (14) components (see Table 5) were retained having complied with the classic Kaiser criterion [i.e. all components with eigenvalues > 1.0 were retained] [77]. However, we used parallel analysis [78] at the 95th percentile of randomly generated eigenvalues to confirm the results presented in Table 5 and nine (9) components (i.e. 1, 2, 3, ..., 9) were retained having their random eigenvalues fall below the eigenvalues of the corresponding components from our data. Components 10, 11, 12, 13, and 14 were dropped because their random eigenvalues fall above the eigenvalues of the corresponding components from our data. Moreover, considering the Scree Plot (see Fig. 3), the eigenvalue cutoff rule (i.e. eigenvalue ≥ 1) would retain 14 components however the Scree Plot suggested 9 components because the slope leveled off at the third time on components 10 with weak eigenvalues and the slope appears to be leveling off at that point. Because of this, 9 interpretable latent components (i.e. components 1, 2, ..., 9 in Table 5) were retained in this study.

3.3.4. Stage IV: Component naming and loading of measured variables

Table 6 presents the component correlation matrix and some values are greater than the Tabachnick and Fidell threshold value of 0.32 [79]; therefore we used the Promax rotation method with Kaiser Normalization and also loading criterion (i.e. the absolute value of 0.40) proposed in [76,80–82] was used to identify and name the measured variables to be loaded on the retained components. Table 7 presents the nine retained components and the variables loaded on each component. The full description of the measured variables is presented in Appendix 1. Forty-two (42) measured variables that met the loading criterion were loaded on the 9 components. The measured variables whose coefficients are less than the 0.4 loading criterion were suppressed. The 42 loaded measured variables relate to the acceptance and use of CDTT.

Table 4 presents the percentage contributions to the variability of data, eigenvalues, and Cronbach’s α values for the extracted components. The extracted components have Cronbach’s α > 0.5 and this implies reliability and internal consistency of data. Though variables loaded under “Government Expectancy and Benefit” have Cronbach’s α = 0.207 but according to [83–85], it is acceptable based on our relatively big sample size of 650 and that our study is exploratory.

3.3.5. Stage V: Presentation of modified UTAUT model for CDTT acceptance and use and hypotheses formulation

The modified UTAUT model for CDTT is presented in Fig. 4. This model is proposed based on: (1) extensive review of literature, (2) results of data analysis for the survey we carried out across the 6 states of the South-West geopolitical zones of Nigeria, and (3) our interviews with a few medical practitioners and some randomly selected individuals in the communities.

The evolution of different digital technologies to serve humanity does motivate researchers to introduce new variables with the view to extend the UTAUT model. Therefore researchers have suggested the need to modify the UTAUT model with the changing times [7,62,86]. From the results of the factor analysis (see Table 6 and Table 7) which is complemented by our findings from the literature and consultation with people, the four basic constructs (i.e. PE, EE, SI and FC) and the moderators (i.e. gender, age, and voluntariness of use) of the original UTAUT model are retained in the modified model while we introduced five new constructs that were identified to influence users’ behavioural intentions (BI) to accept and use CDTT. The new constructs introduced are Public Awareness (PA); Perceived Cost (P-Cost); Data Security and Privacy (DSP); Organization Influence and Benefit (OIB) and Government Expectancy and Benefit (GEB).

The correlation between public awareness and users’ BI is supported in [87,88]. Similarly, the authors in [89–91] also identified the positive influence of perceived financial cost on users’ behavioural intention to accept and use technology. In the same vein, the correlation between data security and privacy and users’ BI is supported by the researchers in [92]. The vulnerability of digital tools is an issue for consideration in technology adoption. People get scared of using a given technology if personal and locational data privacy is not totally secured. Thus, the sense of security in terms of protection of personal and locational data.
Table 5
Total variance explained.

| Component/Factor | Initial Eigenvalues | Extraction Sums of Squared Loadings | Rotation Sums of Squared Loadings |
|------------------|---------------------|-------------------------------------|----------------------------------|
|                  | Total               | % of Variance          | Cumulative% | Total               | % of Variance          | Cumulative% | Total               |
| 1                | 7.851               | 15.395                 | 15.395     | 7.851               | 15.395                 | 15.395     | 7.270               |
| 2                | 6.605               | 12.951                 | 28.346     | 6.605               | 12.951                 | 28.346     | 5.796               |
| 3                | 2.904               | 5.695                  | 34.041     | 2.904               | 5.695                  | 34.041     | 4.691               |
| 4                | 2.041               | 4.002                  | 38.043     | 2.041               | 4.002                  | 38.043     | 2.923               |
| 5                | 1.991               | 3.904                  | 41.947     | 1.991               | 3.904                  | 41.947     | 3.782               |
| 6                | 1.792               | 3.514                  | 45.461     | 1.792               | 3.514                  | 45.461     | 3.758               |
| 7                | 1.555               | 3.049                  | 48.510     | 1.555               | 3.049                  | 48.510     | 1.879               |
| 8                | 1.485               | 2.912                  | 51.422     | 1.485               | 2.912                  | 51.422     | 1.848               |
| 9                | 1.336               | 2.619                  | 54.041     | 1.336               | 2.619                  | 54.041     | 1.511               |
| 10               | 1.250               | 2.450                  | 56.491     | 1.250               | 2.450                  | 56.491     |                     |
| 11               | 1.168               | 2.291                  | 58.782     | 1.168               | 2.291                  | 58.782     |                     |
| 12               | 1.131               | 2.218                  | 61.000     | 1.131               | 2.218                  | 61.000     |                     |
| 13               | 1.076               | 2.109                  | 63.109     | 1.076               | 2.109                  | 63.109     |                     |
| 14               | 1.015               | 1.991                  | 65.100     | 1.015               | 1.991                  | 65.100     |                     |
|                  |                     |                       |            |                     |                       |            |                     |
| 49               | .003                | .006                   | 30.995     | .003                | .006                   | 30.995     |                     |
| 50               | .001                | .003                   | 30.998     | .001                | .003                   | 30.998     |                     |
| 51               | .001                | .002                   | 31.000     | .001                | .002                   | 31.000     |                     |

Extraction Method: Principal Component Analysis.
* When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Table 6
Component correlation matrix.

| Component | 1     | 2     | 3     | 4     | 5     | 6     | 7     | 8     | 9     |
|-----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| 1         | 1.000 | -0.103| -0.027| -0.035| 0.009 | 0.334 | 0.008 | 0.007 | -0.065|
| 2         | -0.103| 1.000 | .498  | .065  | 0.341 | -0.047| 0.053 | 0.175 | 0.087 |
| 3         | -0.027| .498  | 1.000 | 0.051 | 0.310 | 0.000 | 0.001 | 0.129 | -0.057|
| 4         | 0.009 | .341  | .310  | 0.011 | 0.011 | -0.043| 0.015 | 0.033 | 0.022 |
| 5         | 0.334 | -0.047| 0.000 | 0.043 | 0.029 | 1.000 | 0.036 | -0.015| -0.278|
| 6         | 0.008 | 0.053 | 0.001 | 0.015 | 0.044 | 0.036 | 1.000 | -0.051| 0.044 |
| 7         | 0.007 | 0.175 | 0.129 | -0.033| 0.131 | -0.015| -0.051| 1.000 | 0.139 |
| 8         | -0.065| 0.087 | -0.057| 0.022 | -0.061| -0.278| 0.044 | 0.139 | 1.000 |

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.

