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Transitioning to Online Teaching During the Pandemic Period: The Role of Innovation and Psychological Characteristics

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Abstract

Given the effect of the COVID-19 pandemic, which led to the forced adoption of online teaching in several academic institutions across the world, we set out an objective in this paper to examine salient factors that may affect the decision to use online teaching by faculty members (teaching staff). We propose and validate a model based on an extended innovation diffusion theory and 284 online survey responses from Ghana and find that the attitude towards online teaching is predictably influenced by relative advantage and observability. Contrary to theory, complexity boosts rather than inhibits the attitude towards online teaching. The most salient predictors of willingness to use the mode of online teaching are attitude, observability, institutional trust, and compatibility. We conclude with discussions on the important implications for the scientific community and educational policymakers.

Keywords: Online teaching, COVID-19 pandemic, innovation diffusion theory, attitude, institutional trust

Introduction

The COVID-19 pandemic necessitated the digitalization of most aspects of our social lives, if possible, including education. Taking almost every nation by surprise, the disease known as COVID-19, caused by SARS-CoV-2, was first identified in late 2019 in the city of Wuhan, China, but rapidly spread to other parts of the world, which made the World Health Organization (WHO) to declare it as a global pandemic in March 2020 (**WHO, 2020**). According to scientists, it has a high fatality rate among people with pre-existing health conditions and the aged (**Ting et al., 2020**). In response, most affected nations implemented lockdowns, strict travel bans, and other stringent measures on movements. Schools were asked to close, though temporarily, with the expectations that the storm of this deadly virus would come to an end soon and academic work could resume. This has made schools look for alternative means such as an online platform for teaching and learning (**Greenberg & Hibbert, 2020**).

We define online teaching as the sharing of knowledge and other educational instructions/materials remotely with students using digital devices such as computers, tablets, smartphones, and with the help of the internet. While the phenomenon of online teaching is not new to the world (see **Allen & Seaman, 2013**), the COVID-19 pandemic has, however, increased the need for online teaching (**DeVaney et al., 2020**), especially in the higher education, where students are obliged to write their final examinations to face the world of work. Given the official recommendations by national governments across the world to limit physical proximity as much as possible as well as the need to avoid crowd gathering in enclosed spaces such as classrooms and teaching laboratories, online teaching has therefore been generating intense interest among academics, business practitioners, and policymakers (**Heitz et al., 2020**).

The challenge, therefore, is to begin to understand technological and related factors that universities' faculty members (teaching staff) face regarding the use of online teaching, especially in environments such as African countries where the transition to online teaching can be very challenging. It is this call to action that has prompted the current investigation, one among the first theoretically informed studies during and before the COVID-19 era to critically account for the factors affecting the adoption of online teaching by faculty members in an African country. Because of this reason, our current study relies on the innovation diffusion theory (IDT) by **Rogers** (**2003**) to investigate the factors that are likely to affect the decision to use online teaching by faculty members. Moreover, the current investigation extends the IDT by considering how psychological factors such as users' attitudes towards innovation (**Ajzen, 1991; Ntemana & Olatokun, 2012**) will play a key role in the decision of online teaching adoption. Similarly, based on extant studies (**Godefroidt et al., 2017**), we also consider another psychological variable- institutional trust, which we define, in the context of this study, as the level of confidence of citizens have in their government, educational policymakers, and electricity companies. We thus hypothesize that this psychological variable may play a key role in the decision to adopt online teaching, especially in the African continent.

Taken together, the current paper makes a significant contribution to research by highlighting the key role that the characteristics of innovation, such as compatibility, complexity, observability, relative advantages in addition to institutional trust, can play in the attitudinal formation and behavioral intention regarding online teaching especially during COVID-19 era. Findings from this study will help spread theoretical and practical knowledge about this very relevant topic across the world, especially in Africa and in other developing regions, where several schools, including universities, remain closed at the time of the writing owing to the COVID-19 pandemic. The main objective of this study is to examine salient factors that may impact the decision to use online teaching by faculty members and based on extended innovation diffusion theory.

This paper is arranged as follows. After presenting in detail the theoretical background of the study, including the arguments leading to the research hypotheses, we then present a concise account of the research methods used and the research findings. Lastly, the discussion of the findings, implications, recommendations, and limitations are then presented.

Theoretical Background and Development of Hypotheses

Innovation Diffusion Theory (IDT)

In general, innovation is either a new idea, process, or technology—in this case, the innovation is online teaching (**Rogers, 2003**)—while diffusion refers to the process by which the innovation gets disseminated within a social system (**Rogers, 2003; Zhang et al., 2015**). According to **Rogers** (**2003**), the attributes of any innovation are the key factors that determines its adoption. These attributes, which will be explained in the subsequent section, include compatibility, complexity, relative advantage, and observability.

Although IDT has been extensively validated in multiple contexts in the literature (**Zhang et al., 2015**), scholars such as **Karahanna et al.** (**1999**) have noted that classical IDT is rather silent concerning how user attitude is formed, which is a key factor that influences decision to adopt or reject an innovation. In line with this argument, scholars (Al-Jabri & Sohail, 2012; Sabi et al., 2018) have noted the need for the reinforcement of IDT with other salient constructs. Accordingly, the current investigation incorporates user attitude as an additional construct to the existing IDT. The argument, therefore, is that the attributes of innovation will shape the attitudes towards online teaching and ultimately impact the decision to adopt this mode of education.

Furthermore, since the decision to adopt innovations is mainly dependent on context-specific factors such as cultural norms (**Huang et al., 2019; Janssen et al., 2020**), institutional infrastructure (**Ezumah, 2020**), and social trust (**Kaur & Rampersad, 2018**), we further complement IDT with institutional trust (**Gode-froidt et al., 2017**). Consider, for example, the fact that in Ghana and other African countries, the power supply is unreliable (**Kumi, 2017**) and that most of the villages on the continent remain in the dark even now, which poses as a significant challenge in the quest of the universities there to transition to online teaching. Besides, scholars (**Egger et al., 2020**) have noted that institutional trust remains a greater source of concern in African countries, especially during the COVID-19 pandemic, thus adding to the relevance of including this important contextual factor in the decision to adopt online teaching. Furthermore, the role of institutional trust, has slowly been gaining the attention of scholars in the research area of technology adoption (**Alomari et al., 2012**) and thus, needs to be extended to the study on online teaching, especially in the COVID-pandemic. Altogether, this allows us to make a new claim in the literature regarding the proposal that individual beliefs about institutional trust will play a defining role in the attitudinal formation and willingness to use online teaching.

