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# Integration of personality trait, motivation and UTAUT 2 to understand e-learning adoption in the era of COVID-19 pandemic

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## Abstract

The adoption of e-learning in response to COVID-19 is to ensure the continuous development of human capital through alternative means. Nevertheless, the success of e-learning systems depends much on the attitude of the users. This study developed and empirically tested a model to predict antecedents of students' actual usage of e-learning during the COVID-19 period. A synthesis of UTAUT 2, Self Determination Theory and Core Self-Evaluation Theory were employed to examine the behaviour of students using a sample of 1024. PLS-SEM was used to analysed the hypothesised paths in the model. The results revealed that (1) Personality is positively related to behavioural intention (2) Actual usage is positively influenced by motivational factors (3) Behavioural Intention positively mediates the relationship between motivational factors and actual use (4) motivational factors positively mediate the relationship between UTAUT 2 constructs and behavioural intention. The results will guide stakeholders in education, especially e-learning system designers to incorporate personality and motivational factors in the designing of e-learning systems in order to increase the acceptability of the system by students. This study is among the first few attempts to incorporate personality, motivation and UTAUT2 to examine e-learning users' behaviour, especially in Sub-Saharan Africa during the COVID-19 pandemic. This work presents a contemporary perspective of e-learning users' behaviour during the COVID-19 pandemic.

**Keywords** E-learning · UTAUT 2 · Core Self-Evaluation · Self Determination Theory · COVID- 19

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## 1 Introduction

The academic learning environment has seen a lot of opportunities and innovations partly because of the COVID-19 pandemic coupled with advances in information and communication technologies (ICT). The pandemic created the challenge to innovate and create the most efficient and low-cost technological means for learners and teachers to interact. One major information technology (IT) driven innovation that has been created for learners and instructors to interact is e-learning. Consistent with Dhawan (2020 p.7), we conceptualise e-learning as "learning experiences in synchronous or asynchronous environments using different devices (e.g., mobile phones, laptops, etc.) with internet access". E-learning or web-based learning is also referred to as the use of wired and wireless electronic systems to execute learning activities either online or offline with the help of digital tools (Ali et al., 2018) at anytime and anywhere (Yoo et al., 2010). Because of the important role played by e-learning, especially during the pandemic, it has received a lot of attention from both industry and academicians across the globe. Consequently, studies on e-learning adoption, especially in higher institutions, continue to attract scholarly attention from academics of diverse research orientations to demonstrate the crucial significance of the phenomenon in contemporary times (Ali et al., 2018; Ho et al., 2020; Levy et al., 2015). E-learning provides the medium to share knowledge with a wide range of audiences using tools and systems like social network platforms, intranet, wikis, e-books, email, chat, blogs, and digital broadcasting networks and audio-visual technologies.

In Ghana, and across nations, COVID-19 has pushed tertiary educational institutions to transition to online course delivery via e-learning by the application of both asynchronous and synchronous technologies to ensure the continuation of academic work. E-learning offers a flexible and practical framework that supports interaction between learners and teachers at different locations (Wang et al., 2009). Social network platforms, digital collaboration, virtual classrooms, e-books, digital broadcasting networks and audio-visual technologies are all used in e-learning (Chawinga & Zozie, 2016). The upsurge of e-learning is propelled by inexpensive new technologies, constant evolution of the world wide web (Choudhury & Pattnaik, 2020) and the COVID-19 pandemic. The services offered by e-learning can be modified by the experience, competency and knowledge of the learners or students. The phenomenon has transformed global education, especially amid the COVID-19 pandemic and beyond. The ubiquitous nature of e-learning has attracted the attention of diverse researchers (Lin, 2010). Its characteristics of online and offline nature fascinate some researchers (Zengin et al., 2011) and research in the area has been intensified (Aldholay et al., 2018) in contemporary times.

Inspite of this intensity, e-learning adoption and exploitation is believed to have been less successful (Bell et al., 2004). Accordingly – and to date – there is a gaping paucity in research on the knowledge and understanding in the motivating rationale for the adoption of e-learning, especially during a global health emergency such as the COVID-19 (Rai, 2020). Since e-learning is linked to

technology, stakeholders must understand how users comprehend and respond to the system, especially during periods of emergencies. Such knowledge will direct stakeholders on how to improve the system to enhance the experience of users which will, in turn, ensure acceptance and use. It suffices to note that the success of Information Systems lies in the acceptance and usage. Ensuring that users or students adopt and use e-learning, can be very challenging if their expectations are not met. This explains the difficulty in understanding "why not" and/or "why" individuals may or may not embrace a new technology like e-learning. This has been a continuous concern for IS researchers (Tamilmani et al., 2020). Adoption of information technology by individuals occupies a prime position in present-day IS studies (Venkatesh et al., 2007). To unravel this controversy, researchers have proposed and used various theories such as UTAUT2, Model of Personal Computer Utilization (MPCU), Diffusion of Innovation theory (DoI), TPB, and TRA. These theories have been applied in individual (Kizgin et al., 2018; Slade et al., 2014) social context (Hossain et al., 2018; Weerakkody et al., 2017), and organizational context (Martins et al., 2016).

The underlying theory of this study is UTAUT2. The theory was chosen because of its explanatory power and completeness in acceptance and use of IS studies (Lawson-Body et al., 2018). Extant literature is quite silent on the application of UTAUT2 in e-learning studies, especially in terms of personality trait and motivation in the Sub-Saharan Africa. Moreover, prior studies that have used UTAUT2 to understand the adoption and use of e-learning are very limited. Based on these prior observations, this study seeks to examine the factors that influence the adoption of e-learning. This study identifies some gaps in the literature which it seeks to fill. First, while various researchers have examined and validated the potency of the UTAUT model, researchers have argued that it is appropriate to include constructs that reflect the specific nature of the subjects being examined (Lian, 2015; Kováˇríková et al., 2017). Also, Venkatesh et al. (2012) reiterated the importance of including additional predictors and testing the model (UTAUT2) in specific IS contexts. This study attempts to fill this gap in the empirical literature by proposing an extended UTAUT 2 model by introducing Personality and Self-Determination Theory (SDT) to investigate the independent construct(s) which may predominantly affect the dependent construct (actual use) (Fig. 1).