Fig. 4. Proposed research model for CDTT acceptance and utilization.
vis-à-vis protection against attacks or harmful information while using a digital tool for tackling COVID-19 are issues of concern. In addition, the correlation between organizational culture influence and customers’ behavioural intention to use digital services was supported in the work presented in [93]. The authors establish the positive effect of organizational influence on the users’ BI. Similarly, the enactment of government policies to guide the use of new technologies has a significant influence on people in the acceptance and use of technologies. This is supported in the research reported in [49] where the authors conceptualized the relationship between governance and contextual factors of the society that could influence digital contact tracing adoption. Hence, the adoption of digital technologies in the period of COVID-19 has helped government and private organizations in planning and responding to emergencies [50].

Moreover, in the bid to control the spread of COVID-19, various national and international policy guidelines were developed for people to comply with the control measures and ensure the use of the devices developed to tackle the spread of the disease. Hence government expectancy and benefit influence users’ BI. Therefore, the following research hypotheses are proposed in this study:

\[ H_1: \text{Public awareness has a significant effect on the behavioural intention of people to use digital technology for tackling COVID-19} \]

\[ H_2: \text{Perceived cost has a significant effect on the behavioural intention of people to use digital technology for tackling COVID-19} \]

### Table 7
Extracted components and loaded measured variables.

| Construct/Component          | Sub-construct          | Measured Variables                                                                 | Component Loading Coefficient | Number of Measured Variables | Cronbach’s alpha (α) | Eigenvalue | Percentage (%) of Variance |
|------------------------------|------------------------|-------------------------------------------------------------------------------------|-------------------------------|-------------------------------|----------------------|------------|----------------------------|
| Performance Expectancy       | Perceived usefulness   | adapt-cov-dig-tool, cov-dig-tool-improve-jop-perf, cov-dig-tool-easy-use, cov-dig-tool-delay-mismatch, COV-dig tool boost-conf, cov-dig-tool-make-me-work-fast | 0.948                         | 10                            | 0.925                 | 7.851      | 15.395                     |
|                              | Job-fit                | cov-dig-tool-inc-prod, cov-dig-tool-user-id, cov-dig-tool-relwel                    | 0.674                         |                               |                      |            |                            |
|                              | Relative advantage     | cov-dig-tool-tech-nontech, assist-tuneof-cov-dig-tool, cov-dig-tool-not-easy2use, cov-dig-tool-pwmemorize, cov-dig-tool-frightenedme, cov-dig-tool-mang-phil, cov-dig-tool-isihigh, sofinsupport-cov-dig-tool, cov-dig-tool-highpurchase, cov-dig-tool-bulk-purchase | 0.621                         |                               |                      |            |                            |
| Effort Expectancy            | Outcome expectation    | get-company-award, cov-dig-tool-erad-pwtime, cov-dig-tool-istough                    | 0.621                         | 8                             | 0.862                 | 6.605      | 12.951                     |
|                              | Complexity             | cov-dig-tool-tech-nontech                                                             | 0.787                         |                               |                      |            |                            |
|                              | Perceived ease of use | cov-dig-tool-not-easy2use, cov-dig-tool-pwmemorize                                   | 0.732                         |                               |                      |            |                            |
|                              | Ease of use            | cov-dig-tool-frightenedme                                                             | 0.644                         |                               |                      |            |                            |
|                              | Perceived Cost         | cov-dig-tool-not-easy2use, cov-dig-tool-pwmemorize                                   | 0.884                         | 4                             | 0.810                 | 2.904      | 5.695                      |
| Organization Influence and Benefits | cov-dig-tool—prot-envt, const-elct4-cov-dig-tool, policy4-cov-dig-tool, cov-dig-tool-boost-rel, knowlege2-use-cov-dig-tool, cov-dig-tool-pubawareness1, cov-dig-tool-privawareness, cov-dig-tool-schlawareness, cov-dig-tool-safety-improvement, cov-dig-tool-safety-dev, cov-dig-tool-mangtsupport, peopleuse-cov-dig-tool | 0.855                         | 4                             | 0.855                 | 2.041      | 4.002                     |
| Public Awareness             | Social factor          | cov-dig-tool—privawareness, cov-dig-tool—safety-dev, cov-dig-tool—safety-improvement, cov-dig-tool—safety-dev, cov-dig-tool—mangtsupport, peopleuse-cov-dig-tool | 0.888                         | 4                             | 0.766                 | 1.991      | 3.904                     |
|                              | Resource facilitating condition | no-high-speed-internet, nointerntety-telecom, electricity-problem, org-nousofl-cov-dig-tool, cov-dig-tool-pre-info-leak, cov-dig-tool-prot-personal-data, cov-dig-tool-imp-nig-safety, gov-devp-policy4-cov-dig-tool | 0.801                         | 4                             | 0.800                 | 1.792      | 3.514                     |
| Facilitating Condition (FC)  | Compatibility          | no-high-speed-internet, nointerntety-telecom, electricity-problem, org-nousofl-cov-dig-tool, cov-dig-tool-pre-info-leak, cov-dig-tool-prot-personal-data, cov-dig-tool-imp-nig-safety, gov-devp-policy4-cov-dig-tool | 0.798                         |                               | 0.798                 | 1.792      | 3.514                     |
|                              |                       | sointernety-telecom, electricity-problem, organ-nousofl-cov-dig-tool                 | 0.738                         |                               |                      |            |                            |
| Data Security and Privacy    |                       | cov-dig-tool-pre-info-leak, cov-dig-tool-prot-personal-data                           | 0.522                         |                               |                      |            |                            |
|                              |                       | cov-dig-tool-imp-nig-safety, gov-devp-policy4-cov-dig-tool                            | 0.633                         | 2                             | 0.207                 | 1.336      | 2.619                     |

### Table 8
Model summary.

| Model | R    | R Square | Adjusted R Square | Std. Error of the Estimate |
|-------|------|----------|-------------------|---------------------------|
| 1     | .232 | .054     | .030              | .0.9483216                |

**Legend**: Gender (GEND), Age (AGE), Voluntariness of use (VOLUN), Organizational influence & benefit (ORGINF), Social influence (SOCINF), Public awareness (PUBAWAR), Facilitating condition (FACCOND), Performance expectancy (PERFEXP), Effort expectancy (EFFEXP), Perceived cost (PERCOST), Data security & privacy (SECPRIV), Government expectancy & benefit (GOVTEXP).