Summary of Construct Mapping of IDT on Education Research

In this section, we provide the summary results of pre-COVID-19 pandemic publications which used IDT as their theoretical foundation. For instance, while **John** (**2015**) explored e-teaching processes in Universities in an Asian context and found compatibility and relative advantage to influence lecturers' attitude towards educational technologies, **Lai** and **Chen** (**2011**) confirmed compatibility influence on teaching blogs adoption in the Taiwan context. In studying ICT usage in teaching, **Askar et al.** (**2006**) found that all the IDT constructs except Trialability influenced ICT use in teaching in Turkey. Similarly, **Ntemana** and **Olatokun** (**2012**) found that relative advantage, complexity, and observability were the key factors influencing lecturers' attitudes towards adopting ICT in Lesotho. By using document review and thematic analyses, **Jwaifell** and **Gasaymeh** (**2013**) found all the IDT constructs as critical factors affecting electronic teaching. In contrast, **Shiau** and **Chaus** (**2016**), using an integrated theoretical approach, report that compatibility, relative advantage, attitude, perceived behavioral control, perceived ease of use, perceived usefulness determine/affect the adoption of cloud computing

classrooms. Finally, **Sabi et al.** (**2018**) reported that sociocultural factors and result demonstrability influence adopting cloud computing for teaching in Uganda.

Hypotheses Development

Relative Advantage

Relative advantage refers to the extent to which the user of an innovation perceives it as better than its predecessors (**Rogers, 2003**). This means that potential users of innovation would evaluate the innovation, compare it with existing technologies, and determine whether it is worthwhile to adopt the new one. Thus, in theory, the user will adopt the innovation when the evaluation proves using this new technology is more advantageous than continuing to use the prevailing technology. Empirically, extant studies have found that relative advantage leads to positive attitudes towards an innovation (**Jamshidi & Kazemi, 2019**), and adoption decision (**Kapoor et al., 2014**). Based on the above, the following hypotheses are made:

H1a: Relative advantage positively affects attitude towards online teaching.

H1b: Relative advantage positively affects the adoption intention of online teaching.

Compatibility

In accordance with previous studies (**Rogers, 2003**), compatibility refers to the degree to which the innovation is perceived to be congruent with the existing values, experiences, and needs of the prospective adopters. In this context, this paper suggests that attitudes towards online teaching and the corresponding acceptance decision may largely depend on how compatible online teaching is with the university lecturer's needs, experiences, and other lifestyle factors. Given that extant studies have acknowledged the importance of compatibility in attitudinal formation (**Jamshidi & Kazemi, 2019; Kapoor et al., 2014**) and the intention to adopt the innovation (**Askar et al., 2006; Lai & Chen, 2011; Shiau & Chau, 2016; Zhang et al., 2015**), the following are hypothesized:

H2a: Compatibility positively affects attitude towards online teaching.

H2b: Compatibility positively affects the adoption intention of online teaching.

Complexity

Complexity refers to the degree to which an innovation is perceived as difficult in its usage (**Kapoor et al., 2014; Rogers, 2003**). Accordingly, this suggests that the belief that using online teaching platform(s) is difficult may lead to less-favorable attitudes towards online teaching, which can lead to resistance to its adoption. While the findings on the impact of complexity on adoption decisions remain equivocal (**Al-Jabri & Sohail, 2012; Sabi et al., 2018**), other extant studies (**Alo-mari et al., 2012; Askar et al., 2006; Ntemana & Olatokun, 2012**) have shown that complexity can significantly undermine attitudinal and behavioral intentions regarding the adoption of the innovation. In line with the above studies, the following are hypothesized:

H3a: Complexity negatively affects attitude towards online teaching.

H3b: Complexity negatively affects the adoption intention of online teaching.

Observability

Observability, according to **Rogers** (**2003**), refers to the extent to which the benefits of innovation are apparent to potential users. The more obvious the benefits are to potential users, the greater the propensity to adopt the technology. Extant studies have shown that observability has positive correlation with attitudes towards the innovation (**Kapoor et al., 2014; Ntemana & Olatokun, 2012**) and further, with the intention to adopt the innovation (**Jwaifell & Gasaymeh, 2013**). Accordingly, the following are hypothesized:

H4a: Observability positively affects attitude towards online teaching.

H4b: Observability positively affects the adoption intention of online teaching.

Institutional Trust

Earlier, we referred to institutional trust as the extent to which people trust social institutions such as the government and electricity companies since we speculate that this factor will play a key role in the successful adoption of online teaching, especially in developing regions such as the countries in Africa. Aside from basic infrastructures such as the internet, computers, software, and other tools used in online teaching, there is a need for government to ensure a stable supply of electricity for efficient and effective implementation of online teaching and learning. Indeed, in studies on technology adoption, it is known that institutional trust positively relates to attitudes towards technology (**Xie et al., 2017**) and intention to adopt (Alomari et al., 2012; Bélanger & Carter, 2008). The following are hypothesized based on these studies:

H5a: Institutional trust positively affects attitude towards online teaching.

H5b: Institutional trust positively affects the adoption intention of online teaching.

User Attitude

In general, attitudinal formation can be either negative or positive towards a certain object or target (see also **Ajzen, 1991**). Studies have indicated that attitudes can be formed through social and cultural experiences gained from media interaction and others' opinions (**Watts & Dodds, 2007**). Given the considerable research evidence on the impact of users' attitudes on cognitive outcomes such as adoption intention (**Shiau & Chau, 2016**), we believe that the formation of positive attitudes towards online teaching will be critical to its adoption among faculty members and thus, the following hypotheses is formed (**Fig. 1**):

H6: Attitude positively affects the adoption intention of online teaching.