Furthermore, it has been observed that while empirical studies on e-learning adoption are gradually taking shape, the majority of the empirical studies are mostly centered on non-African contexts. Most prior studies (Tarhini et al., 2016; Amirkhanpour et al., 2014) of e-learning are concentrated in developed countries (Boateng et al., 2016). However, the few studies (Namisiko et al., 2014; Boateng et al., 2016) of e-learning adoption conducted in developing economies did not use UTAUT2 as the underpinning theory. Thus, this paper contributes to the extant literature by focusing on an African context (Ghana). Until now research using UTAUT2 as the underpinning theory to examine e-learning adoption is rare. Venkatesh et al. (2012) propound that empirical evidences from different geographical regions are necessary to help validate the model. Thus, this paper provides substantial contextual, theoretical and methodological contributions to the extant literature by extending UTAUT2 with SDT and personality in the context of a developing country using

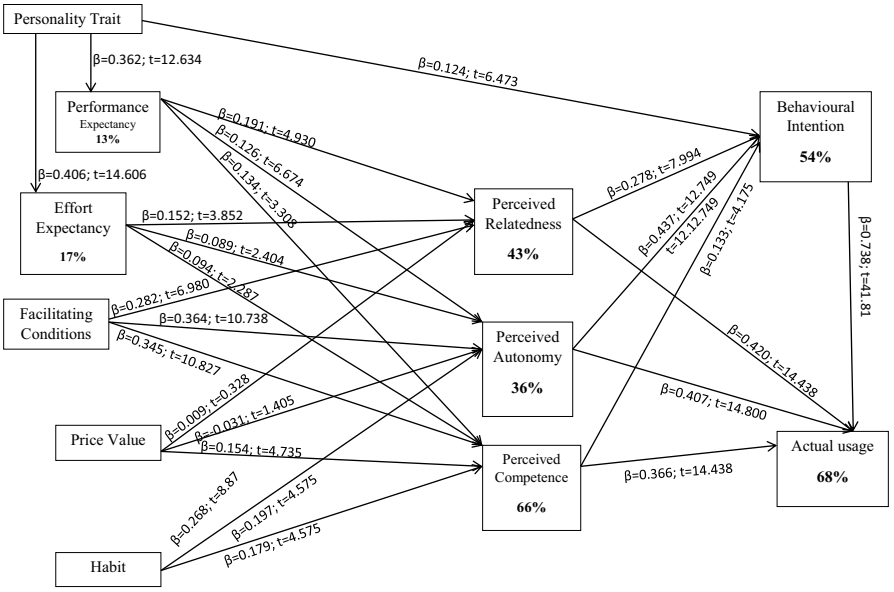


**Fig. 1** Structural Model

the structural equation modelling (SEM) approach. Lastly, this research is vitally important as it seeks to register a contribution to the growing body of the e-learning literature by widening the scope of applicability of the theoretical model of the UTAUT2 to circumstances occasioned by an emergency. It remains to be seen (ontologically and epistemologically) how social factors, informed by motivational conditions, inspire the adoption of e-learning in emergency inspired circumstances. The motivational conditions stimulating e-learning adoption is worthy of research attention. The rest of the paper proceeds as follows: the next section provides a review of the perspectives of e-learning, core self-evaluation as a perspective of personality trait and Self-Determination theory of motivation. Next, the study presents the hypotheses to be tested, followed by the sections on methodology, data analysis and results. The discussions and implications follow next along with the study limitations and future studies to conclude the study.

## 2 Research model and hypotheses development

### 2.1 Core self evaluation (personality) to behavioural intention

Core self-evaluation (CSE) is a broad personality trait that reflects the general and fundamental beliefs that individuals hold about themselves (Judge et al., 1998). It is the positive self-concept regarding one's personality (Di Fabio & Palazzeschi, 2020) that has been associated with different phenomena including creativity, satisfaction, performance, stress and success (Di Fabio & Palazzeschi, 2020). Several

studies have reported that dimensions of personality influence behavioural intentions to engage in the use of technology (Svendsen et al., 2013). However, research has not focused on the effect of core self-evaluation as a personality trait on behavioural intention. An individual with a positive CSE generally believes in their self-worth. They tend to relax in the face of uncertainties, believe in their abilities to accomplish tasks and take responsibility for their behaviours (Chen, 2012; Judge et al., 1998). CSE plays a vital role in students' intention to formulate plans to engage in e-learning to achieve their academic ambitions. Therefore, we hypothesize:

***$H_1$**: CSE positively influence behavioural Intentions*

### 2.2 CSE to UTAT2

Generally, individuals with higher CSE are more sensitive to positive stimuli and tend to raise their self-esteem; and insensitive to negative stimuli. On the other hand, individuals who also have lower CSE are more sensitive to negative stimuli and less sensitive to positive stimuli. Studies by Chavoshi and Hamidi (2019) and Almaiah and Alismaiel (2019) concluded that self-esteem is one of the major determinants of educational systems' acceptance. For students to accept e-learning, it is essential to ensure that students have high self-efficacy to achieve a meaningful result (Sabah, 2016). In this study, we argue that the unexpected implementation of e-learning during the COVID-19 pandemic required students to adjust quickly to the new norm. Students with a high level of propensity to feel relaxed and exhibit less reactivity (emotional stability) (Johnson et al., 2008) to this rapid transition will accept and use the system. This situation also called for students to have the needed or required skills and/or competence to use e-learning. Thus, students with high self-efficacy will envisage a positive performance expectation. Also, a study by Abay et al. (2017) found that individuals with internal locus of control are more likely to adopt new technologies. Consequently, we argue that students with internal locus of control will be motivated to expect a high-performance expectance. Thus, we expect that a student's high self-esteem will predispose the student to put in the expected effort to accept and use the e-learning system during the COVID-19 pandemic. Thus, we propose that.

***$H_2$**: CSE will positively relate to Performance Expectancy*
***$H_3$**: CSE will be positively related to Effort Expectancy*

### 2.3 UTAUT 2 and Self Determination Theory (SDT)

#### 2.3.1 Performance Expectancy (PE) to SDT

PE captures the perception of users with regards to how using a particular technology may help them to achieve their anticipated goal (Macedo, 2017). Evidence in extant literature suggests that PE is a powerful predictor of technology usage in the realms of life (Tennakoon et al., 2013) and work environments (Korunka &

Vartiainen, 2017). PE is a critical factor in the context of Information systems (Alrajawy et al., 2016). In this study, PE denotes the extent to which students believe that e-learning is relevant for them to achieve their learning activities more efficiently and effectively. Even though the relationship between PE and perceived autonomy is less clear because few studies provide a basis for postulating hypotheses between them (Lee et al., 2015), we argue that if students believe that using the e-learning system will enhance their learning, they will be motivated to use the system. For instance, the expected outcome of enhancing their learning more efficiently and effectively will intrinsically motivate the students to use the system. Similarly, based on the arguments above performance expectancy is expected to increase students perceived relatedness through the use of e-learning. Relatedness refers to the ability of the student to develop relationships with significant others (Wood, 2016) through the use of e-learning. For instance, the perceived value, of interacting with lecturers and colleagues as well as having the opportunity to continue their education, will motivate the students intrinsically to use the system. Competence also provides another mechanism for understanding personality traits and motivation for e-learning adoption in health emergency situation, such as the COVID-19 pandemic. Competence refers to the psychological need of a student to feel confident and effective within an e-learning environment, such that they carry the impression that they can perform and complete their learning activities successfully (Deci and Ryan, 2002; Wood, 2016). Students may also perceive competence in the context of e-learning as being able to understand the basic processes of the platform or website (Pennington et al., 2003). If the skills and abilities of students are affirmed by e-learning, the students will consider e-learning positively (Lin, 2011). Thus, with a positive PE through a positive perceived competence students will adopt and use e-learning to execute their learning activities.