* Predictors: (Constant), VOLUN,SOCINF, ORGINF, SOCINF, GEND,PERFEXP, AGE,SOCINF, PUBAWAR, AGE,FACCOND, AGE,EFFEXP, GOVTEXP, SECPRIV, GEND,EFFEXP, FACCOND, PERCOST, AGE,PERFEXP, EFFEXP, PERFEXP.
H₂: Data security and privacy has a significant effect on the behavioural intention of people to use digital technology for tackling COVID-19

H₃: Organisational influence and expected benefits have significant effects on the behavioural intention of people to use digital technology for tackling COVID-19.

H₄: Government expectancy and benefit have significant effects on the behavioural intention of people to use digital technology for tackling COVID-19.

Performance expectancy is made up of perceived usefulness, relative advantage, job-fit, and outcome expectations. Studies carried out on mobile banking adoption established that perceived relative advantage directly and positively influence the behavioural intention of users to adopt digital technologies [94-96]. Similarly perceived usefulness was identified as a strong determinant of behavioural intention with age and gender as moderators [97,98]. Studies presented in [99,100] affirmed that PE significantly influences the users to adopt e-banking and mobile commerce services. Because of this, we posit the following hypotheses:

H₅: Performance expectancy has significant effects on the behavioural intention of people to use digital technology for tackling COVID-19

H₆A: Users’ gender has a significant moderating effect on performance expectancy

H₆B: Users’ age has a significant moderating effect on performance expectancy

Perceived ease of use, complexity and ease of use define effort expectancy (EE). Studies have proved that EE significantly influences the behavioural intention of people to accept and use digital technologies with gender and age as moderators [99,101]. Thus this study posits the hypotheses:

H₇: Effort expectation has significant effects on the behavioural intention of people to use digital technology for tackling COVID-19

H₇A: Users’ gender has a significant moderating effect on effort expectancy

H₇B: Users’ age has a significant moderating effect on effort expectancy

Social influence is composed of social factors; thus the works of [102,103] affirmed the correlation between the influence of friends and family members on an individual and his or her intentions to use technology. The moderating variables are age and voluntariness of use. Thus digital technology users are major stakeholders in the social networks with much peer influence [104]. Because of this, we posit the hypotheses:

H₈: Social influence has significant effects on the behavioural intention of people to use digital technology for tackling COVID-19

H₈B: Users’ age has a significant moderating effect on social influence

H₈C: Users’ voluntariness of use has a significant moderating effect on social influence

Facilitating conditions captures resource facilitating conditions and compatibility. Venkatesh et al. [7] identified BI and FC as the two direct determinants of users’ adoption attitudes. Thus an individual is motivated to use digital technologies when the required instruments and infrastructure for effective use of the technology are available and accessible to him/her [105,106]. The moderating variable is age. In this light we posited these hypotheses:

H₉: Facilitating conditions has significant effects on the behavioural intention of people to use digital technology for tackling COVID-19

H₉B: Users’ age has a significant moderating effect on facilitating condition

The main goal of business organizations is to ensure that consumers do not only accept available technologies but also use these technologies for service delivery. As a result, researchers have reported extensively on the relationship between the behavioural intention to accept different technologies and the actual use of the technologies. For example, the authors in [98] examined the relationship between BI and the actual use of the technology in the mobile banking setting. Similar research was reported in [107] wherein the author examined the relationships in perceived usefulness, behavioural intention to use and the actual use of ATM (Automated Teller Machine) system of Centenary Bank in Uganda. The expectation is that the perception of customers about the usefulness of the ATM system should influence their behavioural intentions to use it and ultimately lead them to the actual usage of the system.

3.3.6. Stage VI: Hypotheses testing

We carried out regression analysis to test the hypotheses. COVID-19 digital technology acceptance and use (E_Digital_use) was used as the dependent variable, while the factors extracted and organizational demographic variables were the independent variables.

The model summary is presented in Table S, which indicates that the multiple linear regression model has a low adjusted R squared value (0.030). This implies that only 3% of the variance for the dependent variable (E_Digital_use) is explained by the independent variables (including the cross-terms –moderator variables) in the regression model.

The Analysis of Variance (ANOVA) (Table 9) provides information about levels of variability within a regression model. Our ANOVA table shows a p-value of 0.003, which implies that the group of independent variables (including cross-terms) can reliably predict the dependent variable, and does not address the ability of any of the particular independent variables to predict the dependent variable (E_Digital_use). The regression coefficients table (Table 10) shows the individual independent variable to predict the dependent variable, thus enabling the testing of the research hypothesis. It also shows the collinearity statistics (all VIF (variance inflation factor) are less than 5), which point to the absence of multicollinearity.

The regression statistics (Table 10) point to fact that H₆, H₇, and H₈ are supported, indicating that the following factors have statistically significant impact on the use of digital technologies for tackling COVID-19 at significance level where p < 0.05: facilitating conditions (β = 0.105, t = 2.640, p = 0.008), social influence (β = -0.163, t = -3.367, p = 0.001), and performance expectancy (β = 0.143, t = 2.929, p = 0.004). The following factors also showed a noteworthy, though not statistically significant effect on the dependent variable: organisational influence and benefit (β = 0.070, t = 1.782, p = 0.075), and government expectancy and benefit (β = -0.068, t = -1.728, p = 0.084). Furthermore, our results indicated that effort expectancy, perceived cost, data security and privacy, and public awareness did not have statistical significance on the behavioural intention of users to use CDIT; hence H₁, H₁₁, H₁₂, H₁₃, H₁₄, and H₈ are not supported. None of the moderating variables showed a statistically significant moderating effect on any of the independent variables (factors); however, age showed some good level of moderating effect on effort expectancy (β = -0.071, t = -1.816, p = 0.070). Thus H₆B, H₇B, H₇C, H₈A, H₈B, H₈A, and H₉B are not supported.
Table 10
Coefficientsa.

