



Emergency e-learning acceptance in second-cycle institutions in Ghana: a conditional mediation analysis

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Abstract

This paper investigates the determinants that will influence students' acceptance of the electronic learning (e-learning) system of education after the COVID-19 emergency. Specifically, the paper assesses the attitudes and intentions of students in second-cycle institutions to accept e-learning after the pandemic, using constructs derived from the health belief model and technology acceptance model. Also, we test if there is any significant difference in the attitudes and intentions of students in public and private institutions. Using data collected from 370 students in upper and lower levels of a second-cycle institutions in Ghana, we found that student attitude is significantly influenced by perceived usefulness and moderately affected by perceived severity, whereas, student's intention is moderately affected by the perceived severity but substantially influenced by the student's attitude towards usage. Also, the results revealed that students' attitudes and intentions to use e-learning are moderately affected by the severity of the ongoing COVID-19 pandemic. Finally, there were no significant differences in the attitudes and intentions of the sampled students in public and private second-cycle institutions in Ghana, regarding their acceptance and usage of e-learning after the COVID-19 emergency. Given the study's findings, the paper concludes that students' attitudes and intention to use e-learning are the main determinants that will influence the students' acceptance of the e-learning system of education in second-cycle institutions in Ghana after the COVID-19 emergency. The paper contributes to knowledge by providing evidence of students' acceptance of the e-learning system of education after the COVID-19 emergency in the context of a developing country like Ghana.

Keywords e-learning · COVID-19 · Perceived severity · Attitude and intentions to use · Perceived usefulness · Second-cycle institutions in Ghana · Perceived Ease of Use

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Introduction

Electronic Learning (e-learning) is becoming more popular as a type of education due to its accessibility, practicability, and affordability (Shevchenko et al. 2021). E-learning is the use of network technology to design, deliver, select, administer, and extend learning across geographical locations to improve learning (Kulikowski et al. 2021; Sułkowski 2020). E-learning systems can be used to deliver education either in asynchronous, synchronous, or hybrid mode to learners (Yawson and Yamoah 2020). E-learning systems offer several benefits including the ability to allow learners to access content from every location. Learners do not need to be physically present in class to receive instructions, thereby saving time and money (Chen et al. 2020; Li et al. 2020). Other benefits include scalability, consistency, and personalization (Al-Harbi 2011). These benefits made e-learning systems the preferred choice during the emergency created by the COVID-19 pandemic (Roman and Plopeanu 2021).

In the first quarter of 2020, the COVID-19 (novel coronavirus disease 2019) pandemic swept through the world and affected global socio-economic activities. The pandemic led to the closure of schools at all levels across the continent and in Ghana between March 2020 and February 2021 (GES 2020). The academic schedules of schools were disrupted and had to be adjusted (Demuyakor 2020). The extent of disruptions in the educational sector was also unprecedented (Azoulay 2020; Demuyakor 2020). Educational institutions at the tertiary levels had to migrate the teaching and learning processes to e-learning systems for continuity (Demuyakor 2020; Hoq 2020; WHO 2020). The disrupted academic calendar was quickly revised for academic activities to resume in those institutions with e-learning systems in place. Academic activities including lectures, assignments, quizzes, assessments, seminars, and workshops were all organized on e-learning platforms (Almaiah et al. 2020). Some tertiary institutions integrated video conferencing and recording capabilities into their e-learning systems to deliver live and interactive lectures (Dhawan 2020; Purwanto and Tannady 2020). By the end of October 2020, the major public universities and some private Universities in Ghana that adopted the use of e-learning systems had completed the academic year and organized virtual graduation ceremonies. These institutions had e-learning systems in place before the outbreak of the pandemic. However, the severity of the COVID-19 pandemic called for a complete switch of the teaching–learning process to e-learning systems overnight (Liguori and Winkler 2020).

This emergency adoption of e-learning systems means that institutions that did not have the needed e-learning infrastructure in place had to improvise and this was largely the case across institutions in developing countries including Ghana. A 2015 study conducted by Wong and Huang (2015) on e-learning systems found limited usage in developing countries in Africa. In Ghana, the majority of second-cycle institutions in Ghana did not have e-learning systems in place before the pandemic. The second-cycle institutions in Ghana mainly relied on a face-to-face approach to teaching and learning and did not consider the implementation of e-learning. Consequently, when COVID-19 struck, all second-cycle institutions

in the country had to close down for several months to re-strategize on ways to resume the teaching–learning process. The emergency created by the COVID-19 pandemic, therefore, forced all institutions including second-cycle institutions that wanted to avoid the disruption of the teaching–learning process irreversibly, to migrate to e-learning systems for continuity.

The decision to accept and use e-learning systems is generally motivated by the institutions' readiness to move academic activities to e-learning systems, the students' and teachers' attitudes, and intentions to accept and use e-learning (Nikou and Economides 2017; Wongwatkit et al. 2020). However, the severity of the pandemic forced educational institutions at all levels to migrate to e-learning platforms whether ready or not ready. Students and teachers had to endure the challenges that come with emergency technology adoption. Educational institutions at all levels either have to look for ways to circumvent these challenges or risk missing several weeks and months as the COVID-19 pandemic rages on. What is not clear in this emergency acceptance and use of e-learning systems is whether the institutions, students, and teachers would continue the usage after the emergency created by the pandemic.

This paper, therefore, investigates the determinants of students' acceptance and use of e-learning systems after the COVID-19 emergency. Specifically, the paper assesses students' attitudes and intention to accept the e-learning system of education, using constructs derived from the health belief model (HBM) and Technology Acceptance Model (TAM). Also, the moderating effects of the perceived severity of the COVID-19 pandemic on the relationship between these constructs and students' intentions to accept e-learning systems are examined. Lastly, it determines if there will be any significant differences in the attitudes and usage intentions of student groups in public and private schools. The paper provides valuable information for policy design and planning to stakeholders in the educational sector as they continue to explore safe and effective ways to continue education in second-cycle institutions after the COVID-19 emergency. It is also one of the first to present the perspectives of students regarding the use and adoption of e-learning systems in second-cycle institutions.

The rest of the paper is structured as follows: the next section discusses research questions, the theoretical framework and hypotheses development. This is followed by the methods applied in the study. Next, the results will be presented and discussed in relation to the objectives of the study. Given the results of the study, implications for practice and future research possibilities are put forward.

Research questions

The key research question to be addressed by this study is: *what are the determinants that will influence students' acceptance of the e-learning system of education after the COVID-19 emergency?* To address the main research question of the study, the following sub research questions are considered:

- What are the effects of the study's construct (perceived severity, perceived usefulness, Perceived Ease of Use) on students' attitudes and intention to accept e-learning?
- What are the moderating effects of the perceived severity of the COVID-19 pandemic on the relationship between the study's constructs and students' intentions to accept e-learning systems?
- IS there any significant difference in the attitudes and usage intentions of student groups in public and private schools?

Ghana's response to the COVID-19 educational disruptions

When the first case of COVID-19 was reported in Ghana in March 2020, educational institutions at all levels had to move their operations to e-learning systems due to the imposed restrictions and closure of schools. Electronic learning systems adoption and use before the pandemic were only available in tertiary institutions and some private basic schools in Ghana. There was, however, limited or nothing to show in the second-cycle institutions. A study by Adarkwah (2021a, b) reported the lack of funds, infrastructure, effective e-learning systems, and ICT gadgets as the factors that impede the adoption of online learning in most developing countries. Ghana, like many other developing countries, faced some challenges including the lack of funds; hence the limited adoption of e-learning in second-cycle institutions.