***$H_{4:}$*** *PE will be positively related to perceived autonomy*
***$H_{5:}$*** *PE will be positively related to perceived competence*
***$H_{6:}$*** *PE will be positively related to perceived relatedness*

### 2.4 Effort expectancy (EE) to SDT

EE refers to how easy it is for an individual to interact with a technology (Venkatesh et al., 2012). In this context, EE is defined as students' belief that they will not struggle to use e-learning or will require little effort to use the e-learning system. The main idea of EE is that the effort required to learn and use e-learning will affect its acceptance and use by students (Venkatesh et al., 2003). Thus, if the e-learning system is user friendly, it will motivate students to use the system and vice versa (He & Lu, 2007). EE emphasizes students' belief that e-learning is easy to use. If students find it easy to use e-learning, it will influence their perceived autonomy to self-control and self-regulate their behavioural intention. EE is expected to positively influence the perceived autonomy of students towards the use of e-learning. In this study perceived relatedness refers to the establishment of relevant relations with important people such as peers

and teachers who share a common purpose (Wood, 2016). Thus, with e-learning requiring less effort to use, it will motivate the student to use it to interact with lecturers and peers. This is because the student will have to put in less effort to use the system. So, we propose that EE will have a positive effect on perceived relatedness. Competence could be related to setting and achieving goals (Skinner & Edge, 2002). Thus, with little effort, students will use e-learning to achieve their set academic goals or target. Amid the COVID-19 pandemic, students were more concerned with systems that will benefit and enhance their set targets and/or goals and when combined with all the other arguments EE will most likely increase the students perceived competence to use e-learning systems.

***$H_{7:}$*** *EE will be positively related to perceived autonomy*
***$H_{8:}$*** *EE will be positively related to perceived competence*
***$H_{9:}$*** *EE will be positively related to perceived relatedness*

### 2.5 Facilitating conditions (FC) to SDT

FC represents "the degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system" (Venkatesh et al., 2003, p. 453). Using e-learning requires technical infrastructure, a kind of skill and some resources. Usually, in the context of the users (students), these facilities are not free (Zhou et al., 2010). In this study, FC refers to students' perception that the institutions existing resources and technical infrastructure will support their use of e-learning systems during the COVID-19 pandemic. UTAUT model holds the view that FC affect behaviour towards new technologies. Thus, when students recognize that the institution is ready to offer support and technical infrastructure in their use of e-learning system, it will enhance their usage intentions. Thus, students with enough infrastructure and adequate support during the COVID-19 pandemic have a high propensity to use the e-learning systems. Thus, FC will influence students to use e-learning out of their own will. In other words, they will have free self-control in their choice to use the system. Again, the desire of students to have the opportunity to interact and connect with others (lecturers and colleagues) will be reinforced by the presence of FC. Even though the pandemic truncated the interaction and connection with others, the e-learning with appropriate FC presents a conduit for students to stay connected and interact with others. In the case of perceived competence, without FC it will be difficult to function efficiently and effectively in the context of e-learning. Thus, the existence of FC will enhance and positively influence the desire of students to be effective and efficient in their performance through e-learning. Therefore, we hypothesize that;

***$H_{10:}$*** *FC will be positively related to perceived autonomy*
***$H_{11:}$*** *FC will be positively related to perceived competence*
***$H_{12:}$*** *FC will be positively related to perceived relatedness*

### 2.6 Habit to SDT

Habit assumes that past learning may influence people to perform actions automatically (Chopdar et al., 2018). Thus, habit is a reflection of past experiences and their results (Venkatesh et al., 2012). An individual is most likely to repeat an action that has produced a satisfactory outcome. Ajzen (2002) posits that regularly exhibited past behaviour is a major determinant of present behaviour. Studies (e.g., Baptista & Oliveira, 2015; Hew et al., 2015) have established the positive influence of habitual use on behaviour. Venkatesh and Zhang (2010) argue that people who frequently use electronic devices have a higher edge to adopt new technologies. Habit is usually included in research studies to understand the behaviour of users because previous habitual behaviours may produce positive feelings towards the behaviour (Masa'deh et al., 2016; Hsiao et al., 2016). In the context of e-learning, we argue that habitual usage of electronic devices by students will affect their willingness to use e-learning system. The habitual behaviour with positive outcomes will motivate students to regulate their behaviour and freely engage in e-learning. It will further enhance the desire of students to use e-learning to associate and connect with their peers and lecturers. Experience through habitual use will improve the competence of the students which will further lead to actual usage of the e-learning system. Thus, we argue that:

***$H_{13}$:*** *Habit will be positively related to perceived autonomy*
***$H_{14}$:*** *Habit will be positively related to perceived competence*
***$H_{15}$:*** *Habit will be positively related to perceived relatedness*

### 2.7 Price Value (PV) to SDT

PV refers to "consumers' cognitive trade-offs between the perceived benefits and cost of using various applications" (Venkatesh et al., 2012, p. 161). This construct is important in a context where users are supposed to consider a cognitive trade-off between the cost associated with the usage of the technology and the perceived benefits (Gunasinghe et al., 2019). The cost may include data charges and/or device costs as well as service charges associated with a particular network where applicable (Chopdar et al., 2018). The price value will positively affect students' self-determination (behaviour) if the perceived benefits gained from using the technology supersede the cost. In this study, it is anticipated that the benefits of using the e-learning system will positively influence students' perceived autonomy, perceived relatedness and perceived competence.

***$H_{16}$:*** *PV will be positively related to perceived autonomy*
***$H_{17}$:*** *PV will be positively related to perceived competence*
***$H_{18}$:*** *PV will be positively related to perceived relatedness*

### 2.8 Motivation (SDT) to behavioural intention

According to the SDT, individuals strategically align their beliefs about future performance with their motives (Deci and Ryan, 2002) in order to put up the

behavioural intentions consistent with the motives. The quality of the motivation to perform actions and the persistence of behaviour are dependent on the satisfaction of the three basic needs of autonomy, competence and relatedness (Hagger & Chatzisarantis, 2009, 2014). SDT suggests that intrinsic motivation is fulfilled when these three basic psychological needs are satisfied. According to Deci and Ryan (2002), needs satisfaction leads to the desire to engage in behaviours that further satisfy these needs (Sheldon, 2002). Thus, needs satisfaction leads to a conscious plan to exhibit or not to exhibit a particular behaviour (Warshaw and Davis, 1985). Universities are currently making substantial capital investments in e-learning to facilitate teaching and learning (Deng & Tavares, 2013). This has become crucial in the face of the COVID-19 pandemic. However, the adoption and continual usage of e-learning system will depend on the motivation of the students to accept the e-learning system and engage in the right behaviours to sustain the usage. An e-learning system that ensures that students are motivated will lead to students engaging in the expected behaviour. In an empirical study by Nikou and Economides (2017), the authors found that the dimensions of SDT – autonomy, relatedness and competence are important determinants of behavioural intention to use. Based on the above we hypothesize that motivation is the basis for behavioural intention.