| Model | Unstandardized Coefficients | Standardized Coefficients | t | Sig. | Collinearity Statistics | Hypothesis Tested | +/- | Conclusion |
|-------|-----------------------------|---------------------------|---|------|-------------------------|----------------------|-----|------------|
|       | B                            | Std. Error                | Beta |      | Tolerance | VIF |       |           |
| 1     | (Constant)                   | .077                      | .040 | .182 | .856       |     |       |           |
|       | PERFEXP                      | .143                      | .049 | .143 | 2.929      | .004 | .629  | 1.591 | H3        | +  | Supported |
|       | EFFEXP                       | −.052                     | .048 | −.052| −1.069     | .285 | .642  | 1.558 | H3        | −  | Not supported |
|       | PERFCOST                     | .030                      | .048 | .030 | .24        | .533 | .656  | 1.524 | H2        | +  | Not supported |
|       | ORGINFL                      | .070                      | .039 | .070 | 1.782      | .075 | .959  | 1.043 | H3        | +  | Not supported |
|       | PUBAWAR                      | −.039                     | .044 | −.039| −.873      | .383 | .762  | 1.312 | H3        | −  | Not supported |
|       | SOFCINL                      | −.163                     | .049 | −.163| −3.367     | .001 | .635  | 1.576 | H2        | −  | Supported |
|       | SECPRIV                      | −.003                     | .039 | −.003| −.075      | .940 | .968  | 1.033 | H2        | −  | Not supported |
|       | GOVTEP                       | −.068                     | .039 | −.068| −1.728     | .084 | .963  | 1.038 | H2        | +  | Not supported |
|       | FACCOND                      | .105                      | .040 | .105 | 2.640      | .008 | .941  | 1.062 | H3        | +  | Supported |
|       | GEND−PERFEXP                 | .015                      | .039 | .015 | .390       | .697 | .961  | 1.040 | H3A       | +  | Not supported |
|       | GEND−EFFEXP                  | −.028                     | .039 | −.028| −.718      | .473 | .957  | 1.045 | H3A       | −  | Not supported |
|       | AGE−FACCOND                  | .009                      | .043 | .009 | .221       | .825 | .954  | 1.048 | H3B       | +  | Not supported |
|       | AGE−PERFEXP                  | −.045                     | .046 | −.045| −.969      | .333 | .682  | 1.466 | H3B       | −  | Not supported |
|       | AGE−SOCINFL                  | −.002                     | .047 | −.002| −.041      | .968 | .986  | 1.458 | H3B       | −  | Not supported |
|       | AGE−EFFEXP                   | −.073                     | .040 | −.071| −1.816     | .070 | .971  | 1.029 | H3B       | −  | Not supported |
|       | VOLUN−SOCINFL                | −.051                     | .040 | −.050| −1.266     | .206 | .976  | 1.025 | H3C       | −  | Not supported |

a Dependent Variable: E_Digital_use.

3.3.7. Stage VII: Presentation of the path diagram for CDTT acceptance and use

Based on the results of the regression analysis, we present the path diagram for CDTT acceptance and use, as shown in Fig. 5. This represents the CDTT acceptance and use model we propose within the context of developing economies like Nigeria. It is shown in the model that performance expectancy, facilitating condition and social influence are the significant predictors of people’s BI to accept and use CDTT. Therefore the following factors loaded under the predictors must be given utmost consideration by management of organizations for the people to accept, use and adhere to the principles of operation of CDTT: Perceived usefulness, Job-fit, Relative advantage, Outcome expectation, Social factor, Resource facilitating condition and Compatibility (See Table 7). Detail discussion on this is presented in Section 4.

4. Discussion of results

The first implication of our results in this study is the extension of the original UTAUT model (see Fig. 1). The original UTAUT model is extended by adding five new constructs (perceived cost; data security and privacy; public awareness; organizational influence and benefit; and government expectancy and benefit) to the four main constructs (performance expectancy; effort expectancy; social influence; and facilitating condition) of the original UTAUT framework. Therefore the proposed modified UTAUT model (see Fig. 4) is composed of nine constructs. Three moderators were recognized in the modified UTAUT model (i.e. age, gender and voluntariness of use) and these could moderate the constructs in the course of identifying the behavioural intention of people to accept and use digital technology for tackling COVID-19. Based on the results of our regression analysis, Fig. 5 is established as the UTAUT framework for acceptance and use of digital technology for tackling COVID-19 in the Nigerian context. Three independent variables: PE, SI, and FC, had significant effects on users’ BI and the actual use of CDTT. Our results indicate that over 70% of the respondents are not using (i.e. 0% compliance level) digital tools such as automated disinfectant tunnel, electronic sanitiser dispenser, digital contact tracing and social distance monitoring (e.g. wrist bands and wristwatches), digital sensors in homes and offices. This implies that people do not have much knowledge about this technology and it becomes difficult to respond well to variables used to measure the following constructs: effort expectancy, the perceived cost for accepting and using CDTT, public awareness, data security and privacy, organization influence and benefit, and government expectancy and benefit. Therefore none of these constructs shows a statistical significance to users’ behavioural intention to use CDTT. By these results, our research questions (i.e. RQ-2 and RQ-3) are answered. We discuss the findings of the study based on the following model constructs and the moderating factors. The implication of the study is also discussed.

4.1. Performance expectancy

Our results showed that PE has the strongest significant impact on users’ BI compared to SI and FC. Performance expectancy has a positive influence on BI and has the highest eigenvalue (0.7851) with a p-value = 0.004. Therefore the relationship between PE and the user’s BI to accept and use CDTT is supported by H2: (β = 0.143, t = 2.929, p = 0.004). The 10 measured variables loaded on PE have strong loading coefficients with very strong internal consistency (α = 0.925) which is greater than the Cronbach’s alpha (α) of SI (α = 0.80, eigenvalue = 1.792) and FC (α = 0.551, eigenvalue = 1.555). This result aligns with the deductions in [7,62,65] that established PE as the strongest predictor of users’ BI and it remains significant at all points of measurement of users’ BI in the technology acceptance and utilization. Based on the questionnaire variables (see Table 7 and Appendix 1) used to measure PE, this implies that people are willing to adapt to new digital technologies that can help them to tackle COVID-19 provided the following measures are considered: (1) the use of the technology will help to improve their performances, boost their confidence level and relationship with one another, and also increase their productivity; (2) the technology is simple and very easy to use; (3) delay and mismatch can be easily resolved in the course of using the technology; (4) there is a unique identification for users that use the technology and good company reward for those that are consistent and obedient with the appropriate use of the technology. These measures align with works of [108–110] where PE was equally identified to be a strong construct for acceptance and use of technology.

4.2. Facilitating condition

Facilitating conditions have positive and significant relationship (β = 0.105, p = 0.008) with behavioural intentions. This is consistent with previous works reported in [7,72,110–112]. Fast internet service is a basic requirement for most of the digital tools (e.g. contact tracing
and social distancing monitoring tools) developed for tackling COVID-19 as well as constant electricity to power the tools. Our finding indicates that the provision of high-speed internet services at a discounted rate by government and telecommunication companies will strongly facilitate the acceptance and use of the tool. Moreover, 98.6% of the respondents agreed that there is no constant supply of stable electricity in the country and therefore regular powering of their digital tools is a problem in the current time. It is further noted in our results that 95.5% of the respondents agreed that their organizations are not using CDTT at the current time and hence necessary infrastructure required to use the tools are not available in the companies. Internet and electricity are basic infrastructures of which their availability will facilitate the acceptance and use of any novel technologies developed to protect lives in this period of COVID-19 pandemic but the availability of stable internet and electricity is currently an issue of concern in Nigeria.