The adoption rate in tertiary institutions is relatively high as compared to the pre-tertiary level (Sarpong et al. 2021). The institutions at the tertiary level can generate enough funds internally and are therefore able to fund capital-intensive projects like acquiring and setting up information and communication technology (ICT) systems needed for e-learning implementation. In addition, some tertiary institutions can obtain funding through research grants and donations from organizations. As a result, some institutions at the tertiary level were able to implement e-learning systems to reinforce the traditional face-to-face classroom learning before COVID-19. Teaching materials, assignments, and quizzes were delivered to students through e-learning systems. Students also submitted assignments and engaged in class discussions using the 'discussion forum' feature provided by the system. Some tertiary institutions integrated video conferencing features such as the Zoom and the Big-Blue button that enabled the delivery of live lectures to students. Therefore when COVID-19 struck and onsite instruction was suspended in March 2020, some tertiary institutions with e-learning systems in already place were able to continue and complete the academic calendar. These institutions simply moved to their already existing e-learning systems to complete the academic year. However, the majority of the tertiary institutions had no e-learning systems in place (Adarkwah 2021a).

At the pre-tertiary level, some private basic schools that made adequate investments into the implementation of e-learning systems to support the traditional classroom teaching were also able to complete the academic calendar. Before COVID-19, these basic schools implemented e-learning systems to provide extra tuition for their students in the evening, on weekends, and during vacation. Therefore, with the

closure of schools due to the pandemic, these private schools continued the rest of the academic year on the existing e-learning systems.

However, the COVID-19 engineered e-learning implementation in tertiary institutions in Ghana (particularly in the public universities and few basic schools) was not without challenges. The National Union of Ghana Students (NUGS) described it as “challenge-ridden online learning” and as a result, appealed to the government to stop the implementation (Anyorigya 2020). The implementation was challenged with “inadequate bundle incentives for lecturers and students, lack of properly laid framework for the implementation of online learning, and the plight of needy students who have been left out of the online learning platforms because of their inability to settle school bills” (Adarkwah 2021b, p. 1668). Also, within the public technical universities sector, Sarpong et al. (2021) found the lack of access to devices, unreliable internet connectivity, and inability to afford the cost of internet data as challenges that hindered the implementation process. Similarly, data from the Afrobarometer Round 8 (2019) survey in Ghana suggest that many students, especially, those living in rural or poor households.

will find it difficult or impossible to participate in the e-learning initiatives due to the lack of access to the required devices, poor internet connectivity, or lack of access to electricity (Dome and Armah-attoh 2020).

The situation was, however, different at the second-cycle level where there was limited implementation of e-learning systems before the outbreak of COVID-19. Although the goal of the ICT for Accelerated Development (ICT4AD) in 2003 was to transform Ghana into information and technology-driven high-income economy through “education any- time anywhere for everyone” (Ministry of Education 2015), this goal is yet to be realized. Schools in Ghana, especially at the second-cycle levels are faced with challenges that hinder the realization of the goal of the ICT4AD policy. These challenges include funding, lack of access to ICT resources and electricity (Adarkwah 2021b; Dome and Armah-attoh 2020). This level of Ghana’s educational system is dominated by schools and institutions established and funded solely by the government. These schools receive very little funding and cannot afford the high cost of acquiring the needed ICT equipment for e-learning systems implementation. Some schools at this level do not have well-resourced computer laboratories for ICT lessons. Some rely on the benevolence of individuals and parent-teacher associations (PTAs) for teaching and learning materials. Accordingly, the impact of COVID-19 was significantly severe in secondary level education in Ghana. Almost all second-cycle institutions in Ghana had to defer the academic calendar because there was no means to continue. Academic activities were halted and the academic calendar was delayed for several months. As a result, the Ghanaian government, through the Ministry of Education (MoE) and the Ghana Education Service (GES), established virtual learning platforms. The implementation featured television (Ghana Learning TV) and online (icampus) programs, as well as a radio reading program, to allow students to continue studying core subjects including mathematics, English, science, and social sciences, as well as selected electives (Dome and Armah-attoh 2020). These platforms did not allow live teacher-student interactions and provide limited mechanisms for receiving feedback. This type of e-learning was therefore not effective to address the educational needs of learners during the

pandemic. The introduction of a more robust learning management system for educational continuity, at the second-cycle level, was thus needed, especially for final year (form 3) students who were preparing for the West Africa Senior School Certificate Examination (WASSCE).

The situation of the final year students at the second-cycle institutions during the COVID-19 lockdown, closure of schools, and the subsequent implementation of online learning were however different from other students across second-cycle institutions. The final year students in second-cycle institutions were the most affected group of students. While students in other levels could afford to relax until the government eases the COVID-19 restrictions, the final year students could not do the same due to the impending external examinations (i.e. WASSCE), which require the completion of the course syllabus and adequate preparation by the students. These students had limited time and were in dire need of effective e-learning systems to resume academic work. Consequently, the students did not have a choice other than to accept the emergency COVID-19 engineered e-learning systems with all its problems. What is, however, not clear is whether the students will continue to accept the e-learning system of education post-COVID-19. Considering the challenges faced by the second-cycle institutions during the period of the emergency e-learning adoption, there is the need to examine the factors that will influence students' acceptance of the e-learning system of education after the COVID-19 pandemic for policy recommendations.

Theory and hypotheses development

In the formulation of a theoretical framework for this study, the HBM and TAM were considered. The choice for TAM was due to its general acceptance and wide application in information systems research for studying users' acceptance behaviours (Lee et al. 2011; Gefen and Larsen 2017). The HBM was also selected due to the severity of the ongoing health crisis (i.e. COVID-19 pandemic). The HBM posits that people will take action to prevent illness if they regard themselves as susceptible to a condition (perceived susceptibility), if they believe it would have potentially serious consequences (perceived severity), if they believe that a particular course of action is available to them would reduce the susceptibility or severity or lead to other positive outcomes (perceived benefits), and if they perceive few negative attributes related to the health action (perceived barriers).

According to Chuttur (2009), the constantly growing demand for technology advancement in the 70s and the unprecedented failure of technology adoption in many countries was the center of attraction for many researchers but the majority of the research carried out failed. This led Davis to propose the TAM (David 1985) which was grounded on Fishbein and Ajzen's (1975) Theory of Reasoned Action. TAM was developed to predict, explain and understand users' motivation toward technology or system adoption (Chuttur 2009). Since then TAM has been demonstrated to be a theoretical model for assessing users' attitudes and behavioural intentions toward technology or system adoption (Brandon-Jones and Kauppi 2018). TAM postulates that the most important indicator of actual system use is the user's

behavioural intention (Davis 1989). This is also influenced by Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU describes the extent to which a user believes that the usage of a system will directly improve productivity (Davis 1989), while PEOU describes the extent to which a user considers the usage of a system as effortless (Davis 1989). Further, TAM posits that PU is directly impacted by PEOU for the reason that when users find a system easier to use, they will as well find it useful. Finally, TAM is preferred over other research models because of its scientific parsimony and rigour (Venkatesh and Davis 2000; Lee et al. 2011). Researchers have simplified TAM by removing the attitude construct found in TRA from the current specification (Venkatesh et al. 2003). Attempts to extend TAM have generally taken one of three approaches: (1) by introducing factors from related models, (2) by introducing additional or alternative belief factors, and (3) by examining antecedents and moderators of Perceived Usefulness and Perceived Ease of Use (Wixom and Todd 2005). In their paper, Gefen and Larsen (2017) demonstrated that TAM's construct relationships primarily emerge from semantic relationships between its questionnaire items. The constructs of the study are discussed next.