***$H_{19}$**: Autonomy positively influences students' behavioural intentions*
***$H_{20}$**: Competence positively influences students' behavioural intentions*
***$H_{21}$**: Relatedness positively influences students' behavioural intentions*

### 2.9 SDT to actual use

Motivation is a fundamental human agency and volition behaviour that explains why individuals choose to engage in certain behaviours (Hattie et al., 2020). Extant literature indicates that SDT predicts several learning outcomes like persistence (Deci & Ryan, 1985). Research in the field of motivation in online studies has not received the needed attention (Chen, 2007). Few studies have focused on SDT in online teaching and learning (e.g., Roca and Gagné, 2008). The satisfaction of students' basic needs determines the extent of actual usage of e-learning. In line with this, Deci and Ryan (1985, 2002) believe that needs satisfaction influences individuals in their actions. SDT's motivational orientation leads to an alignment in beliefs such that students can pursue behaviours that are compatible with their motives and preferences. Ryan and Deci, (2020) highlight the importance of psychological needs satisfaction in learning contexts which is missing in traditional motivational models. Thus, we hypothesize:

***$H_{22}$**: Autonomy positively influences students' actual use of e-learning*
***$H_{23}$**: Competence positively influences students' actual use of e-learning*
***$H_{24}$**: Relatedness positively influences students' actual use of e-learning*

### 2.10 Behavioural intention (BI) to actual use

BI refers to the possibility that a person will use a new technology. In this study, BI encapsulates students' intention to use e-learning to accomplish their learning activities. We believe that if students form the intention to use the e-learning system, they will translate to the actual use of the e-learning system. According to Davis (1989), BI is a major determining factor of individuals' actual usage of information technology (IT) or new technology. Ngai et al. (2007) propose that BI can be used to evaluate the propensity of an individual's commitment to put up a specific behaviour. Researchers (e.g., Ain et al., 2016; Khechine et al., 2016) have confirmed that behavioural intention has a significant positive effect on actual usage of IT. Various e-learning studies (e.g., Lin, 2007; Mohammadi, 2015) have also confirmed that BI has a positive relationship with actual use. To be consistent with prior literature, this study proposes that BI is positively related to AU.

***$H_{25}$**: BI is positively related to Actual Use*

## 3 Data collection and methodology

The population of the study included all tertiary education students in Ghana. COVID-19 has made e-learning an integral part of education worldwide. This phenomenon is pronounced among tertiary education students. Most institutions in the world have been forced by the COVID-19 pandemic to use e-learning mechanisms to complete their semester work. The e-learning supported the students with their curricular activities. Thus, choosing the students as the target population is therefore appropriate. The sample for the study consisted of 1306 tertiary education students (primarily undergraduate students) who are affiliated with various tertiary institutions in Ghana. However, 1024 responses were used for the analyses. The non-useable responses were respondents who were not using e-learning. They all identified themselves as full-time and distance-learning students and users of e-learning during the COVID-19 pandemic. The sample depicts a wide range of levels (undergraduate, postgraduate and doctorate). 52.9% of the respondents were males, 55.8% were between the ages of 18–21 years, 91.7% were undergraduate students, 35.7% were first year's students, 90.7% were students of public universities and 83.8% were regular students.

In this study, the data was collected through an online survey. Online survey presents a new and fast-growing data collection technique (Marjanovic et al., 2007). This technique is very useful in unique situations that are difficult to study or examine and can help the researcher reach out to larger specific groups of respondents at a cheaper cost when compared to other methods (Buchanan & Smith, 1999; Kraut et al., 2004). So far, the reliability and internal validity of online questionnaires are believed to be at par with paper-based questionnaires (Buchanan & Smith, 1999; Kraut et al., 2004). In the opinion of Kraut et al. (2004), the response from an online survey may be biased because it is self-selective. However, this study did not experience this phenomenon because all the respondents are students and also used

e-learning devices for their academic activities during the pandemic. This to a large extent makes the sample representative of the group (tertiary education students). Again, the researchers engaged known class leaders, student group leaders and lecturers to help share the questionnaire with their mates and students (respectively) on social media platforms that they are on and email from May to June 2020. The leaders helped to encourage their mates to participate fully in the study via their social media platforms. The leaders, after a briefing by the researchers, explained to their mates about the importance of collecting data on student's reaction towards their e-learning and requested them to complete the online questionnaire. The questionnaire asked for respondents' affiliation and use of e-learning before having access to the main questionnaire. As stated earlier, a "NO" answer meant that the respondent could not continue to the main questionnaire. Based on these restrictions, it can be concluded that all the respondents who participated and completed the questionnaire were all tertiary education students and used e-learning during COVID-19 pandemic. A statement of confidentiality was provided for all participants to ensure anonymity and voluntary participation. The respondents needed approximately 15 min to complete the questionnaire.

According to Dillman (2007) researchers develop questionnaires based on three main issues including opinion variables (which record data on respondents' feelings, judgement, thoughts, belief about something), behaviour variables (which record data on people and past issues, their current event or future activities), and attribute variables (it captures respondents' gender, age, marital status, education, etc.). Based on this the questionnaire was categorized into three (3) sections namely demographic profile, behaviour variables and the opinion variables. The students were asked to share the extent to which they disagree or agree with existing UTAUT, personality and self-determination measures to determine the reasons behind their acceptance and use of e-learning. The measurement instruments were adapted from existing literature (Bourque et al., 1992). The UTAUT2 constructs were adapted from Venkatesh et al., (2012), Personality constructs were adapted from Judge et al. (2003) and self-determination constructs were adapted from McAuley et al. (1989) and Baard et al. (2004). All the questions were closed-ended and measured with a five-point likert-style rating scale ranging from strongly disagree (1) to Strongly agree (5). The structural equation modelling technique (SEM) was employed to analyze the data. The collected online data were first examined to check for possible inconsistencies or errors. The analyses were conducted and organized in a three (3) tier format: (1) descriptive statistics, (2) reliability and validity and (3) testing of the hypothesized paths. Smart Partial Least Squares (Smart PLS) and SPSS software were used for the analysis.

### 3.1 Data analysis

Common Method Variance was also explored as per Harman's (1967) recommendation. The results revealed that six (6) factors had Eigenvalues above 1.0, which accounted for 80.7% of the variance, with the highest factor accounting for 31% of the explained variance. Since no factor solely explained the majority (50%) of the covariance, the study

concludes that the data has no issues of common method bias. The KMO sampling adequacy of the dimensions of the study was 0.971. Hence, showing a high significance of these variables under this dimension in correlating with each other differently from 0 or an identity matrix.