4.3. Social influence

The study shows that social influence has negative but significant relationship ($\beta = -0.163$, $t = -3.367, p = 0.001$) with behavioural intentions. Prior studies had identified SI to be important in technology adoption and utilization [71,111,112]. People tend to use new technologies if they find out that people around them also use the same technologies with no problems encountered and with utmost safety. Moreover, the managerial influence of an organization is another element of social factor that could either negatively or positively influence people in technology adoption. However, at present, very few people are aware of the use of digital tools or systems for tackling COVID-19. In the real sense, people are used to the use of the conventional measures for hand washing, nose masking, hand sanitizing etc. Over 70% of the respondents (see Table 2) are either not aware of the few people that use the digital tools or are aware of the use of the technologies but they have 0% compliance level; they could not find people around them using the tools in the communities. Thus, as significant as the SI construct is, the poor patronage by people negatively influence the use of the technologies in Nigeria.

4.4. “Organisation influence and benefit” and “Government expectancy and benefit”

Organizational influence and benefit (OIB) ($p = 0.075$) and government expectancy and benefit (GEB) ($p = 0.084$) were noted to affect BI though they are not statistically significant. This aligns with the fact that management of organizations does enforce the use of protective measures (e.g. nose mask, hand sanitiser) to prevent the spread of COVID-19. The policies and ethics of organizations have been revised to align with the policies of the government on protective measures for COVID-19. In view of this users’ BI is influenced such that every individual must comply with the protective measures for tackling COVID-19 whenever he/she is on the premises of any organization. However, compliance with the use of the COVID-19 protective devices is very much closer to zero whenever people are outside of the premises of organizations or
government agencies. The results presented in Table 2 show that people are much used to the conventional preventive measures for hand washing, nose masking, temperature checking etc., but the level of compliance is mostly between 1%-25% for the majority of the people and this is low. The worst case is in the use of digital protective measures. Our results (see Table 2) show that over 70% of the respondents are not using (i.e. 0% compliance level) digital tools such as automated disinfectant tunnel, electronic sanitiser dispenser, digital contact tracing and social distance monitoring (e.g. wrist bands and wristwatches), digital sensors in homes and offices. This is attributed to the following problems (see Table 3): unstable internet connectivity (AS = 352.8); device authentication failure (AS = 313.3); electric power failure (AS = 315.1); and non-availability of the digital devices (AS = 331.3). In addition, many agreed that CDTT is expensive (AS = 300.9) for people to buy in a developing economy like Nigeria with a minimum wage of workers less than $100.00 per month. It is noteworthy that COVID-19 policies of the management of both private and government organizations influence users’ BI to accept and use COVID-19 protective devices, however, the significance is not felt as much as one expects in the real-life practical sense and this is due to the aforementioned problems. Hence we have OIB and GEB having p-values of 0.075 and 0.084 respectively which are slightly above the 0.05 threshold value for p.

4.5. Moderating variables

The non-significant relationships between age and facilitating condition (AGE’FACCOND); age and performance expectancy (AGE’PERFEXP); age and social influence (AGE’SOCINFIL); age and effort expectancy (AGE’EFFEXP); gender and performance expectancy (GEND’PERFEXP); gender and effort expectancy (GEND’EFFEXP); and voluntariness of use and social influence (VOLUN’SOCINFIL) indicate that people may not perceive that their age, gender and voluntariness to use would guide their attitude towards the use of digital technologies to tackle COVID-19. The reason is that CDTT is a new technology that is presently not popular in Nigeria and more also, the technology is not much available and accessible. Thus the moderating variables have no significance in the present time that the technology is still very new and not yet popular. This may be true for every new technology and it aligns with the work reported in [113].

4.6. Policy implications of the study

The findings of this study provide significant implications to the policymakers and government on COVID-19 protective measures. The results indicate that both the government and private organizations should sensitize the populace on the availability and use of CDTT in all communities in Nigeria. Moreover, performance expectancy should be improved because it has a positive and significant relationship with the behavioural intention of the people. In this case, people should be trained about the benefits and usefulness of the tools and also how the use of the tools will help them to boost their confidence, relationships and performance at work. Moreover, the provision of facilitating conditions such as discounted fast internet service and stable electricity are key to behavioural intentions of users, hence government and management of private organizations should make this priority to encourage people in the use of the technology. Also, policies should be made to compel all organizations to install relevant digital tools for social distancing monitoring, contact tracing and face mask monitoring in the company premises. Doing this will compel staff to be cautioned in the use of the tools as the system will automatically alert management of violators. Moreover, the COVID-19 policies should be enhanced with all the measures required for the use of digital tackling tools as a complement to the conventional tackling measures.

4.7. Limitations and directions for future research

Nigeria consists of thirty-six states and the Federal Capital Territory is located in Abuja and with a population of about 200 million. The states are grouped into six geopolitical zones (i.e. North Central, North East, North West, South West, South East and South-South). Our study drew samples (i.e. 650) from the 6 states of the South-West geopolitical zone of Nigeria and this is limited in size compared to the population of the country. However, the samples received from each of the South West states gave a reflection of the exposure of the people in the state to COVID-19 protective measures vis-à-vis the use of digital tools for tackling the disease and hence prevent it from spreading and prevent people from contracting it. Therefore the results and UTAUT based framework (See Fig. 5) proposed in this study is a true picture of exposure of the South West states to COVID-19 digital tackling technologies and this can be extended to the other geopolitical zones with slight modifications to the measured variables. Modification to the measured variables may be required due to diversity in belief/culture, religion, social and educational development. However, we suggest that this study should be replicated in the remaining geopolitical zones of Nigeria believing that each zone has varying exposure to digital technology based on the social, economic, technological, cultural, religious, and educational diversity in Nigeria and to also have a wider coverage.

5. Conclusion

The study developed a modified UTAUT model for CDTT acceptance and use in developing country contexts by the extension of the original UTAUT framework [7]. The original UTAUT model was modified using the factors established to be significant predictors of people’s BI to accept CDTT. The CDTT acceptance and use model in Nigerian is represented by the path diagram presented in Fig. 5. The model serves as a framework that policymakers can adopt and hence use to revise the current policy documents of government on protective COVID-19 measures [114] such that CDTT can be given enough awareness and supports by the management of private and government organizations. This can help to complement the traditional COVID-19 protective measures of hand-washing, nose-mask, social distancing.

The findings of this study indicated that performance expectancy, facilitating condition, and social influence had a significant impact on an individual’s intention to accept and use CDTT with PE having the strongest significant impact. This is not surprising because people tend to accept a technology provided the use of the technology will help to improve their performance at work and enhance their relationships with people. Moreover, FC has a positive and significant relationship with behavioural intentions. Our findings indicate that the provision of high-speed internet services at a discounted rate by government and telecommunication companies will facilitate the acceptance and use of CDTT. The study further shows that SI has a significant relationship with behavioural intentions which implies that people tend to use new technologies if they find out that people around them also use the same technologies with no problems encountered and with utmost safety. Prior studies [111,112] had identified SI to be important in technology adoption and utilization.