Perceived Usefulness

Perceived Usefulness (PU) is one of the two main constructs of the original TAM. Together with Perceived Ease of Use, PU determines the behavioural intentions of users. PU describes the belief that the use of technology will directly enhance productivity (Liu et al. 2009; Abdullah et al. 2016). Davis (1989) explained in the original TAM that PU significantly affects users' attitudes towards the use of technology. This is corroborated in several studies that applied the TAM or its extensions. Consistent with the postulations of TAM, Al-Harbi (2011), Rizun and Strzelecki (2020), and Wu and Chen (2017) found that PU is a strong predictor of Attitude Towards Use. On the back of these findings, we hypothesize that:

H1 PU will positively affect students' attitudes towards the acceptance of the e-learning system of education after the COVID-19 pandemic.

Perceived Ease of Use

Perceived Ease of Use (PEOU) is one of the constructs of TAM, which postulates that the best determinant of users' behaviours is their intentions, which are also affected by PEOU and PU. PEOU refers to the consideration that the usage of a system will be effortless (Davis 1989). According to the TAM, PEOU directly affects PU for the reason that when users see a system to be effortless, they are likely to see it as beneficial. Thus, when users find technology to be useful and easy to use, they are likely to develop a positive attitude towards usage.

Several research studies have found that PEOU has a positive effect on attitude towards the use of technology. In a study to discuss the factors that influenced e-learning adoption in higher education institutions in Saudi Arabia, Al-Harbi (2011) found that PEOU explains a significant percentage of the variance in

students' attitudes towards e-learning acceptance. His study found that PEOU has a stronger effect on attitude towards technology adoption. Additionally, Gefen and Larsen (2017) and Rizun and Strzelecki (2020) found that PEOU is a strong factor that affects attitude towards technology. Contrary to these findings, Wu and Chen (2017) found a rather weak effect of PEOU on attitude and explained that e-learning platforms are relatively easier to use. As a result, PEOU becomes an important factor for consideration among a list of factors that influence attitude. We, therefore, hypothesize that:

H2 PEOU will significantly influence students' attitudes towards the acceptance of the e-learning system of education after the COVID-19 pandemic.

H3 PEOU will be positively affected by perceived usefulness.

Health belief model

The HBM is a social psychological health behaviour change model that was designed to explain and predict health-related behaviours, particularly health care utilization (Janz and Becker 1984; Rosenstock 1974). The HBM was established in the 1950s by social psychologists at the United States Public Health Service and is now one of the most well-known and commonly utilized theories in health behaviour research (Janz and Becker 1984). According to the HBM people will take action to prevent illness if they believe they are susceptible to it (perceived susceptibility), if they believe it will have potentially serious consequences (perceived severity), and if they believe a particular course of action available to them will reduce susceptibility or severity or lead to other positive outcomes (perceived benefits) (Boon Yuen et al. 2009; Carpenter 2010; Janz and Becker 1984; Jones et al. 2015; Rosenstock 1974; Sreelakshmi and Prathap 2020a, b). The HBM originally has five main constructs, namely: perceived susceptibility, perceived severity, health motivation, perceived benefits, and perceived barriers. The combination of perceived severity and perceived susceptibility is referred to as a perceived threat. Therefore, this study applies perceived severity to assess its additive impact on students' attitudes and intentions to accept e-learning after the pandemic.

Perceived severity of the COVID-19 pandemic

Perceived severity is described as "how threatening the condition is to the person" (Champion 1984; Sreelakshmi and Prathap 2020a, b). Researchers have evaluated perceived severity in a variety of research context; Abdullah et al. (2020) confirmed that perceived severity significantly influence human choices. Also, Melznera et al. (2014) combined the constructs of the unified theory of acceptance and use of technology (UTAUT) and theory of planned behaviour (TPB) with perceived severity (HBM) in a framework to examine the users' acceptance of mobile health applications. Similarly, Wei et al. (2020) combined perceived severity with the constructs

of UTAUT to examine the factors affecting acceptance of fitness mobile applications and confirmed the indirect impact of perceived severity constructs on usage intention. Further, Zhao (2017) confirmed a significant effect of perceived severity on users' intention to adopt the technology. Zhang et al. (2019) extended the UTAUT model to study the factors affecting the usage of diabetes management applications and found a significant effect of the HBM construct of perceived severity on the adoption of technology.

The outbreak of COVID-19 as confirmed in Wuhan, China at the beginning of 2020 has spread to almost every corner of the world and has created vast havoc around the globe (WHO 2020). World Health Organization declared it a pandemic on March 11, 2020. The outcome of the pandemic influences behaviour of an individual (Kok et al. 2010). Some studies were conducted in different places to analyse the influence of age and gender over the behavioural response and showed that older people and women take more preventive measures to fight against the pandemic than others (Quah and Hin-Peng 2004). While, in contrast to the previous study, the other study conducted in the Netherlands showed no association between age and taking preventive measures (Brug et al. 2004). Basilaia and Kvavadze (2020) stated that the transition from traditional to online setup during the COVID-19 pandemic was successful though, to ensure the quality of learning further research is required. Saxena et al., (2021) found that the perceived benefits of maintaining social distance during the COVID-19 pandemic partially moderate the relationship between e-learning quality and student satisfaction. In all cases reported in the previous studies, e-learning was planned and accepted by the learners before enrolment. However, because the present pandemic has compelled students to adopt e-learning, the factors that will influence students' acceptance of e-learning after the pandemic will differ (Hodges et al. 2020). The gap between planned e-learning and forced e-learning has not made a good impression on the large general public about online education in general (Gacs et al. 2020). The perceived severity of this pandemic may influence the students' intention and attitude while using the e-learning system. Technology acceptance will also be influenced by the perception of the severity of this infection. PEOU and PU were both affected by external variables in past research (Abdullah et al. 2016). The study will examine the moderating influence of the external variable 'perceived severity of the COVID-19 pandemic' on the constructs of TAM, student attitude, and intentions to use e-learning. Basing on this, we hypothesize that:

H4 Perceived severity of the COVID-19 pandemic will have a significant effect on students' attitudes towards the acceptance of e-learning systems in the future.

H5 Perceived severity of the COVID-19 pandemic will positively affect students' intentions to accept e-learning systems in the future.

Attitude and intentions to use e-learning

Attitude towards action is characterized as the certainty or otherwise of individual acting. It is addressed by evaluating the individual's feelings regarding the results

developing from the action and assessing the appropriateness of the results. Overall attitude can be generally evaluated as the total of the actual results compounded by the appropriateness appraisals for every single predictable result of the action.

In some studies, user attitude demonstrates a positive effect on intentions to perform an act. In these studies (Amankwa et al. 2018; Ifinedo 2014; Rizun and Strzelecki 2020; Safa et al. 2016), attitude was found to have a significant influence on behavioural intentions. Purwanto and Tannady (2020) also confirmed that attitude influences behavioural intentions to e-learning. This finding was corroborated by Rizun and Strzelecki (2020). However, in a few studies, attitude showed no significant effect on intentions. (Masrom 2007) study, for instance, found that attitude did not affect college students' intention to use e-learning. Nonetheless, following the postulations of the TPB, the following hypothesis is put forward:

H6 Attitude towards e-learning will positively affect students' intentions to accept e-learning systems after the COVID-19 pandemic.