The study also explored the extent to which individual constructs were divergent from other constructs (Hair et al., 2010; Henseler et al., 2016). All the diagonal values in parentheses (square root of AVE) of each latent variable should have a higher value than its highest correlation of the construct (see Table 3). Based on Fornell-Larcker (1981) recommendation, the results confirm the absence of multicollinearity (Bryne, 2013). Additionally, the heterotrait-monotrait ratio of correlations (HTMT) method was used to further confirm the presence of discriminant validity (Henseler et al., 2015). The results indicate that all the values passed the HTMT threshold of 0.90 (Gold et al., 2001). Consequently, using both the Fornell and Larcker (1981) criterion and the HTMT, the results indicate that discriminant validity is realized.

## 4 Results and Discussions

### 4.1 Descriptives

The results as presented in Table 1, shows that 52.9% of the respondents were males, 55.8% were between the ages of 18–21 years, 91.7% were undergraduate students,

**Table 1** Descriptive Statistics of Respondents Demographics

| Category | Variable | Frequency | % |
|---|---|---|---|
| Gender | Female | 482 | 47.1 |
| | Male | 542 | 52.9 |
| Age | Below 18 | 12 | 1.2 |
| | 18—21 | 571 | 55.8 |
| | 22—25 | 229 | 22.4 |
| | 26—29 | 86 | 8.4 |
| | 30—33 | 62 | 6.1 |
| | 34 + | 64 | 6.3 |
| Educational | Doctorate | 6 | 0.6 |
| | Masters | 79 | 7.7 |
| | Undergraduate | 939 | 91.7 |
| Level | First Year | 366 | 35.7 |
| | Fourth Year | 121 | 11.8 |
| | Second Year | 335 | 32.7 |
| | Third Year | 200 | 19.5 |
| Type of University | Private | 95 | 9.3 |
| | Public | 929 | 90.7 |
| Session | Distance-learning | 166 | 16.2 |
| | Regular | 858 | 83.8 |
| | **Total** | **1024** | **100** |

35.7% were first year's students, 90.7% were students of public universities and 83.8% were regular students. Further information on the descriptive statistics of respondents' demographics is provided in Table 1.

### 4.2 Reliability and validity

The study employed Confirmatory Factor Analysis (CFA) to ascertain the extent of reliability and validity of the measurement model before the structural model or hypotheses testing (Voorhees et al., 2016; Ab Hamid et al., 2017). The measurement model test included construct reliability, indicator reliability and convergent validity which are shown in Table 2. Construct Reliability was explored using Composite Reliability (CR). The CR coefficient of 0.70 or higher is considered to have a good scale reliability (Hair et al., 2010). The results as shown in Table 1 indicate that the computed Composite Reliability of all the latent variables ranged between 0.837 and 0.958 and were above the 0.70 threshold. Therefore, there are evidence that all the latent variables have good reliability. Additionally, Cronbach alpha was also measured to determine the items' reliability. Although Wang and Tai (2003) believe that composite reliability is very similar to Cronbach alpha, Nunnally and Bernstein (1994) hold the view that there is the need to measure the two. The Cronbach alpha values ranged between 0.611 and 0.935. All the latent variables were above the 0.60 threshold as recommended by (Huang et al., 2017; Nuanally and Berntein, 1994). For convergent validity, it is required that AVE values should be greater than 0.5. The results in Table 2 depicts that AVE and Factor Loadings were greater than 0.5. Hence, the results confirm the constructs' ability to explain over half of the variations of its indicators. The variance of inflation factor (VIF) displayed in Table 1 also showed ideal collinearity statistics (VIF < 3) (Hair et al., 2019). Collinearity arises when two indicators are highly correlated.

The study also explored the extent to which individual constructs were divergent from other constructs (Hair et al., 2010; Henseler et al., 2016). To confirm discriminant validity, it is required that the diagonal values (square root of AVE) of each latent variable should have a higher value than its highest correlation of the construct. Thus, the result in Table 3 supports discriminant validity. The result again confirms the absence of multicollinearity (Byrne, 2013). Additionally, Henseler et al., (2015) is of the view that, to further confirm the presence of discriminant validity, the heterotrait-monotrait ratio of correlations (HTMT), which is a multitrait-multi method matrix, ought to be explored to validate the result (Fornell-Larcker, 1981). Therefore, the HTMT technique was used to test the discriminant validity. According to Kline (2011), to confirm discriminant validity, the HTMT value should not be better than 0.85. Gold et al., (2001) are of the view that the HTMT value should not be more than 0.90 to confirm discriminant validity. The result as presented in Table 4 indicates that all the values passed the HTMT 0.90 (Gold et al., 2001). Consequently, using both the Fornell and Larcker (1981) criterion and the HTMT, the results indicate that discriminant validity was realized.

**Table 2** Quality Criteria and Factor Loadings

| Constructs | Items | Loadings | Cronbach's Alpha | Composite Reliability | AVE | VIF |
|---|---|---|---|---|---|---|
| Actual Use | AU1 | 0.850 | 0.868 | 0.909 | 0.715 | 2.154 |
| | AU2 | 0.870 | | | | 2.234 |
| | AU3 | 0.855 | | | | 2.178 |
| | AU4 | 0.807 | | | | 1.880 |
| Perceived Autonomy | AUT1 | 0.876 | 0.737 | 0.883 | 0.791 | 2.616 |
| | AUT3 | 0.903 | | | | 2.242 |
| Behavioral Intention | BI1 | 0.933 | 0.935 | 0.958 | 0.885 | 2.268 |
| | BI2 | 0.943 | | | | 2.425 |
| | BI3 | 0.945 | | | | 2.635 |
| Perceived Competence | COMP1 | 0.901 | 0.881 | 0.926 | 0.807 | 2.817 |
| | COMP2 | 0.889 | | | | 2.240 |
| | COMP3 | 0.906 | | | | 1.703 |
| Effort Expectancy | EE1 | 0.861 | 0.611 | 0.837 | 0.719 | 2.107 |
| | EE2 | 0.835 | | | | 2.240 |
| Facilitating Condition | FC1 | 0.788 | 0.848 | 0.898 | 0.688 | 1.754 |
| | FC2 | 0.854 | | | | 1.237 |
| | FC3 | 0.862 | | | | 1.082 |
| | FC4 | 0.810 | | | | 1.223 |
| Hedonic Motivation | HM1 | 0.924 | 0.930 | 0.955 | 0.877 | 2.650 |
| | HM2 | 0.942 | | | | 2.654 |
| | HM3 | 0.943 | | | | 2.326 |
| Habit | Habit 1 | 0.879 | 0.902 | 0.931 | 0.773 | 2.030 |
| | Habit 2 | 0.876 | | | | 1.684 |
| | Habit 3 | 0.855 | | | | 1.973 |
| | Habit 4 | 0.905 | | | | 1.760 |
| Performance Expectancy | PE1 | 0.890 | 0.915 | 0.940 | 0.797 | 1.744 |
| | PE2 | 0.909 | | | | 1.516 |
| | PE3 | 0.875 | | | | 1.516 |
| | PE4 | 0.898 | | | | 2.449 |
| Personality Trait | PT1 | 0.787 | 0.828 | 0.886 | 0.660 | 2.395 |
| | PT3 | 0.847 | | | | 2.499 |
| | PT5 | 0.803 | | | | 2.897 |
| | PT7 | 0.810 | | | | 1.417 |
| Price Value | PV1 | 0.775 | 0.797 | 0.879 | 0.708 | 2.568 |
| | PV2 | 0.851 | | | | 1.081 |
| | PV3 | 0.893 | | | | 2.840 |
| Perceived Relatedness | REL1 | 0.907 | 0.892 | 0.933 | 0.823 | 1.309 |
| | REL2 | 0.928 | | | | 2.279 |
| | REL3 | 0.886 | | | | 1.566 |