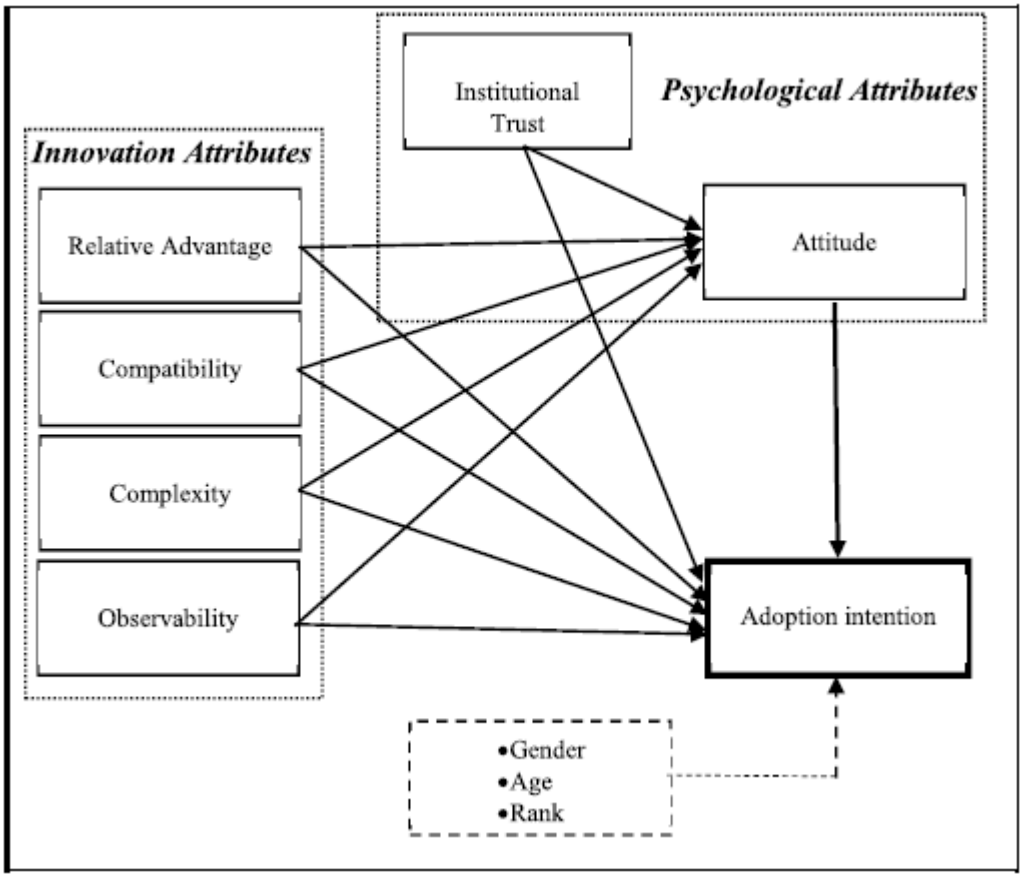

Fig. 1 Depicts the above relationships and our research model

Research Method

Study Setting and Data

The population of this study comprised faculty members from both public and private higher academic institutions in Ghana. Indeed, the outbreak of the COVID-19 disease in Ghana led to commencement of emergency online teaching in some of the country's universities in late April 2020 (**Mohammed, 2020**). Online teaching was literally impractical in some countries such as Ghana due to dearth of infrastructure and preference for face-to-face teaching. We thus believe that Ghana was an appropriate study setting.

The current study relied on web-based surveys, in line with studies on the COVID-19 pandemic (**Laato et al., 2020**). A web-based questionnaire was then created using Google forms. In most cases, the email addresses of the research participants were retrieved from their university's website, and then, a general email was sent which asked for their permission to partake in the study. This email also had the survey link embedded in it. In all, we distributed 624 questionnaires to the respondents. After two follow-ups within four weeks, 160 questionnaires were returned indicating a lower response rate (26%). This low response rate can be attributed to the pandemic still at its peak in Ghana. To increase the response rate and get an appreciable sample size for the study, we politely sent the third reminder asking the faculty members again to complete the survey. To our dismay, an additional 137 responses were successfully retrieved via google docs, increasing our total response rate to (47%). We must emphasize that, there were also instances where some of the research participants obliged our request to share the survey link with colleagues whose email addresses were not retrievable. Overall, the final data revealed that respondents were Professors (8.1%), Associate Professors (15.5%), Senior lecturers

(24.3%), Lecturers (35.9%), Assistant Lecturers (7.4%) whiles Teaching Associates (8.8%). The survey was conducted between May and August of 2020. In the end, 284 out of 297 received responses were adequately filled and were thus used in the analysis. This means 13 responses were deleted using the case-wise deletion method. However, the question of whether this remaining sample size was adequate to test the model was answered statistically, specifically the use of G*Power (**Faul et al., 2009**). According to **Faul et al.** (**2009**), G*Power, apart from its ability to assess the required minimum sample size, can avoid disturbances of statistical significance. Therefore, in this study, the G*Power analysis showed that we needed 45 responses as the minimum sample size given an effect size of 0.15 at 0.1 significance level and 0.90 as statistical power. (see appendix A for details). In addition, reflection on the works of **Ringle et al.** (**2014**), we targeted three or four times the required minimum sample size to create a more reliable model.

Table 1 Characteristics of research respondents ($N = 284$)

Category	Sub-Category	Frequency	Percentage (%)
Gender	Female	98	34.5
	Male	186	65.5
Age	26–30	35	12.3
	31–40	112	39.4
	41–50	82	28.9
	Above 50	55	19.4
Rank	Professor	23	8.1
	Associate Professor	44	15.5
	Senior Lecturer	69	24.3
	Lecturer	102	35.9
	Assistant Lecturer	21	7.4
	Teaching Associate	25	8.8
Type of Institution	Public University	193	68.0
	Private University	91	32.0

Teaching Associate- Post-graduate students temporarily employed to assist in teaching and research; Assistant Lecturer-A faculty member without a Ph.D. degree

Accordingly, our sample size of 284 shows sufficient statistical power. We provide details on the demographics of the research participants in **Table 1**.

Study Measures

The survey instruments for this study consisted of two main sections with a cover letter. The first section explores the demographics of respondents such as age, gender, rank, and the type of institution. The second section comprises the measurement items selected and modified from our literature review of related studies, which used similar constructs as the current investigation. Specific measurement items, scale, and their sources can be found in **appendix B**.

Common Method Bias

In accordance with **Podsakoff et al.** (**2003**), the current study assured respondents of data confidentiality. Aside the fact the questions were simple and specific, three procedural approaches

were used in the detection of the presence of common method bias (CMB). In the first case, we used bivariate correlation (**Bagozzi et al., 1991**). Evidence from this showed that no bivariate correlation coefficient exceeded 0.9 (**Bagozzi et al., 1991**). Similarly, we used the procedure outlined by **Kock** (**2015**) and the results showed that none of the variance inflation factors (VIFs) exceeded the cut-off value of 3.3. Finally, we relied on Harman's single-factor test to examine our study for CMB. Results from this technique showed that the most dominant factor merely accounted for 22.03% of the shared variance in the data. In conclusion, CMB is not a problem in this study.

Empirical Strategy

The statistical objective of this study is both exploratory and predictive in nature. Thus, the method of partial least square structural equation modelling (PLS-SEM) is highly recommended for use by scholars such as **Hair et al.** (**2019**). In addition, recent studies regarding adoption intention and decisions have also utilized PLS-SEM (**Janssen et al., 2020**). Indeed, SEM has been used in most extant studies (**Ghasemy et al., 2020; Wang, 2019**). Further, SEM also can detect measurement error with observed variables (**Hair et al., 2006**). In addition, unlike the first generational statistical technique such as linear regression, which examines the relationship with one dependent variable at a time, thereby resulting in inaccurate results in the case of mediated relationships (**Iacobucci, 2009**), SEM as a second generational statistical technique offers the opportunity to test all relationships between observed and latent variable at the same time. In doing so, SEM combines multiple regression and factor analyses and subsequently provides fit indexes (**Iacobucci, 2009**). This study uses the traditional PLS algorithm with bootstrapping set to 5000 sub-samples and no sign changes. All analysis was performed using SmartPLS 3.3.2 (**Ringle et al., 2014**).