Moderating effect of perceived severity of COVID-19 pandemic

The COVID-19 pandemic which began in China has extended to nearly every country around the globe and has since generated immense mayhem for governance and the daily lives of the ordinary citizen (WHO 2020). EdTech (2020) investigated the severity of the COVID-19 pandemic on education in Africa. Their survey, which involved 1650 respondents from 52 African countries, reported that 97% of schools in African countries are closed due to the severity of the pandemic and the rate at which it is spreading globally (EdTech 2020). Furthermore, 1393 (92%) of the respondents agreed that it is necessary to close down the schools due to the severity of the pandemic (EdTech 2020). In line with this, students are forced to rely on e-learning platforms for the continuation of their studies (Baber 2020). The consideration of the perceived severity of COVID-19 (PSC) in the study is to investigate if it causes significant differences in the relationship between the constructs of the study. We, therefore, hypothesize that:

H2a Perceived severity of COVID-19 will have a moderating influence on the relationship between perceived ease of use and students' attitude towards e-learning systems acceptance.

H6a Perceived severity of COVID-19 will have a moderating influence on the relationship between students' attitudes and intentions to accept e-learning systems.

Multi-group analysis: private and public schools

Public and private schools differ in terms of infrastructure, specifically ICT and other resources. Private second-cycle institutions are usually equipped with robust ICT infrastructure for e-learning implementation. As a result, e-learning systems are used to augment face-to-face classroom delivery. This establishes positive attitudes

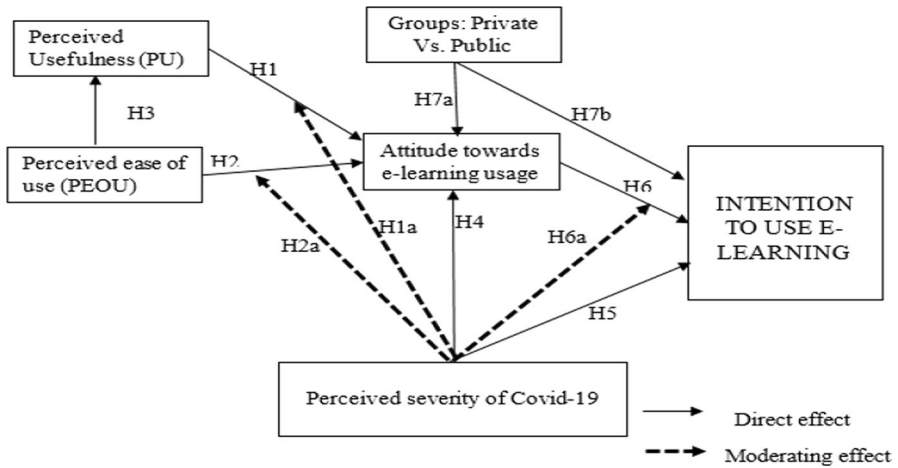


Fig. 1 Research model

in students from private schools in relation to e-learning usage. However, this is not the case in public schools where there is a lack of the requisite ICT resources for e-learning adoption. The majority of the students in public schools will never have a shot at e-learning systems during the period of their studies. We, therefore, hypothesize that:

H7a The effects of the factors on attitude towards e-learning acceptance after the COVID-19 emergency will differ across student groups.

H7b The positive effect of attitude on intentions to accept e-learning after COVID-19 will differ across the two groups.

Basing the discussions and hypotheses above, the research model in Fig. 1 is developed for the study.

Materials and methods

Population and sample

The scope of this study is within the Ghanaian context focusing on second-cycle private and public institutions in Ghana. The Ghana Education Service (GES) categorizes second-cycle institutions in Ghana into senior high schools (SHS) and technical and vocational education training institutes (TVET) (GES 2020). The study’s population involved students of three-second-cycle institutions from the technical and vocational institutes, the public and private senior high schools in Ghana. These students are either in the lower or upper levels of the selected second-cycle institutions.

The reason for the selection is that e-learning is sparingly used by students in these institutions in Ghana. Moreover, the selected schools have the full complement of programmes, teachers, and students for a typical second-cycle institution. Academic programmes available in the three selected institutions include science, general arts, visual art, business, home economics, Fashion Design Technology, Electrics Engineering, and Mechanical Engineering Technology. The population is estimated at 6250 students. Yamane's (1967) sample size formula ($n = N/(1 + N e^2)$) was applied to select a sample of 375 students who were randomly selected from the lower and upper levels of three-second-cycle institutions in Ghana.

Data collection

A quantitative approach involving the use of a questionnaire was applied to collect data from 375 students in the lower and upper levels of the three selected second-cycle institutions in Ghana. The questionnaire was pilot-tested on a cross-section of secondary school students. This was done to ensure that difficult, confusing, ambiguous, and misleading questions are corrected. After this, the final questionnaire was printed.

The researchers after seeking the needed permission from gatekeepers of the selected schools distributed the final questionnaire to the students with the assistance of their teachers. The researchers could not get physical access to the students due to the COVID-19 pandemic and the subsequent policy to prevent visitors to the schools. Teachers were given copies of the printed questionnaires to assist with data collection. The completed questionnaires were returned to the researchers after one month.

In the final analysis, 370 valid responses collected from students in upper and lower second-cycle institutions in Ghana were considered after dropping five (5) incomplete responses from the dataset.

Scale of measurement

The measurements scaled items for the constructs Attitude Towards Use (ATU), Behaviour Intentions to Use (BIU), Perceived Usefulness (PU), and Perceived Ease of Use (PEOU) were adopted from (Coman et al. 2020) whereas items for Perceived severity of COVID-19 (PSC) were adopted from prior literature (Baber 2020, 2021; Sreelakshmi and Prathap 2020a, b). The items for the study were measured on a 5-point Likert scale ranging from Strongly Disagree (1) to Strongly Agree (5). Furthermore, the study utilized multiple measurements for each construct to get rid of the various limitations associated with high measurement dimension inaccuracies or errors of a single item. A single measurement

item has a limitation in that it is highly defined to capture all the elements or attributes of a particular construct in a study.

Data analysis approach

The partial least squares-structural equation modelling (PLS-SEM) technique involving the use of the SmartPls software developed by Ringle et al. (2015) was applied for data analysis in this study. This approach was selected due to the smaller sample size of the study (Chin et al. 2003; Hair et al. 2011a, b; Wong 2013). The study conducted an outer model evaluation to test reliability and validity and an inner model evaluation to test the hypotheses.

Results

This study was set out to investigate the determinants of students' acceptance and use of e-learning systems during the COVID-19 pandemic. Students of three-second-cycle institutions in Ghana were surveyed using an online questionnaire and the results of the PLS-SEM data analysis are discussed in the sections that follow.

Respondents' demographics

A total of 370 valid questionnaire responses were used in the final analysis after dropping five (5) incomplete responses. Table 1 summarizes the respondents' demographic information in terms of age, gender, class, and school type.

From Table 1, 175 of the respondents were selected from private second-cycle institutions and the remaining 195 were from the public second-cycle institutions.