Furthermore, the findings indicate that over 70% of the respondents have low compliance levels in the use of digital tools such as automated disinfectant tunnel, electronic sanitiser dispenser, digital contact tracing and social distance monitoring (e.g. wrist bands and wristwatches), digital sensors in homes and offices. This shows that people do not have much knowledge about this technology and it becomes difficult to respond well to variables used to measure: effort expectancy, the perceived cost (P-Cost) for accepting and using CDTT, public awareness (PA), data security and privacy (DSP), organization influence and benefit (OIB), and government expectancy and benefit (GEB). Thus, the study did not have any of these constructs showing a statistical significance to users’ behavioural intention to use CDTT. We recommend that pub-
lic awareness on the use of CDTT should be facilitated by agencies of government on public awareness program. This can help to improve the knowledge of people about the positive significance of CDTT to human-
ity during the COVID-19 pandemic.

In addition, there is no chapter on the adoption and enforcement of the use of digital technologies by individuals and organizations to tackle COVID-19 in the present COVID-19 Health Protection Regulation 2021 of Nigeria [114]. The chapters included in the regulation are Restrictions on gatherings; Operations of public places; Mandatory compliance with treatment protocols; offences and penalties; enforcement and application; and interpretation and citation. The CDTT acceptance model presented in this study and the results of our analysis provide a useful guide to the government to revise the current COVID-19 Health Protection regulation to encourage individuals and organizations to accept and use CDTT.

Funding

The authors declare that there has been no significant financial sup-
port for the work that could have influenced its outcome.

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.

CRediT authorship contribution statement

Boluwaji A. Akinnuwas: Conceptualization, Resources, Methodology, Data curation, Formal analysis, Investigation, Validation, Visualization, Writing – original draft, Writing – review & editing, Project administration. Faith-Michael E. Uzoka: Conceptualization, Methodology, Data curation, Formal analysis, Investigation, Visualization, Writing – original draft. Stephen G. Fasho: Conceptualization, Methodology, Validation, Writing – original draft. Elliot Mbungue: Conceptualization, Methodology, Validation, Writing – review & editing. Adedoyin Odumabo: Resources, Writing – review & editing, Data curation, Formal analysis. Oluwaseun O. Amusa: Data curation, Formal analysis, Validation, Writing – review & editing. Moses Okpek: Conceptualization, Methodology, Validation, Writing – review & editing. Olumide Owolabi: Conceptualization, Methodology, Validation, Writing – review & editing.

Acknowledgement

The authors appreciate friends, colleagues and all the people that assisted in the course of data collection. We appreciate the supports of all the community leaders in the communities within the South-West geopolitical zone of Nigeria. Also we express our gratitude to the medi-
cal practitioners that guided us in the course of the study.

Appendix 1

Measured Variables

I will adapt to the COVID-19 digital tackling tool (adapt-cov-dig-tool)
Use of COVID-19 digital tackling tool improve my job performance (cov-dig-tool-improve-jop-perf)
COVID-19 digital tool are easy to use (cov-dig-tool-easy-use)
Delay and mismatch do occur when I use COVID-19 digital tackling tools but this is easily resolved (cov-dig-tool-delay-mismatch)
Use of COVID-19 digital tackling tool will boost my confidence to relate with colleagues (COV-dig-tool-boost-conf)
Use of COVID-19 digital tackling tools make me work faster (cov-dig-tool-make-me-work-fast)
Using COVID-19 digital tackling systems increase my productivity (cov-dig-tool-inc-prod)
Using COVID-19 digital tackling tools effectively and uniquely identify user (cov-dig-tool-userid)
My consistent use of COVID-19 digital tackling tools has been helping me to relate well with people without fear of being infected (cov-dig-tool-relwel)
I will get a company award for consistently using COVID-19 digital tackling tool (get-company-award)
The use of COVID-19 digital tackling tools does not help to eradicate extra time spent on resetting passwords (cov-dig-tool-erad-pwtime)
It is tough to operate some of the digital systems for tackling COVID-19 (COV-dig-tool-istough)
COVID-19 digital tackling tool can be operated by both technical and non-technical persons (cov-dig-tool-tech-nontech)
I will need assistance to use the COVID-19 digital systems (assist-dueof-cov-dig-tool)
COVID-19 digital tools are not easier to use compared with the traditional tools that tackle COVID-19 (cov-dig-tool-not-easy2use)
The use of COVID-19 digital systems does not relieve me from memorizing passwords and pins (cov-dig-tool-pwmemorize)
Using COVID-19 digital tackling systems does not frighten me (cov-dig-tool-frightenme)
COVID-19 digital tools implementation need managers to change their management philosophy (cov-dig-tool-mang-phil)
The cost of executing and sustaining digital tools is high (cov-dig-tool-ishigh)
My agency/organization does not provide financial supports for staff and public to acquire COVID-19 digital tackling tools (nofinuspopt-cov-dig-tool)
The cost of purchasing a COVID-19 digital tackling tool is relatively high for low income earners (cov-dig-tool-highpurchcost)
Bulk purchase of COVID-19 digital tackling tools by organizations is cost effective for staff members to acquire a tool (cov-dig-tool-bulk-purchase)
Installation of COVID-19 digital tackling systems within the premises of organization create a more friendly and protected environment for staff to relate (cov-dig-tool—prot-env)
Management of organizations should provide constant electric power for COVID-19 digital tackling systems to function effectively (const-elct4-cov-dig-tool)
My agency/organization does not have a clear policy on the use COVID-19 digital tackling tools (policy4-cov-dig-tool)
Use of COVID-19 digital tackling tools will boost the relationship among organizational staff and hence improve productivity (cov-dig-tool-boots-rel)
I have knowledge on how to use COVID-19 digital system (knowledge2-use-cov-dig-tool)
There is no enough public awareness by National Orientation Agency Nigeria (cov-dig-tool-pubawareness)
There is enough public awareness of COVID-19 digital tackling tools by private agencies (cov-dig-tool-privaAwareness)
The digital tools are not well publicized in Nigerian schools (cov-dig-tool-schlawareness)
Management is interested in new technology to improve safety (safety-improvement)
COVID-19 digital tackling tools are the best safety device for COVID-19 (cov-dig-tool-safety-dev)
Management support the use of digital systems (cov-dig-tool-mangsupport)
I use the digital systems because people around me use it (peopleaseuse-cov-dig-tool)
There is no high speed internet service (no-high-speed-internet)
Telecommunication companies do not provide affordable discounted internet services (nointernetby-telecom)
The instability of electric power has been a hindrance to digital tool usage in Nigeria (electricity-problem)
My organization presently does not use the COVID-19 digital tackling system (organisationdoesnotc-dig-dig)
Data privacy and security control measures are required to prevent the leakage of personal information due to the use of COVID-19 digital tools (cov-dig-tool-prev-info-leakg)
COVID-19 digital systems can prevent unlawful right to personal data (cov-dig-tool-prot-personaldata)
The use of digital tools will help to improve the state of safety in Nigeria against COVI-19 (cov-dig-tool-imp-nig-safety)
Government should develop national policy to support the use of COVID-19 digital tackling tools in Nigeria (gov-devp-policy4-cov-dig-tool)
References

[1] J. Budd, B.S. Miller, E.M. Manning, V. Lampos, M. Zhuang, M. Edelstein, G. Rees, V.C. Emery, M.M. Stevens, N. Keegan, Digital technologies in the public health response to COVID-19 in two Indian states, Science 370 (6517) (2020) 691–697.