Results

Measurement Model

The model assessment was first initiated by determining model fit using the saturated model indices in line with the literature (**Henseler et al., 2016**). For instance, the standard root means square residual (SRMR), one of the fit indices, was established with a value of 0.043, below the minimum baseline of 0.08, thus indicating a good model fit for PLS path models (**Henseler et al., 2016**). Second, we established the psychometric properties of the reflective scales by assessing the magnitude and statistical significance of factor loadings, Cronbach's alpha (CA), and composite reliability (CR) values in addition to the average variance extracted (AVE). The results, which are shown in **Table 2**, confirm that assumptions about convergent validity have been met. All the reported values are generally in line with the reported thresholds in the methods and PLS-SEM literature (**Hair et al., 2019**). For instance, the factor loadings are all statistically significant and exceed the 0.5 threshold; similarly, both CA and CR values are greater than 0.7 and with AVEs exceeded the reported threshold of 0.5 (**Henseler et al., 2016**).

Table 2 Descriptive statistics and convergent validity assessment

Construct	Item	Mean	Standard deviation	Factor loading	CA	CR	AVE
Compatibility	COMP1	3.739	1.114	0.947	0.869	0.868	0.690
	COMP2	3.877	0.965	0.823			
	COMP3	4.004	1.016	0.704			
Complexity	CPX1	3.275	1.400	0.802	0.832	0.832	0.623
	CPX2	3.313	1.398	0.794			
	CPX3	3.401	1.412	0.771			
Observability	OBV1	3.440	1.123	0.768	0.834	0.834	0.627
	OBV2	3.673	1.158	0.784			
	OBV3	3.708	1.237	0.822			
Relative Advantage	RLA3	3.211	1.421	0.782	0.884	0.884	0.717
	RLA4	3.070	1.412	0.855			
	RLA5	3.412	1.320	0.900			
Attitude	ATT2	3.366	1.436	0.737	0.729	0.730	0.575
	ATT3	3.489	1.341	0.778			
Institutional Trust	INST1	3.440	1.384	0.761	0.803	0.801	0.574
	INST3	3.644	1.291	0.698			
	INST4	3.500	1.352	0.809			
Adoption Intention	INT1	3.743	1.208	0.726	0.745	0.748	0.598
	INT2	3.704	1.235	0.818			

We dropped ATT1 and RLA1 from the analysis due to very low loadings. Cronbach's alpha (CA), composite reliability (CR), average variance extracted (AVE)

Table 3 Discriminant validity based on HTMT approach

		1	2	3	4	5	6	7	8	9	10
1	Age*										
2	Attitude	0.199									
3	Compatibility	0.016	0.288								
4	Complexity	0.020	0.503	0.216							
5	Gender*	0.008	0.090	0.185	0.057						
6	Institutional Trust	0.131	0.301	0.215	0.339	0.066					
7	Adoption Intention	0.056	0.663	0.384	0.435	0.108	0.454				
8	Observability	0.036	0.572	0.317	0.521	0.049	0.479	0.672			
9	Relative Advantage	0.109	0.507	0.285	0.336	0.037	0.262	0.392	0.461		
10	Rank*	0.816	0.097	0.037	0.047	0.018	0.072	0.058	0.035	0.045	

**Control variables*

Additionally, based on recent recommendations in the literature by **Hair et al.** (**2019**) and **Henseler et al.** (**2016**), we assessed discriminant validity using the heterotrait-monotrait ratio (HTMT) approach, and the results as contained in Table 3 provide evidence for discriminant validity. All HTMT values were below the conservative value of 0.85 (**Henseler et al., 2016**).

Structural Model

In the assessment of our structural model, we followed the procedure recommended by **Hair et al.** (**2019**). Further, since our hypotheses were directional in nature, we used a one-tailed test, calculating at 90% confidence level (**Carrión et al., 2017**). The results presented in **Table 4** show that relative advantage positively affects attitude towards online teaching, and hence hypothesis H1a (β = 0.269, $p < 0.01$) was supported. However, Relative advantage did not affect the intention to adopt online teaching, and thereby H1b is rejected (β = -0.004, p = 0.603). Hypothesis H2a was not supported, implying that compatibility does not affect attitude towards online teaching ($\beta = 0.067$, $p = 0.337$). However, Hypothesis H2b was supported, suggesting that compatibility positively affects intention towards online teaching ($\beta = 0.134$, $p < 0.05$). Contrary to our expectation, we find that complexity positively rather than negatively affects online teaching attitudes; therefore, H3a was rejected (β = 0.239, $p < 0.05$). Similarly, H3b was rejected ($\beta = -0.014$, p = 0.879), suggesting that complexity does not affect the intention to use online teaching. As expected, hypotheses H4a ($\beta = 0.306$, $p < 0.01$) and H4b (β = 0.327, $p < 0.01$) received support implying that observability has a positive effect on both attitude and intention towards online teaching. On the contrary, the positive relationship between Institutional trust and attitude was rejected i.e. H5a ($\beta = -0.008$, $p = 0.928$).

Table 4 Results of the hypotheses (with bootstrap sample size = 5000)

Hypothesis	Path	β	SE	*t*-value	*p*-value	90% Confidence interval	Decision	VIF	Effect size (f^2)
H1a	RLA—> ATT	0.269	0.089	3.022	0.003***	[0.094, 0.438]	Accept	1.328	0.099
H1b	RLA—> INT	-0.044	0.085	0.520	0.603	[-0.218,0.119]	Reject	1.461	0.003
H2a	COMP-> ATT	0.067	0.070	0.961	0.337	[-0.070,0.203]	Reject	1.152	0.007
H2b	COMP-> INT	0.134	0.077	1.735	0.083*	[-0.023,0.281]	Accept	1.204	0.039
H3a	CPX—> ATT	0.239	0.102	2.358	0.018**	[0.045, 0.438]	Reject	1.413	0.074
H3b	CPX—> INT	-0.014	0.093	0.152	0.879	[-0.212,0.162]	Reject	1.532	0.000
H4a	OBV—> ATT	0.306	0.112	2.728	0.006***	[0.081, 0.528]	Accept	1.832	0.093
H4b	OBV—> INT	0.327	0.120	2.730	0.006***	[0.079, 0.545]	Accept	2.033	0.136
H5a	INST—> ATT	-0.008	0.087	0.090	0.928	[-0.177,0.163]	Reject	1.329	0.000
H5b	INST—> INT	0.163	0.082	1.992	0.046**	[0.004, 0.324]	Accept	1.361	0.050
H6	ATT—> INT	0.437	0.139	3.154	0.002***	[0.200, 0.750]	Accept	1.906	0.260
Controls:									
	Gender-> INT	0.073	0.060	1.223	0.222	[-0.046, 0.189]			0.013
	Age—> INT	-0.166	0.094	1.770	0.077*	[-0.380,-0.010]			0.022
	Rank—> INT	-0.132	0.100	1.312	0.189	[-0.356, 0.043]			0.015
Endogenous Latent Variable				R^2(%)		Predictive Relevance Q^2 (= 1-SSE/SSO)			
	ATT			43.9			0.212		
	INT			60.1			0.308		