Table 1 Respondents demographic characteristics

Variable	Characteristics	<i>N</i>	%	Mean ± SD
Gender	Male	190	51.4	
	Female	180	48.6	
Age	11–14 years	108	29.2	
	15–18 years	247	66.8	1.75 ± .52
	Above 18 years	15	4.1	
Form	Form 1	105	28.4	
	Form 2	150	40.5	
	Form 3	115	31.1	
School type	Public	195	52.7	
	Private	175	47.3	

Table 2 Indicator loadings and extracts of survey questions

Authors	Indicator	Items descriptive statistics	Items	Mean ± SD	Skew (Kurt)	Factor loadings (γ)/95% CI]	Outcome
	Perceived ease of use						
	PEOU_1		I believe e-learning systems are easy to use	3.75 ± 1.19	- 0.61 (- 0.71)	0.992	Significant
	PEOU_2		I believe interacting with the e-learning systems will require less mental efforts	1.78 ± 1.09	- 0.94(.25)	0.341	Dropped
	PEOU_3		I believe interacting with e-learning systems will NOT be frustrating	3.78 ± 1.09	- 0.04(- 0.85)	0.981	Significant
	PEOU_4		I believe I will need less assistance from friends and teachers whenever I want to use e-learning systems	3.75 ± 1.17	- 0.67(- 0.66)	0.990	Significant
	PEOU_5		Overall, I believe e-learning systems will be easy to use	4.09 ± 6.76	2.84 (- 0.17)	0.072	Dropped
	Perceived usefulness						
	PU_1		I believe e-learning systems will save me money from the time and cost of travelling to school	4.01 ± .76	2.88 (- 1.17)	0.972	Significant
	PU_2		I believe e-learning systems will be of significant benefit to me	5.78 ± 1.09	2.04 (- 0.85)	0.411	Dropped
	PU_3		I believe e-learning systems will make it easier for me to access education from the comfort of my home	.28 ± 1.09	1.84 (- 0.85)	0.363	Dropped
	PU_4		I am satisfied with the services available on e-learning systems	3.83 ± .76	1.89 (- 1.03)	0.937	Significant
	PU_5		Overall, I find e-learning systems to be useful	4.11 ± .76	3.94 (- 1.37)	0.951	Significant
	Perceived severity of Covid-19						
	PSC_1		If anyone gets infected with the COVID-19, the results will be severe.	3.81 ± .88	0.56 (- 0.69)	0.958	Significant
	PSC_2		If anyone gets infected with the COVID-19, the results will be risky	3.92 ± .75	2.28 (- 1.06)	0.960	Significant
	PSC_3		If anyone gets infected with the COVID-19, he/she won't be able to manage daily activities	3.97 ± .82	1.02 (- 0.78)	0.974	Significant

Table 2 (continued)

Authors	Indicator	Items descriptive statistics	Mean ± SD	Skew (Kurt)	Factor loadings (γ)/95% CI]	Outcome	
	PSC_4	I think the COVID-19 pandemic is so severe therefore, I intend to use e-learning systems	3.94 ± .87	2.11 (- 1.14)	0.982	Significant	
	Attitude towards E-learning usage						
	ATU_1	During COVID-19, I feel e-learning will be useful	3.81 ± .88	0.56 (- 0.69)	0.987	Significant	
	ATU_2	I am likely to use e-learning during the COVID-19 pandemic due to fear of contracting the virus in school	5.81 ± .82	2.66 (- 0.99)	0.387	Dropped	
	ATU_3	In my view, it would be desirable to use e-learning during COVID-19 rather than traditional face-to-face education	8.90 ± .89	2.47 (- 0.03)	0.517	Dropped	
	ATU_4	During COVID-19, I feel that e-learning will be the most efficient means to receive education	4.13 ± .71	4.26 (- 2.15)	0.474	Dropped	
	ATU_5	I am willing to use e-learning during the COVID-19 pandemic	4.07 ± .77	2.48 (- 1.21)	0.987	Significant	
	Behavioral intention to use						
	BIU_1	I intend using e-learning for receiving course instructions during COVID-19	3.99 ± .81	1.37 (- 1.03)	0.977	Significant	
	BIU_2	I intend to use the e-learning for submitting all my assignments during COVID-19	4.13 ± .71	3.26 (- 1.15)	0.974	Significant	

Table 3 Constructs reliability and validity

Constructs	CR/ <i>a</i>	AVE	ATU	BIU	PU	PEOU	PSC
Attitude Towards Use (ATU)	0.987/.973	0.974	0.987				
Behaviour Intentions to Use (BIU)	0.975/.949	0.951	0.95	0.975			
Perceived Usefulness (PU)	0.968/.950	0.909	0.97	0.966	0.953		
Perceived Ease of Use (PEOU)	0.992/.987	0.976	0.874	0.881	0.903	0.988	
Perceived Severity of Covid-19 (PSC)	0.984/.978	0.938	0.96	0.947	0.947	0.941	0.968

This shows a balanced representation of students from public and private institutions for the analysis in the study.

Measurement model test: validity and reliability

The measurement model also called the outer model represents the relationships between the observed data and latent variables (unobservable variables). The outer measurement model is essential for assessing the reliability and validity levels of a study's constructs. In this study, the measurement model was tested using confirmatory factor analysis. The study considered factor loading, composite reliability (CR), average variance extracted (AVE), and Fornell–Larcker Criterion, for assessing the validity and reliability of the study's constructs (Hair et al. 2020).

To ensure the reliability of the instrument, indicator loadings and CR values for each construct should be 0.7 or higher (Hair et al. 2011a, b, 2020; Sarstedt et al. 2016; Wong 2013). Items that had values less than the 0.7 threshold were dropped in the final analysis. The loadings, in the final analysis, ranged from 0.937 to 0.992 and 0.968 to 0.992 for indicator loadings and CR values, respectively. This indicates the achievement of internal consistency reliability in this study. Tables 2 and 3, respectively, show the indicator loadings and CR values.

For validity, the values of the AVE for each construct should be 0.5 (50%) or higher (Hair et al. 2020).

From Table 3, the AVE values for the current study range from 0.909 to 0.974, confirming the achievement of convergent validity. However, discriminant validity is demonstrated when the shared variance within a construct (AVE) exceeds the shared variance between the constructs. The table also shows the assessment of discriminant validity using the Fornell–Larcker criterion. From Table 3, discriminant validity is also confirmed since the AVE values are higher than the shared variance between the constructs. The overall results of the measurement model, therefore, show that the instruments were valid and reliable for this study.

Structural model test: hypotheses testing and multi-group analysis

This study utilized the values of path coefficients (β) and squared R (R^2) to present information about the path significance of hypothesized relationships. The strength

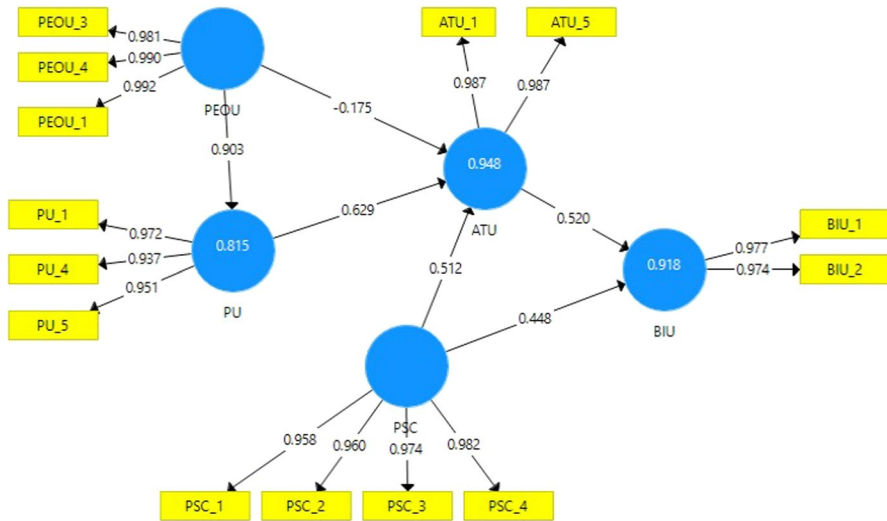


Fig. 2 Results of the PLS-SEM analysis

of the relationship is specified by the values of the path coefficients. Figure 2 presents the summarized results of the PLS-SEM data analysis using SmartPls version 3.2 software.