**Table 3** Discriminant Validity

| Constructs | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Actual Use | (0.846) | | | | | | | | | | | |
| 2. Behavioural Intention | 0.785 | (0.941) | | | | | | | | | | |
| 3. Effort Expectancy | 0.680 | 0.699 | (0.848) | | | | | | | | | |
| 4. Facilitating Condition | 0.682 | 0.664 | 0.744 | (0.829) | | | | | | | | |
| 5. Habit | 0.762 | 0.754 | 0.673 | 0.679 | (0.879) | | | | | | | |
| 6. Hedonic Motivation | 0.711 | 0.728 | 0.704 | 0.680 | 0.734 | (0.936) | | | | | | |
| 7. Perceived Autonomy | 0.687 | 0.647 | 0.622 | 0.645 | 0.613 | 0.623 | (0.889) | | | | | |
| 8. Perceived Competence | 0.730 | 0.708 | 0.681 | 0.738 | 0.711 | 0.696 | 0.679 | (0.898) | | | | |
| 9. Perceived Relatedness | 0.550 | 0.551 | 0.530 | 0.529 | 0.604 | 0.598 | 0.541 | 0.616 | (0.907) | | | |
| 10. Performance Expectancy | 0.714 | 0.703 | 0.717 | 0.653 | 0.705 | 0.726 | 0.614 | 0.693 | 0.546 | (0.893) | | |
| 11. CSE (Personality Trait) | 0.403 | 0.378 | 0.406 | 0.418 | 0.367 | 0.356 | 0.369 | 0.422 | 0.304 | 0.362 | (0.812) | |
| 12. Price Value | 0.478 | 0.457 | 0.455 | 0.505 | 0.530 | 0.507 | 0.405 | 0.435 | 0.465 | 0.468 | 0.246 | (0.841) |

**Table 4** Heterotrait-Monotrait Ratio (HTMT)

| | Constructs | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Actual Use | | | | | | | | | | | | |
| Behavioural Intention | 0.866 | | | | | | | | | | | |
| Effort Expectancy | 0.825 | 0.826 | | | | | | | | | | |
| Facilitating Condition | 0.786 | 0.744 | 1.028 | | | | | | | | | |
| Habit | 0.858 | 0.821 | 0.808 | 0.775 | | | | | | | | |
| Hedonic Motivation | 0.785 | 0.781 | 0.834 | 0.765 | 0.801 | | | | | | | |
| Perceived Autonomy | 0.852 | 0.777 | 0.824 | 0.813 | 0.748 | 0.750 | | | | | | |
| Perceived Competence | 0.830 | 0.778 | 0.824 | 0.851 | 0.795 | 0.768 | 0.839 | | | | | |
| Perceived Relatedness | 0.622 | 0.603 | 0.719 | 0.608 | 0.673 | 0.656 | 0.664 | 0.694 | | | | |
| Performance Expectancy | 0.797 | 0.760 | 0.860 | 0.742 | 0.776 | 0.787 | 0.745 | 0.769 | 0.604 | | | |
| CSE (Personality Trait) | 0.472 | 0.430 | 0.568 | 0.497 | 0.424 | 0.404 | 0.474 | 0.493 | 0.354 | 0.416 | | |
| Price Value | 0.551 | 0.513 | 0.627 | 0.595 | 0.604 | 0.568 | 0.505 | 0.502 | 0.538 | 0.527 | 0.287 | |

### 4.3 Structural model and hypotheses testing

The hypotheses and construct relationships were tested using the standardized path coefficients (Fig. 1). The paths significance level was calculated using the bootstrap resampling procedure (Henseler et al., 2009), with 500 iterations of resampling (Chin, 1998). The results as presented in Fig. 1 show that the model accounts for 54% of variations in behavioural intentions and 68% in actual usage of e-learning among tertiary education students. Again, the result showed that personality trait has a statistically significant effect on behavioural intention (see

**Table 5** Direct Relationships

| Hypotheses | Path Coefficients | STD | T Statistics | P Values |
|---|---|---|---|---|
| Personality Trait—> Behavioural Intention (H1) | 0.124 | 0.019 | 6.473 | 0.000 |
| Personality Trait—> Effort Expectancy(H2) | 0.407 | 0.027 | 14.8 | 0.000 |
| Personality Trait—> Performance Expectancy(H3) | 0.362 | 0.03 | 12.21 | 0.000 |
| Performance Expectancy—> Perceived Autonomy(H4) | 0.216 | 0.033 | 6.674 | 0.000 |
| Performance Expectancy—> Perceived Competence(H5) | 0.134 | 0.04 | 3.308 | 0.001 |
| Performance Expectancy—> Perceived Relatedness(H6) | 0.191 | 0.039 | 4.93 | 0.000 |
| Effort Expectancy—> Perceived Autonomy(H7) | 0.089 | 0.037 | 2.404 | 0.017 |
| Effort Expectancy—> Perceived Competence(H8) | 0.094 | 0.041 | 2.287 | 0.023 |
| Effort Expectancy—> Perceived Relatedness(H9) | 0.152 | 0.039 | 3.852 | 0.000 |
| Facilitating Condition—> Perceived Autonomy(H10) | 0.364 | 0.034 | 10.738 | 0.000 |
| Facilitating Condition—> Perceived Competence(H11) | 0.083 | 0.04 | 2.093 | 0.037 |
| Facilitating Condition—> Perceived Relatedness(H12) | 0.282 | 0.04 | 6.98 | 0.000 |
| Habit—> Perceived Autonomy(H13) | 0.268 | 0.03 | 8.87 | 0.000 |
| Habit—> Perceived Competence(H14) | 0.309 | 0.042 | 7.248 | 0.000 |
| Habit—> Perceived Relatedness(H15) | 0.179 | 0.04 | 4.575 | 0.000 |
| Price Value—> Perceived Autonomy(H16) | -0.031 | 0.023 | 1.405 | 0.161 |
| Price Value—> Perceived Competence(H17) | 0.154 | 0.033 | 4.735 | 0.000 |
| Price Value—> Perceived Relatedness(H18) | 0.009 | 0.027 | 0.328 | 0.743 |
| Perceived Autonomy—> Behavioural Intentions(H19) | 0.437 | 0.034 | 12.749 | 0.000 |
| Perceived Competence—> Behavioural Intentions(H20) | 0.133 | 0.031 | 4.175 | 0.000 |
| Perceived Relatedness—> Behavioural Intentions(H21) | 0.278 | 0.035 | 7.994 | 0.000 |
| Perceived Autonomy—> Actual Use(H22) | 0.407 | 0.027 | 14.8 | 0.000 |
| Perceived Competence—> Actual Use(H23) | 0.366 | 0.025 | 14.438 | 0.000 |
| Perceived Relatedness—> Actual Use(H24) | 0.42 | 0.028 | 14.683 | 0.000 |
| Behavioural Intentions—> Actual Use(H25) | 0.738 | 0.018 | 41.81 | 0.000 |