*RLA-Relative Advantage; INT - Adoption intention of online teaching; COMP-Compatibility; CPX-Complexity; OBV-Observability; ATT—Attitude towards online teaching; INST - Institutional trust. * p <0.1; ** $p < 0.05$; *** p <0.01, one-tail test*

Both hypotheses H5b ($\beta = 0.163$, $p < 0.05$) and H6 ($\beta = 0.437$, $p < 0.01$) were also supported, suggesting that Institutional trust and attitude have a positive effect on the intention to adopt online teaching. In sum, there was statistical support for most of the research hypotheses (i.e., H1a, H2b, H4a, H4b, H5b, and H6). The details of the size and significance of the path coefficients of these direct hypotheses appear in Table 4. The explained variance, i.e., R2, for attitude towards online teaching was 44% while it was 60% for the intention to adopt this innovation. We also examined the f2 which

assesses whether an independent variable has a functional contribution to the explained variance of the dependent variable(s) to which it is directly linked (**Hair et al., 2019**). Finally, Stone-Geisser's Q^2 value, which was obtained using the blindfolding procedure, offered evidence regarding the predictive relevance of the research model given that Q^2 values for the two endogenous constructs were positive and above zero.

Evaluation of the Predictive Power of the Research Model

To evaluate the predictive power of our model, we followed the PLSpredict technique procedure (**Shmueli et al., 2019**). In this procedure, the root mean square error (RMSE) and mean absolute error (MAE), which quantify the number of prediction errors are compared in both the PLS-SEM model (PLS) and the linear regression model (LM). Accordingly, as **Table 5** depicts, all RMSE values in the PLS were lesser than that of the LM for all measurement indicators of all the dependent variables (attitude and intention to use). Thus, we conclude that our model has high predictive power (**Hair et al., 2019; Shmueli et al., 2019**).

Discussion

The main objective of the study was to shed light on the technological, psychological, and institutional factors influencing the adoption decision of online teaching. Specifically, our research model proposed that, along with the well-known IDT constructs, the factors of user's attitude and institutional trust will play a salient role regarding the adoption of online teaching by faculty members.

Crucially, the results show that both relative advantage and observability have a direct effect on the attitude towards online teaching. This finding is consistent with prior studies (**Ntemana & Olatokun, 2012**) but differs from extant studies that have not confirmed the importance of relative (dis)advantage (**Vishwanath & Goldhaber, 2003**) or observability on attitudinal formation regarding technology adoption.

Table 5 Results of out-of-sample prediction based on PLSpredict

		PLS			LM			PLS-LM		
Construct	Item	RMSE	MAE	Q^2predict	RMSE	MAE	Q^2predict	RMSE	MAE	Q^2predict
Attitude	ATT2	1.277	1.032	0.217	1.293	1.039	0.196	-0.016	-0.007	0.021
	ATT3	1.201	0.950	0.205	1.233	0.981	0.162	-0.032	-0.031	0.043
Intention	INT2	1.070	0.809	0.255	1.076	0.825	0.247	-0.006	-0.016	0.008
	INT1	1.063	0.807	0.230	1.064	0.796	0.228	-0.001	0.011	0.002

Contrary to common knowledge, we find that complexity boosts rather than diminishes lecturers' attitudes towards online teaching. While the result is surprising, this may suggest that faculty members are quite comfortable working with online teaching since they feel its procedures and devices would not be difficult to understand and use. We believe that faculty members may be familiar with using similar digital technologies as some may have had the opportunity to attend conferences and academic seminars in Western nations, where these technological platforms are used in such programs. In short, the result seems to imply that, irrespective of the learning cost that might be involved in shifting to

online teaching, university teachers, especially those in Ghana, will develop a strong attitude towards online teaching. An alternative explanation could be that complexity is viewed more favorably by faculty members (teaching staff) in the context of forced online teaching, because it represents a depth of resource rather than a burden to overcome because there is no simpler alternative (i.e., face-to-face instruction). Indeed, our finding is inconsistent with IDT (**Rogers, 2003**) and other empirical studies (**Ntemana & Olatokun, 2012**). Specifically, complexity enhances rather than inhibits attitude towards online teaching. Similarly, the finding that compatibility is not a significant contributor to user attitude toward the innovation is in agreement with some related research (**Ntemana & Olatokun, 2012**), but inconsistent with other previous research (**Kapoor et al., 2014**).

Futher, the results demonstrate that observability and compatibility have a direct influence on adoption intention, which is consistent with existing theory (Rogers, 2003) and empirical investigations (**Jwaifell & Gasaymeh, 2013; Shiau & Chau, 2016**). However, our work shows that both relative advantage and complexity have weak impacts on online teaching adoption intention. These results, while offering limited evidence regarding the impact of the IDT factors of relative advantage and complexity on the willingness to use online teaching, are congruent with past research regarding innovation adoption that finds the limited direct influence of both relative advantage (**Sabi et al., 2018**) and complexity (**Al-Jabri & Sohail, 2012**) on behavioral intention.

Our results further demonstrate that the fortification of IDT with institutional trust, adds to empirical knowledge since we find it has a significant direct influence on adoption intention, though it did not directly influence attitudes towards online teaching. While the finding supports prior studies (**Alomari et al., 2012; Bélanger & Carter, 2008**), the current study is, however, the first to report on the significance of institutional trust with respect to adoption decision. In short, this research has confirmed the study's assumption that institutional trust is an important factor in the decision to adopt online teaching, especially in developing African societies and in developing societies across the world.

Finally, by including attitude in our model, the results show that faculty members' attitude is the most important factor in the decision to adopt online teaching. This research reinforces the conclusions in **Ajzen's paper** (**1991**) and other works on user attitude and behavioral intention, in this case, adoption intention of online teaching (**Shiau & Chau, 2016**).

Conclusion

Implications for Research

From the theoretical point of view, our study contributes to the literature by demonstrating that only observability of the IDT attributes, has a significant consequence on user attitudes and use intention of online teaching. The implication of this finding to existing knowledge regarding IDT is that, within the context of attitudinal formation and usage of online teaching and especially among faculty members, observability is the most important factor. As far as this study is concerned, it is one of the first to report on the fundamental role of observability in faculty members' attitudes and willingness to adopt online teaching.

Our study also adds to the literature by reinforcing previous research conclusions (**Ajzen, 1991; Rogers, 2003**) regarding the importance of compatibility and attitude in the adoption intention of online teaching. This observation supports the need for the extension of IDT with classic psychological constructs like attitude (see also **Shiau & Chau, 2016**).

Another theoretical implication is that institutional trust plays a key role in the adoption intention of online teaching. This finding corroborates with the work of **Beaunoyer et al.** (**2020**) and suggests that it is important for scholars to consider the role of institutional trust, in decisions regarding the acceptance of an innovation. To the best of our knowledge, this paper is the first to provide an evidence base regarding the contribution of institutional trust in the adoption decision of online teaching from at least emerging economy perspective.