From the results of the SEM data analysis presented in Fig. 2, the coefficient of determination, R^2 , value for the Attitude Towards Use endogenous latent variable is 0.948. This means that the three latent variables (Perceived Ease of Use, Perceived Usefulness, and perceived severity of COVID-19) substantially explain 94.8% of the variance in Attitude Towards Use. Additionally, Attitude Towards Use and perceived severity of COVID-19 together explain 91.8% of the variance in behavioural intentions to use e-learning systems during the COVID-19 pandemic. Also, Perceived Usefulness explains 81.5% of the variance in Perceived Ease of Use. This means that when students find e-learning systems useful, they will as well find them easy to use (Larsen and Eargle 2015). The inner model suggests that Perceived Usefulness has the strongest effect on Attitude Towards Use (0.629), followed by perceived severity of COVID-19 (0.511) and Perceived Ease of Use (-0.175). Also, Attitude Towards Use has the strongest effect on behavioural intentions to use (0.521) as compared to the effect of perceived severity of COVID-19 (0.447).

The effects of perceived severity, perceived usefulness, and Perceived Ease of Use on students' attitudes and intention to accept e-learning

To measure the effects of the perceived severity, Perceived Usefulness, and Perceived Ease of Use on students' attitudes and intentions to accept e-learning, a bootstrapping resampling procedure (with 500 samples) was carried out to estimate the significance of paths in the structural model. Table 4 shows the results of hypothesis testing.

Table 4 Summary of hypothesis testing results without moderating effect

Paths	Original Sample (O)	Mean (M)	Standard Deviation (SD)	t	p values	Decision
H1: Perceived Usefulness (PU) → Attitude Towards Use (ATU)	0.629	0.634	0.093	6.782	0.00	Accept
H2: PERCEIVED Ease of Use (PEOU) → Attitude Towards Use (ATU)	-0.175	-0.176	0.045	3.862	0.00	Accept
H3: Perceived Usefulness (PU) → Perceived Ease of Use (PEOU)	0.903	0.903	0.008	111.275	0.00	Accept
H4: Covid-19 Severity (PSC) → Attitude Towards Use (ATU)	0.511	0.508	0.099	5.151	0.00	Accept
H5: Covid-19 Severity (PSC) → Behaviour Intentions to Use (BIU)	0.447	0.451	0.082	5.441	0.00	Accept
H6: Attitude Towards Use (ATU) → Behaviour Intentions to Use (BIU)	0.521	0.516	0.084	6.2	0.00	Accept

Table 5 Summary results of hypotheses testing with moderating effect

Paths	Original Sample (O)	Sample mean (M)	SD	t	P Values	Decision
H1a: PU_Mod → Attitude Towards Use (ATU)	0.098	0.1	0.046	2.11	0.035	Accept
H2a: PeoU_Mod → Attitude Towards Use (ATU)	- 0.111	- 0.114	0.058	1.931	0.053	Reject
H6a: ATU_Mod → Behaviour Intentions to Use (BIU)	- 0.01	- 0.01	0.007	1.369	0.171	Reject

Table 6 Multi-group analysis—private vs public schools

Paths	Path coefficients— difference	<i>p</i> value original 1-tailed (SchoolType_ ST(2.0) vs SchoolType_ ST(1.0))	<i>p</i> value new (SchoolType_ ST(2.0) vs SchoolType_ ST(1.0))
Attitude Towards Use (ATU) → Behaviour Intentions to Use (BIU)	- 0.934	1	0.00
Perceived Usefulness (PU) → Attitude Towards Use (ATU)	- 0.835	1	0.00
Perceived Usefulness (PU) → Perceived Ease of Use (PEUS)	0.13	0	0.00
Perceived Ease of Use (PEUS) → Attitude Towards Use (ATU)	- 0.325	1	0.001
Covid-19 severity (PSC) → Behaviour Intentions to Use (BIU)	1.009	0	0.00

Private = 1 and public = 2

Table 4 shows the results of the two-tailed test with a significance level of 5%. This was computed to ascertain if the path coefficients of the inner model are significant or not. The path coefficients are significant if the T-Statistics is larger than 1.96 for a 5% significance level (Hair et al. 2020; Wong 2013). From the results presented in Table 4, the hypothesized path relationships were all significant at the 5% significance level and all path relationships had t-statistic values above the 1.96 thresholds for acceptance.

Results of the moderating effects of perceived severity of COVID-19

In a time of a pandemic such as Covid19, perceived severity becomes an important consideration in the assessment of intentions to perform an act with risk implications (Baber 2020, 2021; Sreelakshmi and Prathap 2020a, b). Accordingly, the path relationships in the study were moderated with the perceived severity of COVID-19 to determine if there will be any significant differences in the relationships. The results of the study with the moderation effect are presented in Table 5.

Table 5 shows the results of the moderating effect of perceived severity of COVID-19 on the hypothesized paths in the two-tailed test with a significance level of 5%. This was computed to ascertain if the effect of perceived severity of COVID-19 could strengthen the relationship between the hypothesized paths and whether the effects will be significant or not. The path coefficients are significant if the T-Statistics is larger than 1.96 for a 5% significance level (Hair et al. 2020; Wong 2013). From the results presented in Table 5, the hypothesized path relationships were all insignificant at the 5% significance level except the path Perceived Usefulness to Attitude Towards Use, which had a T-statistic value above the 1.96 thresholds for acceptance.

Differences in the attitudes and usage intentions of student groups in public and private schools

To determine if there is any significant difference in the attitude and usage intentions of students groups in public and private schools, a multi-group analysis (MGA) was conducted. The MGA assessed whether the original structural model tests are different across the two groups of schools (private and public schools) involved in the study. Table 6 shows the results of the MGA between private and public schools.

The figures in Table 6 show no significant differences between the two groups (i.e. students of private and public schools).

Discussions, implications, comparison, and limitations

Discussions

The purpose of the study was to investigate the determinants that will influence students' to accept e-learning after the COVID-19 pandemic. In the literature, it is argued that attitude and behavioural intentions are essential determinants of technology acceptance and use (Al-Harbi 2011; Mohajerani et al. 2015; Nikou and

Economides 2017; Purwanto and Tannady 2020; Shahzad et al. 2020). Moreover, we hypothesized that attitude is significantly predicted by Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and perceived severity of COVID-19 (PSC) by students. The study further predicted that students' intention to use e-learning after COVID-19 will be influenced by the students' attitude and perceived severity of COVID-19 in the e-learning system. Using structural equation modelling techniques, the research model (see Fig. 1) was tested and the results indicated a good fit for the data.