Table 5), performance expectancy and effort expectancy, all with $p < 0.05$, thus confirming hypotheses $H_1$, $H_2$ and $H_3$. Performance expectancy was found to be statistically significant in explaining motivation (perceived autonomy, perceived competence and perceived relatedness) for e-learning usage among tertiary education students at 5% level of significance. This confirms hypotheses $H_4$, $H_5$ and $H_6$. Similarly, effort expectancy, facilitating conditions, and habit were found to be statistically significant in explaining motivation (perceived autonomy, perceived competence and perceived relatedness) for e-learning usage among tertiary education students at 5% level of significance, thus confirming hypotheses $H_7$, $H_8$, $H_9$, $H_{10}$, $H_{11}$, $H_{12}$, $H_{16}$, $H_{17}$ and $H_{18}$. On the contrary, price value was found to be statistically insignificant in explaining perceived autonomy and perceived relatedness at 5% level of significance thus rejecting hypotheses $H_{13}$ and $H_{15.}$ However, price value was found to be statistically significant in explaining perceived competence at 5% level of significance, thus, confirming hypothesis $H_{14}$. Perceived autonomy, perceived competence and perceived relatedness were all found to have significant effects on behavioural intentions and actual use respectively at 5% level of significance, thus confirming hypotheses $H_{19}$, $H_{20}$, $H_{21}$, $H_{22}$, $H_{23}$ and $H_{24}$. The effect of behavioural intentions on actual usage was found to be statistically significant at 5% level of significance, thus confirming hypothesis $H_{25}$.

The mediating effect was examined following Preacher and Hayes (2008) and Hair et al. (2013)'s recommendation for exploring indirect effects (see Table 6). Performance expectancy and effort expectancy were found to mediate the relationships between personality trait and SDT dimensions (perceived autonomy, perceived competence, perceived relatedness). Furthermore, the SDT dimensions of perceived autonomy, perceived competence and perceived relatedness were found to mediate several relationships between the UTAUT2 dimensions and behavioural intentions. However, perceived competence did not mediate the relationship between effort expectancy and behavioural intentions. Likewise, perceived autonomy and perceived relatedness did not mediate the relationship between price value and behavioural intentions. Lastly, behavioural intentions positively mediated the relationship between SDT dimensions and actual usage of e-learning. In all, the results from Tables 5 and 6 indicate that twenty-three (23) out of the twenty-five (25) direct hypotheses were supported while nineteen (19) out of twenty-two (22) indirect hypotheses were supported. In all, forty-five (45) out of the forty-nine (49) hypotheses were confirmed (Table 3).

## 5 Discussion

The purpose of the study was to examine the underlying factors influencing or depriving the usage behaviour of e-learning among tertiary education students in Ghana. The framework for the study was developed based on UTAUT2 with two factors: personality trait and motivation incorporated in the model. The outcome of the study showed that the UTAUT2 model is a useful technology acceptance framework in understanding students' acceptance of e-learning with empirical evidence from Ghanaian university students. The outcome of the study validated

**Table 6** Indirect Relationships

| Hypotheses | Path Coefficients | T Statistics | P Values |
|---|---|---|---|
| Personality Trait—> Performance Expectancy—> Perceived Autonomy | 0.078 | 5.458 | 0.000 |
| Personality Trait—> Performance Expectancy—> Perceived Competence | 0.049 | 3.108 | 0.002 |
| Personality Trait—> Performance Expectancy—> Perceived Relatedness | 0.069 | 4.359 | 0.000 |
| Personality Trait—> Effort Expectancy—> Perceived Autonomy | 0.036 | 2.325 | 0.020 |
| Personality Trait—> Effort Expectancy—> Perceived Competence | 0.038 | 2.266 | 0.024 |
| Personality Trait—> Effort Expectancy—> Perceived Relatedness | 0.062 | 3.726 | 0.000 |
| Performance Expectancy—> Perceived Autonomy—> Behavioural Intentions | 0.094 | 5.883 | 0.000 |
| Performance Expectancy—> Perceived Competence—> Behavioural Intentions | 0.053 | 4.428 | 0.000 |
| Performance Expectancy—> Perceived Relatedness—> Behavioural Intentions | 0.053 | 4.428 | 0.000 |
| Effort Expectancy—> Perceived Autonomy—> Behavioural Intentions | 0.039 | 2.294 | 0.022 |
| Effort Expectancy—> Perceived Competence—> Behavioural Intentions | 0.013 | 1.883 | 0.060 |
| Effort Expectancy—> Perceived Relatedness—> Behavioural Intentions | 0.042 | 3.420 | 0.001 |
| Facilitating Condition—> Perceived Autonomy—> Behavioural Intentions | 0.010 | 2..091 | 0.037 |
| Facilitating Condition—> Perceived Competence—> Behavioural Intentions | 0.011 | 1.959 | 0.051 |
| Facilitating Condition—> Perceived Relatedness—> Behavioural Intentions | 0.078 | 5.581 | 0.000 |
| Price Value—> Perceived Autonomy—> Behavioural Intentions | -0.014 | 1.383 | 0.167 |
| Price Value—> Perceived Competence—> Behavioural Intentions | 0.021 | 3.033 | 0.003 |
| Price Value—> Perceived Relatedness—> Behavioural Intentions | 0.003 | 0.327 | 0.744 |
| Habit—> Perceived Autonomy—> Behavioural Intentions | 0.117 | 7.265 | 0.000 |
| Habit—> Perceived Competence—> Behavioural Intentions | 0.041 | 3.325 | 0.001 |
| Habit—> Perceived Relatedness—> Behavioural Intentions | 0.050 | 3.414 | 0.001 |
| Perceived Autonomy—> Behavioural Intentions—> Actual Use | 0.323 | 11.896 | 0.000 |
| Perceived Competence—> Behavioural Intentions—> Actual Use | 0.098 | 4.126 | 0.000 |
| Perceived Relatedness—> Behavioural Intentions—> Actual Use | 0.206 | 7.716 | 0.000 |