It is also important to note that the current study conflicts with the literature in at least one important way, especially regarding the fact that complexity, rather than diminishing, increases positive attitudes towards online teaching by university lecturers. An alternative explanation for this contradiction is that faculty members show determined efforts to use online teaching despite any short-term challenges they might experience from using it due the Covid- 19 pandemic. With this finding, we open the door for further investigation in this field to examine context specific influence on IDT. Similarly, we also find that complexity plays no significant role in the willingness to adopt online teaching, implying that faculty members do not see online teaching as a difficult thing to do, especially if supporting resources are provided. We also think that the academic background of university lecturers in this age of information put them at an advantage, i.e., they are more likely to be familiar with the use of digital platforms such as Zoom and Cisco WebEx for academic activities like conferences and meetings before the onset of the COVID-19 pandemic. Moreover, some of the lecturers might have also had experience with teaching short courses and developmental programs through online platforms. Further, the relative high prediction power of the research model (see **Tables 4** and **5**) implies that our model can accurately predict the outcome value when used in a new context (**Shmueli et al., 2019**).

Implications for Practice

The most outstanding of our study's implications is the finding concerning the positive role of institutional trust in adoption intention. Practically, institutional commitment matters a lot for the successful uptake of online teaching, especially in environments such as African countries where reliable power supply and implementation of innovative educational programs and policies remain a key challenge (**Ezumah, 2020**) coupled with the perennial issue of institutional distrust in these societies (**Bratton & Gyimah-Boadi, 2016**). In particular, the importance of critical investment in education and complementary areas such as the provision of stable electricity, affordable and reliable internet supply, and other logistics is highly needed for effective adoption of online teaching.

Further, some curricula must be redesigned to suit the digital platform while equally equipping faculty members with the necessary tools and training. For instance, the use of chalk/marker and backboard to sketch graphs and other physical classroom demonstrations is not the same as using annotations in the digital classroom. Hence, investment in retraining or upgrading of faculty members' skills is of immense importance.

Moreover, as compatibility was found to have a positive association with the intention to adopt, we suggest that the adoption rate for online teaching can be increased if the developers of online teaching apps can make these apps more compatible with the ways through which lecturers teach traditionally. For instance, regarding teaching mathematics, statistics, and other courses that involve more sketching, app developers and programmers should consider more engaging ways that lecturers can interact and use digital pens/markers which will closely match the traditional means of teaching.

Finally, the positive association between observability, user attitude, and adoption intention indicates that university administrators can significantly alter the attitudes toward and the adoption of online

teaching through, for example, providing detailed information about the workings of online teaching, through the university's website, partners' sites, email, and so on. Thus, training and retraining should be a continuous process as this forms the basis for observability.

Limitations and Future Research

We accept that this study has limitations despite the efforts we took to initially address them. The first limitation is that the research model may not be comprehensive enough since it only considered IDT and two psychological concepts, in the investigation of factors influencing the adoption intention of online teaching. Accordingly, we implore future research to address this concern by considering other relevant factors which may influence online teaching in universities and related environments.

In addition, given that the research evidence came from responses gathered in a single country, we cannot convincingly claim that our results are generalizable. Given the fact that, the Covid-19 was global in nature and affected almost every school in the world, taking samples from different countries would have been more ideal for generalization. This implies that further study would be needed in other settings to validate our findings to improve understanding on this timely and necessary topic. Additionally, future studies may also extend the current study to the context of high schools, given the role these schools play around the world and for the fact that they supply universities with students.

Finally, this study has provided insights on the relevance of IDT factors in explaining faculty members' decision to adopt online teaching in a developing country. We also found that attitude and institutional trust play a vital role in online teaching adoption in higher education. The implication is that both government and the top management of the higher learning institutions in developing countries such as Ghana, should work hand in hand to ensure smooth and feasible online structures for the universities. This will help ensure the continuity of academic work in the event of any similar pandemic in the future.