From the study's results (see Fig. 2 and Table 4), all three variables that were predicted to significantly influence students' attitudes were supported, accounting for 94.8% of the total variance in students' attitudes towards acceptance of e-learning after COVID-19. All variables except PEOU had a direct and significant influence on students' attitudes towards e-learning usage. This result corroborates that by Larmuseau et al. (2018) and Tiwari (2020) who found that attitude is significantly affected by the extent to which a given technology will make a user productive. Also in line with the postulation so the TAM (Davis 1989), when technology makes users productive, they will as well find it to be useful. Additionally, considering the current physical restriction and closure of schools due to the COVID-19 pandemic, technology such as e-learning systems become very useful since it provides access to education, which became impossible during the outbreak of the pandemic. However, the lack of a direct and significant relationship between PEOU and attitude deviates from the findings of studies (Al-Harbi 2011; Sipiior et al. 2011; Tiwari 2020) that found PEOU to be significantly correlated with attitude. During the current period of the COVID-19 pandemic, students' main desire is how to continue to access educational content and instructions. Therefore, a technology that provides a solution becomes an asset irrespective of how easy or difficult it may be to use. Accordingly, PEOU was found to be of less concern to students during the period of the COVID-19 pandemic. In contrast to e-learning acceptance before the COVID-19 pandemic, existing research evidence showed that students' acceptance of e-learning was significantly affected by how easy or difficult they perceived its usage (Larmuseau et al. 2018; Yuen and Ma 2008). Besides, TAM (Davis 1989) posits that when students find a technology to be easy to use, they will as well use it and vice versa. But during a pandemic, how difficult or easy a technology is of less importance, as the drive for education continuity increases students' Perceived Usefulness of the technology, which will ultimately affect attitude and intention to use the technology. As a result, PEOU in this study was found to have no significant and direct effect on students' attitude towards usage of e-learning during the COVID-19 pandemic.

The result also showed all two variables (i.e. attitude and perceived severity of COVID-19) hypothesized to positively affect students' intentions to use e-learning were supported, explaining 91.8% of the variance in students' e-learning usage intentions during the COVID-19 pandemic. Both attitude and perceived severity of COVID-19 had a significant and direct relationship with students' intentions to use e-learning during the COVID-19 pandemic. This result is consistent with Purwanto and Tannady (2020), Amankwa et al. (2018) and Rizun and Strzelecki (2020). Purwanto and Tannady (2020) found that a positive attitude is crucial to creating interest in the acceptance of platforms. Amankwa et al. (2018) also found that users'

attitude will ultimately affect their behavioural intentions. More so, in a recent study to investigate students' acceptance of the COVID-19 impact on shifting higher education to distance learning in Poland, Rizun and Strzelecki (2020) revealed that attitude has the strongest effect on intentions to use technology.

From the results of the moderating effect, the effect of perceived severity of COVID-19 was found to positively affect both attitude and intentions to use e-learning. However, in both cases, the perceived severity of COVID-19 produced the second strongest effect. This finding from the study supports Baber (2021), Sreelakshmi and Prathap (2020a, b), who found perceived severity to be superior to other constructs in the intention to accept technology. This finding shows that during a pandemic such as the ongoing COVID-19, the consideration of the perceived severity of COVID-19 becomes secondary to achieving the end goal (i.e. access to educational content and instructions). This also shows that when students find e-learning systems to be useful and able to provide the enabling environment for educational continuity or resumption, they will develop a positive attitude and intention to use the system. In such instances, perceived severity will have minimal impact on attitude and intention to use. This shows that students will accept and use e-learning systems whether or not they perceive COVID-19 to be severe. Contrary to the direct effects, the indirect effects of the perceived severity of COVID-19 were insignificant in two relationships but significant in one. The study hypothesized that the relationship between the Perceived Usefulness of e-learning and attitude towards usage is moderated by the extent to which students perceive the COVID-19 pandemic to be severe. The finding lends support to this hypothesis for acceptance. This means that students find e-learning useful for acceptance when they perceive the effects of COVID-19 to be severe. They will develop positive attitudes over time for its usage. The perceived severity of COVID-19, therefore, strengthens the relationship between usefulness and attitude to use. The study also hypothesized that the relationship between Perceived Ease of Use of e-learning systems and attitude towards usage during COVID-19 is moderated by the perceived severity of COVID-19. The findings did not support this hypothesis. This means that the perceived severity of COVID-19 does not affect the relationship between Perceived Ease of Use and attitude to use. Students may perceive COVID-19 to be severe but will not necessarily find e-learning systems easy to use and will have no influence on their attitude. Further, the study hypothesized that the relationship between attitude towards usage and intentions to use e-learning during COVID-19 is moderated by the perceived severity of COVID-19. This claim was also not supported by the finding. The finding indicates that the perceived severity of COVID-19 has no significant effect on the relationship between attitude towards usage and intentions to use e-learning. The outbreak of COVID-19 led to the closure of schools and the subsequent suspension of academic activities in schools at all levels. As a result, the attention of stakeholders is more focused on how to resume academic activities. This, therefore, explains the lack of support for this hypothesis.

In the MGA, the results showed no significant difference in attitude and intention to use between students in private and public or state-owned schools. Private second-cycle institutions are usually equipped with robust ICT infrastructure for e-learning implementation. As a result, e-learning systems are used to augment

face-to-face classroom delivery. This establishes positive attitudes in students from private schools in relation to e-learning usage. However, this is not the case in public schools where there is a lack of the requisite ICT resources for e-learning adoption. The majority of the students in public schools may never have had a shot at e-learning but for the outbreak of the COVID-19 pandemic. This led to the speculation that students in private second-cycle schools will have positive attitudes toward e-learning usage whereas their counterparts in public will show negative attitudes. However, the results of the MGA showed no significant differences in the attitudes and behavioural intentions of the two groups of students.

Implications for practice

Based on the findings of the study, some recommendations to improve students' attitudes and intentions for continuous usage of e-learning systems even after the COVID-19 pandemic are as follows:

1. *E-learning readiness* From the study's findings, it is evident that students in Ghanaian second-cycle institutions, like those in other developed countries, intend to use e-learning systems to restart and continue with education following the disruptions by the COVID-19 pandemic. However, for this intention to materialize into actual usage, second-cycle institutions should be prepared and ready to move major academic activities including teaching and assessment to e-learning systems. The institutions must have in place the requisite ICT infrastructure to support full-scale e-learning systems. It is only when the requisite ICT infrastructure is available that the implementation of e-learning systems can be plausible. Additionally, teachers should also be ready for the e-learning take-off. Teacher readiness here means that teachers should be equipped with the needed resources, knowledge, and skills to successfully deliver courses on the e-learning systems. Also, parents should be able and willing to provide the needed resources to support students' online learning activities during the COVID-19 stay-home periods. These resources may include computers and other smart devices with internet connections for accessing e-learning systems. Finally, the government should support the provision of fast and affordable broadband internet access to students to facilitate and promote the usage of e-learning systems during the COVID-19 stay-home period.
2. *A positive recommendation* Most students of second-cycle institutions are below the age of 18 years and describe as minors (in the case of Ghana). As a result, social influence will significantly affect the behavioural intentions of these students, who are likely to continue or discontinue the usage of e-learning systems due to positive or negative recommendations by a referent. Accordingly, parents and teachers, who are students' first point of call on issues relating to academic decisions, should always highlight the positive sides of e-learning systems to stimulate continuous usage by students. Teachers should further demonstrate mastery of e-learning systems to engender confidence and positive students' attitude towards usage.