the relationship of personality trait with PE and EE. The positive effect of PT on PE and EE is consistent with previous studies (Lee et al., 2016; Wang & Yang, 2005). This implies that students' perceptions regarding PE and EE vary depending on the individual personality traits. Personality trait was also found to significantly affect behavioural intention to adopt e-learning systems which is consistent with previous studies (Chiu et al., 2015; Gisella et al., 2019; Nesa and Noorminshah, 2014; Alfie, 2012). The findings indicate that individual differences constitute beliefs which in turn manifest as the behavioural intention of an individual to engage in e-learning. The finding also showed that PE significantly relates to motivation (thus PA, PC and PR). The findings are in line with previous studies (Moez et al., 2015). Again, effort efficiency was also related to all the three (3) dimensions of motivation to use e-learning systems among tertiary education students. This relationship is also consistent with the outcome of (Rahman et al., 2020; Hamid et al., 2019; Moez et al., 2015). In addition, facilitating condition significantly relates with all three (3) dimensions of motivation such as PA, PC and PR. The findings of the study relate to a similar study of Kesse et al., (2015). The findings from the study also revealed that habit significantly relates with PA, PC and PR to determine the dimensions of motivations of motivation to use e-learning systems among tertiary education students. The results implied that habit significantly relates to motivation. The significant relationship of habit with all the three (3) dimensions of motivation is consistent with previous studies (e.g., El-Seoud et al., 2014). The findings from the study showed that price value was significantly related to only one dimension of motivation (perceived competence). Price value did not significantly relate to the other two dimensions of motivation (perceived relatedness and perceived autonomy). The relationship between price value and perceived autonomy, though insignificant, was negative, supporting Lee et al. (2015). Furthermore, all three dimensions of motivation significantly related to behavioural intentions. This implies that self-motivated and self-determined university students will have a positive intention to use e-learning. The finding is in line with a similar study by Su and Chen (2020). Again, the study revealed that all three (3) dimensions of motivation (PA, PC and PR) significantly relate to the actual use of e-learning systems among tertiary education students. The study, therefore, showed that the three dimensions of motivation as well as behavioural intentions to use e-learning relate to actual use among tertiary education students. This means that basic psychological needs support and influence the attitude of university students to use e-learning. The outcome of the study is in line with a similar study of (Khan et al., 2018). The research model validated the mediatory role played by motivation (PA) between EE, habit, PE and behavioural intentions. Again, the study validated the mediatory role played by PC between habit, price value and behavioural intention. However, the mediatory role of PA between PV and behavioural intention was not supported. The mediatory role of PC between EE and FC was not supported. Also, the model validated the mediation role of PR between EE, FC, Habit, PE and BI. However, the model did not confirm the mediatory role of PR between PV and BI. The model validated the mediation role of BI between motivation (PR, PC and PA) and usage behaviour of e-learning among tertiary education students.

## 6 Theoretical contribution

In the acceptance and use of technology, intrinsic and extrinsic factors play a role. Researchers have argued that studies on technology acceptance should incorporate intrinsic and extrinsic factors. In this study, we follow suit by combining the extrinsic and intrinsic factors. We, therefore, combined the constructs of UTAUT2 (without hedonic motivation), Self-determination theory and Core self-evaluation (Personality). We believe that SDT has been accepted as a tool to examine individuals' intrinsic motivation in various contexts. Again, the SDT was treated as a second-order construct to improve the explanatory power. Previous learning experiences placed the focus on the instructor in the physical space. With the introduction of virtual learning, the focus has shifted to the individual learners' motivation to take advantage of technology and self-direct, self-reflect and self-regulate their learning experiences. This study is the first attempt to combine the SDT, CSE and UTAUT 2 to examine technology (e-learning) acceptance and usage. Empirical support, evident in this study, for the combination of SDT, CSE and UTAUT2 as antecedents and pathways underpins the importance of individual differences and motivation in influencing e-learning acceptance and usage. The study also contributes to the e-learning literature during pandemics. E-learning has been studied with regards to adoption and in this study, we offer insights into the UTAUT2 model. We extend the UTAUT2 model and also apply the model in a new setting and context, namely e-learning in Sub-Saharan Africa, thus validating the second-order model of UTAUT2 which contains five first-order constructs (performance expectancy, effort expectancy, habit, facilitating conditions, and price value). The integration of the three theories created a rigid model in this context explaining 68% of the actual use variance in this context, better than other adoption models (e.g., Ameri et al., 2020; Venkatesh et al., 2012).

## 7 Practical contributions

The COVID-19 pandemic has heightened the urgency for the academic community to embrace e-learning not only for distance learning students but also for regular students who preferred face-to-face lectures. This study provides data for e-learning providers and decision-makers to understand users' points of view to keep students engaged with the e-learning system as a tool to gain knowledge and learning experience. A good understanding of the factors that influence the use of e-learning will help stakeholders to implement strategies and incorporate designs that will encourage students to use the system. The design of the system should incorporate various motivating and engaging interfaces. Students will be motivated to use e-learning for educational activities if they receive enough support and guidance from lecturers and administrators. Appropriate use of e-learning, in this COVID-19 pandemic era, will enhance autonomy supported environment (Deci & Ryan, 2016) which will in turn improve learning.

Again, the outcome of this study can be used as a guide for educational institutions in Ghana. It presents the relevant factors and the ability of e-learning to solve the myriad of problems facing education as a result of the pandemic (COVID-19). The problems that emerged in the wake of the pandemic indicate that e-learning can enhance the quality of education and maximize cost efficiency. E-learning has the potential to improve the quality of education with minimum resources (Shukor et al., 2015; Chang, 2015). Another contribution of this study is that there is a positive relationship between motivation and actual use. This implies that intrinsically motivated students will use the e-learning system. According to Deci and Ryan (1985), intrinsic motivation is supported when the three basic needs of autonomy, competence and relatedness are satisfied.

## 8 Conclusion

Normal classroom lectures have shifted overnight into e-classrooms, together with the entire pedagogy in response to the COVID-19 initiated changes in tertiary institutions worldwide. The next big question is: is everybody ready for the transition to e-learning? (Carey, 2020). We studied one key stakeholder that is affected by this rapid transition – students. The success of e-learning and the continual usage of e-learning depends hugely on the perception and acceptance of e-learning. This study assesses the influence of students' motivation and core self-evaluation in the acceptance and actual use of e-learning for hitherto classroom-based learners. This study combines the UTAUT2, CSE, and the SDT in a model that assesses the comprehensive acceptance of e-learning by students. The main limitation of this study was the cross-sectional nature of the research. However, the use of the cross-section design was appropriate due to the period of the research, where COVID-19 was at its peak and e-learning has become mainstream for the first time to replace physical learning completely. Future studies can adopt a longitudinal or an experimental design to determine causality among the variables. Furthermore, we did not examine the effects of personality on some of the constructs of UTAUT2. Future studies should examine the influence of students' personality traits on all the constructs of UTAUT.

### Declarations

**Conflict of interest** None.

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