[2] J. Da, H.-w. Zhang, Y. Yu, H.-j. Xu, H. Chen, S.-p. Lu, H. Zhang, L.-h. Liang, X.-l. Wu, Y. Lei, CT imaging and differential diagnosis of COVID-19, Can. Assoc. Radiol. J. 71 (2) (2020) 195–200.

[3] A.J. Bokolo, Exploring the adoption of telemedicine and virtual software for care of patients during and after COVID-19 pandemic, Ir. J. Med. Sci. (1971) (2020) 1–10.

[4] E. Hernández-Orallo, C.T. Calafate, J.C. Cano, P. Manzoni, Evaluating the effectiveness of COVID-19 Bluetooth-based smartphone contact tracing applications, Appl. Sci. 10 (20) (2020) 1–19.

[5] J. Budd, B.S. Miller, E.M. Manning, V. Lampos, M. Zhuang, M. Edelstein, G. Rees, V.C. Emery, M.M. Stevens, N. Keegan, M.J. Short, D. Pillay, E. Manley, I.J. Cox, D. Heymann, A.M. Johnson, R.A. McKenzie, Digital technologies in the public health response to COVID-19, Nat. Med. 26 (8) (2020) 1192–1200/08/01.

[6] S. Gerke, C. Shachar, P.R. Chai, I.G. Cohen, Regulatory, safety, and privacy concerns of home monitoring technologies during COVID-19, Nat. Med. 26 (8) (2020) 1176–1182/2020/08/01.

[7] T. Sharma, B. Mishur, At risk of apps in the COVID-19 response and the loss of privacy protection, Nat. Med. 26 (8) (2020) 1165–1176/2020/08/01.

[8] M. Ienca, E. Vayena, On the responsible use of digital data to tackle the COVID-19 pandemic, Nat. Med. 26 (4) (2020) 463–464/2020/04/01.

[9] M. Amir, H. Kimhi, T. Butler, J. Chen, E. Glasberg, A. Benov, Mass-surveillance technologies to fight coronavirus spread: the case of Israel, Nat. Med. 26 (8) (2020) 1167–1169/2020/08/01.

[10] Y. Sweeney, Tracking the debate on COVID-19 surveillance technologies, Nat. Mach. Intell. 2 (6) (2020) 301–304/2020/06/01.

[11] S. Maaslen, R. Dowling, Covid-19 and the accelerating smart home, Big Data Soc. 7 (2) (2020) 1–5.

[12] D. Goldinelli, E. Boetto, G. Carullo, M.P. Landini, and M.P. Fantini, “How the COVID-19 pandemic is favoring the adoption of digital technologies in healthcare: a rapid literature review,” MedRxiv, 2020.

[13] D. Goldinelli, E. Boetto, G. Carullo, A.G. Nuzzolese, M.P. Landini, M.P. Fantini, Adoption of digital technologies in health care during the COVID-19 Pandemic: systematic review of early scientific literature, J. Med. Internet. Res. 22 (11) (2020) e22880.

[14] M.I. Effendi, D. Sugandini, Y. Istanto, Social Media adoption in SMEs impacted by COVID-19: the TOE model and a mixed methods study, Int. J. Electron. Bus. Res. 18 (10) (2020) 383–403/2020/10/01.

[15] L.J. Akpan, E.A.P. Udoh, B. Adebisi, Small business awareness and adoption of state-of-the-art technologies in emerging and developing markets, and lessons from the COVID-19 pandemic, J. Small Bus. Entrp. (2020) 1–18.

[16] R.S. Al-Marroof, S.A. Salloum, A.E. Hassanien, K. Shalan, Fear from COVID-19 and technology adoption: the impact of Google Meet during Coronavirus pandemic, Interact. Learn. Environ. (2020) 1–16.

[17] Z. Huang, H. Guo, H.Y. Lim, and A. Chow, “Awareness, acceptance, and adoption of the national digital contact tracing tool post COVID-19 lockdown among visitors of a public hospital in Singapore,” Clinical microbiology and infection: the official publication of the European Society of Clinical Microbiology and Infectious Diseases, S1168-743X(21)60003-7. Advance online publication, 2021.

[18] W. Perriat, S. Tripognato, Managing an Adoption and continuation intention to use contactless payment technologies during the COVID-19 pandemic, Emerg. Sci. J. 5 (1) (2021) 85–95.

[19] M. Razzif, B.A. Miraj, S.P. Persad, R. Nadiflabin, P.F. Belgian, A.A.N.P. Redi, L. Zhang, Investigating the role of economic concern and the unified theory of acceptance and use of technology on work from home technologies adoption during COVID-19, Entrep. Sustain. Issues 8 (2020) 3785.

[20] K. Riemer, C. Ciriello, S. Peter, D. Schlagenw, Digital contact-tracing adoption in the COVID-19 pandemic: empirical evidence for collective action at the societal level, Eur. J. Inf. Syst. 29 (2) (2020) 731–745.

[21] S. Whitehall, M.A. Maman, E. Topol, H.G. Van Spall, Applications of digital technology in COVID-19 pandemic planning and response, Lancer Digit. Health 2 (e440) (2020) 1–6.

[22] N.E. Aly, Factors affecting technology acceptance during COVID-19 crisis in Egyptian higher education, Sci. Bus. Environ. Stud. 11 (4) (2020) 287–346.

[23] G. Vladova, A. Ulrich, B. Bender, N. Gronau, Students’ acceptance of technology-mediated teaching – How it was influenced during the COVID-19 pandemic in 2020: a study from Germany, Front. Psychol. 12 (69) (2021) 1–2021 Jan–uary-28.

[24] W. Dai, S. Rajani, E. Abbas, Cultural and individual characteristics in adopting computer-supported collaborative learning during covid-19 outbreak: willingness or obligatory to accept technology? Manag. Sci. Lett. 11 (2) (2021) 373–378.

[25] S. Bhandari, A.S. Shakhtavak, A. Bat, P. Patel, J. Shukla, S. Singhal, K. Gupta, J. Gupta, S. Kakkar, A. Dube, Logistic regression analysis to predict mortality in COVID-19 patients from routine hematological parameters, Ibnosina J. Med. Biomed. Sci. 12 (2) (2020) 123–129.