3. *Availability of relevant content* The findings showed that students' attitudes incline to positivity when they perceive e-learning systems as useful. It was realized that the use of an e-learning system depends on its ability to satisfy the educational needs of students by continuously supporting teaching and learning during the stay-home period of the COVID-19 pandemic. Accordingly, teachers and heads of educational institutions need to ensure that the needed contents are always available and can be accessed by students on e-learning systems.
4. *Constant metacognitive communication* Although the findings showed that students will learn and adapt to e-learning systems when they find them useful, it is imperative to note that continuous usage cannot be sustained when a given e-learning system is overly difficult to use. It is therefore important that institutions provide simple guidelines on how to perform the basic tasks on e-learning systems. Such guidelines should be updated as and when the system is updated or when new features are introduced. Also, there should be constant communication with students regarding their progress and challenges, and words of encouragement to assuage students' fears, anxiety, and uncertainties regarding the effectiveness of the e-learning system usage. Such metacognitive dialogues ensure efficient monitoring of the learning process and engender self-regulation skills (Patricia 2020).
5. *Change of attitude and perception towards online learning and teaching* When educational institutions were closed down as a result of COVID-19 some resorted to online teaching. Online teaching has proven to be a reliable mode of teaching. This has been the case for quite a long time in some countries like South Africa where educational institutions run programmes online up to the Ph.D. level. However, in Ghana some frown on online programmes. Holders of online degree certificates are at times not given the due recognition as their counterparts who had their degrees through face-to-face programmes. The advent of COVID-19 has demonstrated that educational institutions including second-cycle institutions cannot continue to operate within the four walls of the institutions. Second-cycle institutions should adopt a hybrid system of teaching and learning where in-person campus academic work would be complemented by online teaching and learning after COVID-19. Online teaching and learning have significant value and should be encouraged and prioritized.
6. *Provision of ICT resources* To make the running of online programmes effective, second-cycle institutions should develop and implement proactive and innovative policies that will ensure that all students and staff have personal computers, laptops, and/or tablets or have access to institutional ICT resources. The availability of such resources will make online teaching and learning easy and meaningful and will also ensure that e-learning systems become engrained in the academic structure of second-cycle institutions.

Comparison

We compare the results from the current study with other similar studies from other geographical locations to ascertain corroboration or deviations in patterns.

In the existing literature, studies on e-learning during the COVID-19 pandemic and subsequent closure of schools have been conducted mainly in higher educational institutions. Studies including (Aristeidou and Cross 2021; Kulikowski et al. 2021; Stotz et al. 2021; Vittorini and Galassi 2021; Yawson and Yamoah 2020) are some of the recent e-learning studies that were conducted during the period of the pandemic.

Unfortunately, evidence from basic schools and secondary or second-cycle institutions is limited. There exists limited research focusing on e-learning acceptance during the period of the COVID-19 pandemic in lower educational levels.

One of the few studies that focused on e-learning implementation during the period of the COVID-19 pandemic is that by Mailizar et al. (2020). The authors assessed the opinions of secondary school mathematics teachers on e-learning implementation barriers during the COVID-19 pandemic at four barrier levels, namely teacher, school, curriculum, and student. The authors collected data from 159 students from lower and upper secondary schools in Indonesia. The descriptive and inferential statistics involving means and standard deviations were employed in the final analysis to analyse and present the results using tables. ANOVA was also employed to examine significant differences in barriers across the categories. Lastly, Spearman correlation coefficients were calculated to assess relationships between barriers across the levels, and Cohen's (1992) guidelines for the interpretation of a correlation coefficient were used to interpret the correlation. According to the conclusions of their study, the student-level barrier had the greatest influence on e-learning use. Furthermore, there was a substantial positive link between the student-level barrier and the school level barrier, and the curriculum level barrier. The study found that the backgrounds of teachers did not affect the level of barriers. This study encourages additional debate on how to overcome e-learning challenges while also maximizing the advantages of e-learning during and after the pandemic by emphasizing the value of students' opinions.

On account of the recommendations made by Mailizar et al. (2020), the current study examined the factors that will influence students' acceptance of e-learning after the pandemic using the opinions of 370 students from lower and upper levels of second-cycles institutions in Ghana. The results suggest that students' attitudes and intentions are the main determinants that will influence the acceptance of e-learning by students after the pandemic. This finding compares favourably with the findings of Mailizar et al. (2020) that student-level barriers had the greatest influence on e-learning usage. The two studies conducted in Ghana and Indonesia, though have different environmental factors, have shown similar results across the two geographical locations. The factors that will influence students in Ghana are therefore similar to or maybe the same as those that will influence students in Indonesia in the acceptance of e-learning. This also implies that the factors that affect students' acceptance of e-learning may be consistent across Africa and Asia.

Limitations and future study

In this study, data were collected using a questionnaire, which had items that were tested for the first time and may therefore not be standardized. Additionally, the fear and uncertainty of the COVID-19 pandemic could affect the responses provided by the study's respondents. Moreover, the use of a questionnaire is prone to social desirability errors. There is the possibility that the information provided by the respondents may differ from their actual behaviour after the COVID-19 emergency. Finally, data collection involved students of only three-second-cycle institutions, thereby limiting the generalizability of the findings. Future studies could extend the study to cover more second-cycle institutions for a larger sample and statistical power.

Additionally, the country in which the study was conducted is a developing country in Africa, as such geographical, economic, and cultural biases may have contributed to the outcome of the study. Future studies could extend the discourse across Africa by comparing it with evidence obtained from other parts of the world.

Another limitation of the study is the focus on only attitudes and intentions. Technology infrastructure plays an important role in e-learning. For instance, a student having access to only a smartphone may have limitations when compared to a student having a laptop. Further study would be needed to observe the difference in technology infrastructure. Also, future research may focus on educational institutions' readiness to move academic activities to e-learning systems, and teachers' intention to accept and use e-learning systems to continue with academic work during the period of the COVID-19 pandemic.

Conclusion

In this paper, we investigate the factors that will influence students' acceptance of the e-learning system of education after the COVID-19 emergency in second-cycle institutions in Ghana. By analysing data collected from 370 students selected from three-second-cycle institutions in Ghana, we discovered that student attitude is highly impacted by Perceived Usefulness and somewhat influenced by perceived severity. Also, student intention was found to be moderately influenced by COVID-19's perceived severity but significantly influenced by attitude toward usage. Given the study's results, it is evident that the students' attitudes and intentions will influence the acceptance of the e-learning system of education after the COVID-19 pandemic. A positive attitude and intention towards e-learning systems of education should therefore be developed in second-cycle institution students. Stakeholders in the education value chain must guarantee that the required steps are in place to make e-learning systems appealing, user-friendly, and valuable in the eyes of students. It was also found that positive students' attitudes and intention to use e-learning systems are largely influenced by how useful students perceive e-learning systems. Other determinants include ease of use and the perceived severity of the COVID-19 pandemic. Although the perceived severity of a pandemic, hitherto, was of significant consideration in technology acceptance discourse, in this study, it was found to be of less importance compared to Perceived Usefulness. Consequently,

the moderating effect of perceived severity of COVID-19 on the relationship between Perceived Ease of Use and attitude, and attitude and intention to use were insignificant.

The paper, therefore, concludes that the determinants that will influence the students' acceptance of the e-learning system of education after the COVID-19 emergency are students' attitudes and intention to use e-learning. Also, attitudes and intentions are the same across students in public and private second-cycle institutions. Consequently, factors that influence the attitudes and intentions of students in public second-cycle institutions are most likely to influence those in private second-cycle institutions.

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Data availability The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this manuscript.

Ethical approval This research was given by the Presbyterian University College Ghana Research and Ethics Committee.

Informed consent Informed consent was obtained from each participant of the study.

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