Appendix A

Figure 2

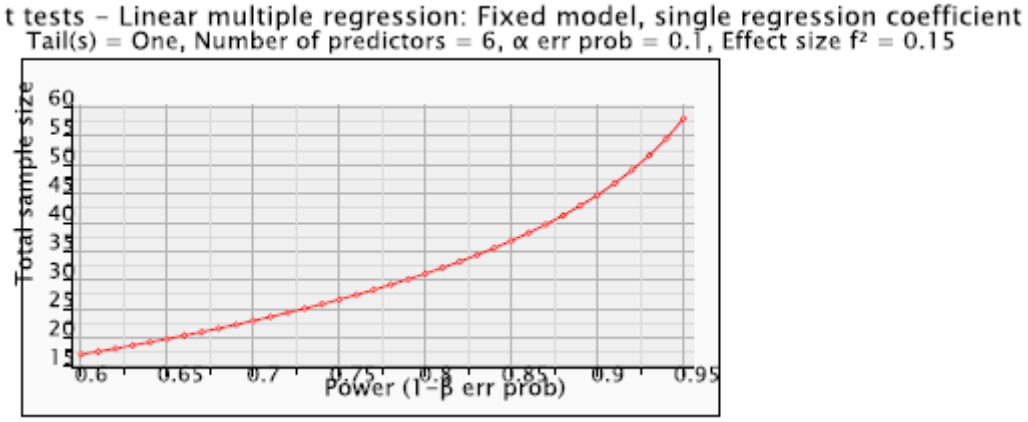

Fig. 2 Sample size calculation

Appendix B

Table 6

Table 6 Constructs and their sources

Intention to adopt online teaching (1-Strongly disagree to 5– strongly agree); adapted from Shiau and Chau (2016);
INT1: I intend to use/adopt online teaching platform during this semester because of the COVID-19 pandemic
INT2: I intend to use online teaching platform frequently for my class during this COVID-19 pandemic
Attitude towards online teaching (1-strongly disagree to 5-strongly agree); adapted from Shiau and Chau (2016););
ATT1: Using the online platform to teach my students in this season of COVID-19 pandemic is a good idea
ATT2: I like the idea of using online platform for my teaching during this COVID-19 pandemic period
ATT3: Using the online platform to teach my students in this COVID-19 pandemic period is a wise idea
Institutional trust (1-very low to 5–very high); adapted from Ciziceno and Travaglino (2019)
INST1: How would you rate your level of trust in electrical power generation agencies (VRA/GRDCO/ECG) in Ghana?
INST2: How would you rate your level of trust in the Educational agencies and Educational policy Makers (Min of Education, GES etc.) in Ghana?
INST3: What is your level of confidence in your government and its officials?
Relative advantage (1-strongly disagree to 5-strongly agree; adapted from Moore and Benbasat, (1991)
RLA1: Using online teaching platform would enable me to accomplish my teaching workload quickly during this COVID-19 pandemic
RLA2: Using online teaching platform would improve the quality of my teaching during this COVID-19 pandemic
RLA3: Using online teaching platform would make it easier for me to teach my students during this COVID-19 pandemic
RLA4: Using online teaching platform would enhance my teaching effectiveness during this COVID-19 pandemic
RLA5: Using online teaching platform gives me greater control over my class during this COVID-19 pandemic
Compatibility (1-strongly disagree to 5-strongly agree); adapted from Moore and Benbasat (1991); Shiau and Chau (2016)
CP1.Using the online teaching platform is compatible with all aspects of my teaching work in this COVID-19 pandemic period
CP2.I think that using online teaching platform in this era of COVID-19 fits well with the way I teach
CP3.Using online teaching platform fits into my working style in this era of COVID-19 pandemic
Observability (1-strongly disagree to 5-strongly agree; adapted from Al-Jabri and Sohail (2012)
OBV1: Online teaching can be conducted anytime and anywhere in Ghana in this era of the pandemic (COVID-19)
OBV2: Online teaching can be conducted anytime and anywhere when abroad/outside the country in this pandemic (COVID-19) era
OBV3: I can administer a short assessment/quiz for students' feedback during online teaching so far as COVID-19 is concerned
Complexity (1-strongly disagree to 5-strongly agree); adapted from Al-Jabri and Sohail (2012)
CPX1: Online teaching requires a lot of mental effort during this pandemic (COVID-19) era
CPX2: Online teaching requires technical skills during this pandemic (COVID-19) era
CPX3: Online teaching can be frustrating during this pandemic (COVID-19)

Appendix C

Figure 3

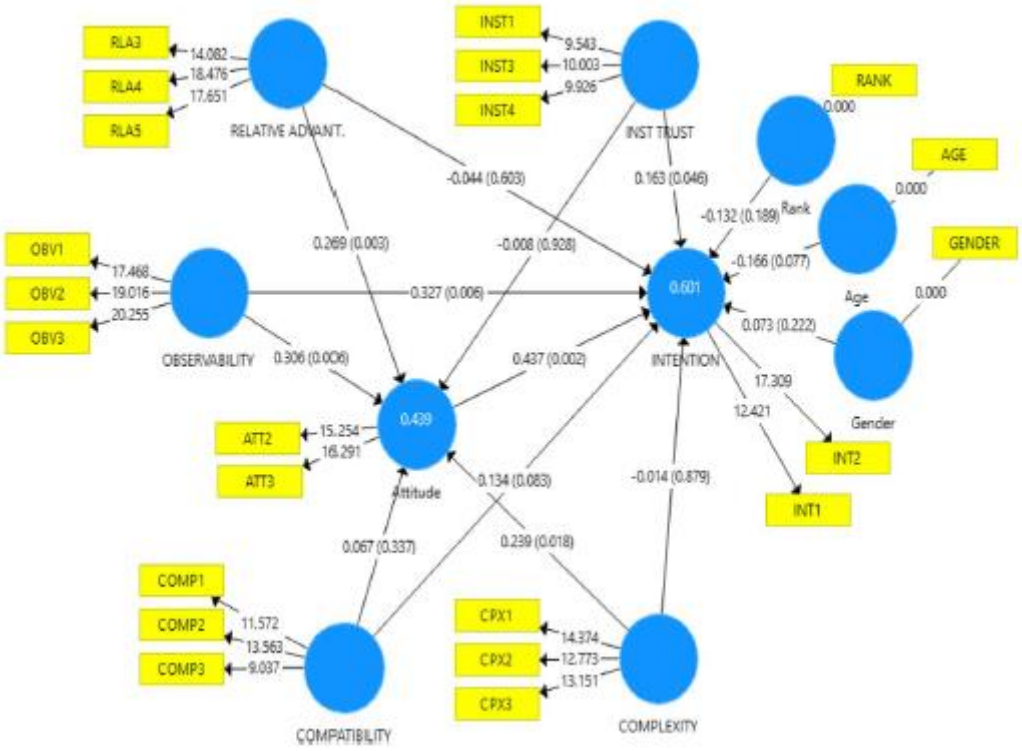

Fig. 3 Image of the structural results

References

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179-211.

Al-Jabri, I. M., & Sohail, M. S. (2012). Mobile banking adoption: Application of diffusion of innovation theory. Journal of Electronic Commerce Research, 13(4), 379-391.

Allen, I. E., & Seaman, J. (2013). Changing course: Ten years of tracking online education in the United States. Sloan Consortium.

Alomari, M., Woods, P., & Sandhu, K. (2012). Predictors for e-government adoption in Jordan. Information Technology & People. **https://doi.org/10.1108/09593841211232712**

Askar, P., Usluel, Y. K., & Mumcu, F. K. (2006). Logistic regression modeling for predicting task-related ICT use in teaching. Journal of Educational Technology & Society, 9(2), 141-151.

Bagozzi, R. P, Yi, Y., & Phillips, L. W. (1991). Assessing construct validity in organizational research. Administrative Science Quarterly, 421—458.

Beaunoyer, E., Dupéré, S., & Guitton, M. J. (2020). COVID-19 and digital inequalities: Reciprocal impacts and mitigation strategies. Computers in Human Behavior, 111, 106424. **https://doi.org/10.1016/j.chb.2020.106424**

Bélanger, F., & Carter, L. (2008). Trust and risk in e-government adoption. The Journal of Strategic Information Systems, 17(2), 165-176. **https://doi.org/10.1016Zj.jsis.2007.12.002**

Bratton, M., & Gyimah-Boadi, E. (2016). Do trustworthy institutions matter for development? Corruption, trust and government performance in Africa. Afrobarometer. **https://www.afrobarometer.org/wp-content/uploads/migrated/files/publications/Dispatches/ab_r6_dispatchno112_trustworthy_institutions_and_development_in_africa.pdf**

Carrión, G. C., Nitzl, C., & Roldán, J. L. (2017). Mediation analyses in partial least squares structural equation modeling: Guidelines and empirical examples. In Partial least squares path modeling (pp. 173-195). Springer.

Ciziceno, M., & Travaglino, G. A. (2019). Perceived corruption and individuals' life satisfaction: The mediating role of institutional trust. Social Indicators Research, 141(2), 685-701. **https://doi.org/10.1007/s 11205-018-1850-2**

DeVaney, J., Shimshon, G., Rascoff, M., & Maggioncalda, J. (2020). Higher Ed needs a long-term plan for virtual learning. Harvard Business Review/Recuperado de: **https://hbr.org/2020/05/higher-ed-needs-a-long-term-plan-for-virtual-learning**

Egger, E. M., Jones, S., Justino, P., Manhique, I., & Santos, R. (2020). Africa's lockdown dilemma: High poverty and low trust (No. wp-2020-76). World Institute for Development Economic

Ezumah, B. A. (2020). Challenges of educational technology adoption in Africa. In Critical perspectives of educational technology in Africa (pp. 69-89). Palgrave Macmillan.