[26] H.R. Niazkar, M. Niazkar, Application of artificial neural networks to predict the COVID-19 outbreak, Glob. Health Res. Policy 5 (1) (2020) 1–11.

[27] J. Born, N. Wiedemann, G. Brändle, C. Buhre, B. Rieck, and K. Borgwardt, “Accelerating COVID-19 differential diagnosis with explainable ultrasound image analysis,” arXiv preprint arXiv:2009.06116, 2020.

[28] T. Khalakthar, S. Ghosh, A. Baskaran, N. Thapan, R. Dhakadalli, K. Santoshi, K. Roy, Deep neural network to detect COVID-19: one architecture for both CT scans and chest x-rays, Appl. Intell. (2020) 1–13, doi:10.1007/s10489-020-01943-6.

R. Laksmirayanan, B. Wall, S.R. Dudala, K. Gopal, S. Neelima, K.J. Reddy, J. Radhakrishnan, A.J. Lewnard, Epidemiology and transmission dynamics of COVID-19 in two Indian states, Science 370 (6517) (2020) 691–697.
C.S. Yu, Factors affecting individuals to adopt mobile banking: empirical evidence from the UTAUT model, J. Electron. Commer. Res. 13 (2) (2012) 104–121.

F.C. Tung, M.S. Lee, C.C. Chen, Y.S. Hsu, An extension of financial cost and TAM model with IIT for exploring users’ behavioral intentions to use the CRM information system, Soc. Behav. Personal. Int. J. 37 (5) (2009) 621–626.

F.C. Tung, T.W. Yu, J.L. Yu, An extension of financial cost, information quality and IIT for exploring consumer behavioral intentions to use the internet banking, Int. J. Manag. Bus. Res. 2 (2) (2014) 1229–1235.

T.G. Winston, S. Paul, L. Iyer, A study of privacy and security concerns on doctors’ and nurses’ behavioral intentions to use RFID in hospitals, in: 2016 49th Hawaii International Conference on System Sciences (HICSS), Koloa, HI, USA, 2016, pp. 3115–3122.

H. Hallikainen, B. Paaschugre, T. Laukkanen, D. Rangaranjan, M. Gabrielsson, How Individual technology propensities and organizational culture influence B2B customer’s behavioral intention to use digital services at work? in: In Proceedings of the 50th Hawaii International Conference on System Sciences, 2017, pp. 4577–4585.

I. Brown, Z. Cajes, D. Davies, S. Stroebell, Cell phone banking: predictors of adoption in South Africa—An exploratory study, Int. J. Inf. Manag. 23 (5) (2003) 381–394.

A.S. Yang, Exploring adoption difficulties in mobile banking services, Can. J. Adm. Sci. 26 (2) (2009) 136–149 Revue Canadienne des Sciences de l’Administration.

J. Püschel, J.A. Mazzon, J.M.C. Hernandez, Mobile banking: proposition of an integrated adoption intention framework, Int. J. Bank Mark. 28 (5) (2010) 389–409.

H. Karjalohu, H.E. Biquelme, R.E. Rios, The moderating effect of gender in the adoption of mobile banking, Int. J. Bank Mark. 28 (5) (2010) 328–341.

J. Sripalawat, M. Thongnak, A. Ngramyarn, M-banking in metropolitan Bangkok and a comparison with other countries, J. Comput. Inf. Syst. 51 (3) (2011) 67–76.

S.A. Sair, R.Q. Danish, Effect of performance expectancy and effort expectancy on the mobile commerce adoption intention through personal innovativeness among Pakistani consumers, Pak. J. Commer. Soc. Sci. (PJCSS) 12 (2) (2018) 501–520.

K. Ghalandari, The effect of performance expectancy, effort expectancy, social influence and facilitating conditions on acceptance of e-banking services in Iran: the moderating role of age and gender, Middle-East J. Sci. Res. 12 (6) (2012) 801–807.

S. Dasgupta, R. Paul, S. Fuloria, Factors affecting behavioral intentions towards mobile banking usage: empirical evidence from India, Rom. J. Mark. 1 (1) (2011) 6–28.

H. Khatmah, P. Susanto, N.L. Abdullah, Hedonic motivation and social influence on behavioral intention of e-money: the role of payment habit as a mediator, Int. J. Entrep. 23 (1) (2019) 1–9.

H.N. Stung, D.Y. Jeong, Y.S. Jeong, J.I. Shin, The effects of self-efficacy and social influence on behavioral intention in mobile learning service, Adv. Sci. Technol. Lett. 103 (2015) 27–30.

S. Singh, V. Srivastava, R. Srivastava, Customer acceptance of mobile banking: a conceptual framework, Sies J. Manag. 7 (1) (2010) 55–64.

J.C. Ho, C.G. Wu, C.S. Lee, T.T.T. Pham, Factors affecting the behavioral intention to adopt mobile banking: an international comparison, Technol. Soc. 63 (2020) 1–9.

A. Joshua, M.P. Koshy, Usage patterns of electronic banking services by urban educated customers: glimpses from India, J. Internet Bank. Commer. 16 (1) (2011) 1–12.

N. Nakayima, Doctoral Dissertation, Makerere University, 2011.

P.Y. Chua, S. Rezaei, M.L. Gu, Y. Oh, M. Jambulingam, Elucidating social networking apps decision: performance expectancy, effort expectancy and social influence, Nankai Bus. Rev. Int. 9 (2) (2018) 118–142.

M. Katherine, K.M. Gerome, M.B. Moya, G. Allah, Effort expectancy, performance expectancy, social influence and facilitating conditions as predictors of behavioural intentions to use ATMs with fingerprint authentication in Ugandan banks, Glob. J. Comput. Sci. Technol. 17 (5) (2018) 1–19.

U. Tandon, Factors influencing adoption of online teaching by school teachers: a study during COVID-19 pandemic, J. Public Affairs Adv. Online Publ. e5250 (2020) 1–11.

T.H. Tseng, S. Lin, Y.S. Wang, H.X. Liu, Investigating teachers’ adoption of MOOCs: the perspective of UTAUT2, Int. J. Learn. Environ. (2010) 1–16.

Q. Liao, J.P. Shim, X. Luo, Student acceptance of web-based learning environment: an empirical investigation of an undergradu- ate IS course, in: Proceedings of the Tenth Americas Conference on Information Systems, NewYork, New York, 2004 Available @ https://aisel.aisnet.org/cgi/viewcontent.cgi?article=1953&context=amcis2004. Date accessed: July 14, 2021, pp. 3092-3098.

S. Al-Qessi, G. Dennis, E. Almansos, C. Jayawardhana, Website design quality and usage behavior: unified theory of acceptance and use of technology, J. Bus. Res. 67 (11) (2014) 2282–2290.

H. National Republic-of-Nigeria, “Coronavirus disease (COVID-19) health protection regulation 2021,” Retrieved 15 November2021, from https://www.health.gov.ng/ pdf/COVID-REG.pdf 2021.