Faul, F., Erdfelder, E., Buchner, A., & Lang, A. G. (2009). Statistical power analyses using G* Power 3.1: Tests for correlation and regression analyses. Behavior Research Methods, 41(4), 1149-1160.

Ghasemy, M., Teeroovengadum, V., Becker, J. M., & Ringle, C. M. (2020). This fast car can move faster: A review of PLS-SEM application in higher education research. Higher Education, 80(6), 1121.

Godefroidt, A., Langer, A., & Meuleman, B. (2017). Developing political trust in a developing country: The impact of institutional and cultural factors on political trust in Ghana. Democratization, 24(6), 906-928. **https://doi.org/10.1080/13510347.2016.1248416**

Greenberg, D., & Hibbert, P. (2020). From the editors—Covid-19: Learning to hope and hoping to learn. Academy of Management Learning & Education, 19(2), 123-130. **https://doi.org/10.5465/amle.2020.0247**

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). Multivariate data analysis (6th Ed). Pearson.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review. **https ://doi.org/10.1108/EBR-11-2018-0203**

Heitz, C., Laboissiere, M., Sanghvi, S., & Sarakatsannis, J. (2020). Getting the next phase of remote learning right in higher education. Mckensy & Company.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. International Marketing Review, 33(3), 405-431. **https://doi.org/10.1108/ IMR-09-2014-0304**

Huang, F., Teo, T., Sánchez-Prieto, J. C., García-Penalvo, F. J., & Olmos-Miguelánez, S. (2019). Cultural values and technology adoption: A model comparison with university teachers from China and Spain. Computers & Education, 133, 69-81.

Iacobucci, D. (2009). Everything you always wanted to know about SEM (structural equations modeling) but were afraid to ask. Journal of Consumer Psychology, 19(4), 673-680.

Jamshidi, D., & Kazemi, F. (2019). Innovation diffusion theory and customers' behavioral intention for Islamic credit card. Journal of Islamic Marketing. **https://doi.org/10.1108/JIMA-02-2018-0039**

Janssen, M., Weerakkody, V., Ismagilova, E., Sivarajah, U., & Irani, Z. (2020). A framework for analysing blockchain technology adoption: Integrating institutional, market and technical factors. International Journal of Information Management, 50, 302-309.

John, S. P. (2015). The integration of information technology in higher education: A study of faculty's attitude towards IT adoption in the teaching process. Contaduría y Administración, 60, 230-252. **https://doi.org/10.1016/j.cya.2015.08.004**

Jwaifell, M., & Gasaymeh, A. M. (2013). Using the innovation diffusion theory to explain the degree of english teachers' adoption of interactive whiteboards in the modern systems school in Jordan: A case study. Contemporary Educational Technology, 4(2), 138-149.

Kapoor, K. K., Dwivedi, Y. K., & Williams, M. D. (2014). Rogers' innovation adoption attributes: A systematic review and synthesis of existing research. Information Systems Management, 31(1), 74-91. **https://doi.org/10.1080/10580530.2014.854103**

Karahanna, E., Straub, D. W., & Chervany, N. L. (1999). Information technology adoption across time: A cross-sectional comparison of pre-adoption and post-adoption beliefs. MIS Quarterly, 183-213.

Kaur, K., & Rampersad, G. (2018). Trust in driverless cars: Investigating key factors influencing the adoption of driverless cars. Journal of Engineering and Technology Management, 48, 87-96.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration (ijec), 11(4), 1-10.

Kumi, E. N. (2017). The electricity situation in Ghana: Challenges and opportunities. Center for Global Development.

Laato, S., Islam, A. K. M. N., Islam, M. N., & Whelan, E. (2020). What drives unverified information sharing and cyberchondria during the COVID-19 pandemic?. European Journal of Information Systems, 29(3), 288-305.

Lai, H. M., & Chen, C. P. (2011). Factors influencing secondary school teachers' adoption of teaching blogs. Computers & Education, 56(4), 948-960.

Mohammed, W. F. (2020). COVID-19 and challenges to teacher education in rural Ghana. Retrieved from **https://africasacountry.com/2020/06/covid-19-and-challenges-to-teacher-education-in-rural-ghana**

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. Information Systems Research, 2(3), 192-222.

Ntemana, T. J., & Olatokun, W. (2012). Analyzing the influence of diffusion of innovation attributes on lecturers' attitude towards information and communication technologies. Human Technology: An

Interdisciplinary Journal on Humans in ICT Environments, 8(2), 179-197. **https://doi.org/10.17011/ht/urn.201211203034**

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879. **https://doi.org/10.1037/0021-9010.88.5.879**.

Ringle, C., Da Silva, D., & Bido, D. (2014). Structural equation modeling with the SmartPLS. Brazilian Journal of Marketing, 13(2), 56-73.

Rogers, E. M. (2003). Diffusion of innovations (5th ed.). Free Press.

Sabi, H. M., Uzoka, F. M. E., & Mlay, S. V. (2018). Staff perception towards cloud computing adoption at universities in a developing country. Education and Information Technologies, 23(5), 1825-1848. **https://doi.org/10.1007/s10639-018-9692-8**.

Shiau, W. L., & Chau, P. Y. (2016). Understanding behavioral intention to use a cloud computing classroom: A multiple model comparison approach. Information & Management, 53(3), 355-365. **https:// doi.org/10.1016/j.im.2015.10.004**.

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. European Journal of Marketing. **https://doi.org/10.1108/EJM-02-2019-0189**.

Ting, D. S. W., Carin, L., Dzau, V., & Wong, T. Y. (2020). Digital technology and COVID-19. Nature Medicine, 26(4), 459-461. **https://doi.org/10.1038/s41591-020-0824-5**.

Vishwanath, A., & Goldhaber, G. M. (2003). An examination of the factors contributing to adoption decisions among late-diffused technology products. New Media & Society, 5(4).

Wang, F. H. (2019). On the relationships between behaviors and achievement in technology-mediated flipped classrooms: A two-phase online behavioral PLS-SEM model. Computers & Education, 142, 103653.

Watts, D. J., & Dodds, P. S. (2007). Influentials, networks, and public opinion formation. Journal of Consumer Research, 34, 441—458.

WHO (2020). WHO Director-General's opening remarks at the media briefing on COVID-19—11 March 2020. March 11, 2020. **https://www.who.int/dg/speeches/detail/whodirector-general-s-opening-remarks-atthe-media-briefing-on-covid-19—11-march-2020. Accessed 1 Apr 2020**

Xie, Q., Song, W., Peng, X., & Shabbir, M. (2017). Predictors for e-government adoption: Integrating TAM, TPB, trust and perceived risk. The Electronic Library, 35, 2—20. **https://doi.org/10.1108/ EL-08-2015-0141**

Zhang, X., Yu, P., Yan, J., & Spil, I. T. A. (2015). Using innovation diffusion theory to understand the factors impacting patient acceptance and use of consumer e-health innovations: A case study in a primary care clinic. BMC Health Services Research, 15(1), 71.