Contemporary Educational Technology, 2022, **14**(4), ep379
ISSN: 1309-517X (Online)

OPEN ACCESS

Research Article

Promoting Voluntary Use Behavior of Learning Management Systems Among Tutors for Blended Learning in Distance Higher Education

Brandford Bervell [1,2*]
0000-0002-3925-6877

Irfan Naufal Umar [2]
0000-0003-1719-5679

Mona Masood [2]
0000-0002-3200-8918

Jeya Amantha Kumar [2]
0000-0002-6920-0348

Justice Kofi Armah [1]
0000-0002-6528-0440

Beatrice Asante Somuah [3]
0000-0002-0917-4504

[1] College of Distance Education, Maths, Science & ICT Department, University of Cape Coast, Cape Coast, GHANA
[2] Center for Instructional Technology and Multimedia, Universiti Sains Malaysia, Penang, MALAYSIA
[3] College of Distance Education, Education Department, University of Cape Coast, GHANA
[*] Corresponding author: b.bervell@ucc.edu.gh

Citation: Bervell, B., Umar, I. N., Masood, M., Kumar, J. A., Armah, J. K., & Somuah, B. A. (2022). Promoting Voluntary Use Behavior of Learning Management Systems Among Tutors for Blended Learning in Distance Higher Education. *Contemporary Educational Technology, 14*(4), ep379. https://doi.org/10.30935/cedtech/12193

ARTICLE INFO

Received: 23 Feb 2022

Accepted: 16 Jun 2022

ABSTRACT

Contemporary distance higher education is hinged on modern technologies to deliver purely online and blended modes of learning mostly through learning management system (LMS). This is to bridge the transactional gap between students and instructors as well as among students themselves. However, the use of technologies such as LMS for dispensing distance tertiary education is at a cross-road of mandatoriness or voluntariness of use. Nonetheless, current literature supports the voluntary use of LMS by instructors in order to foster positive attitudes and personalization among instructors. Based on this, there is the need to unravel the determining facts that promote voluntary usage of LMS among tutors.

This study thus, employs a quantitative approach based on a survey design to purposively collect data from 267 tutors in a blended distance education setting using a questionnaire. Generalized structural component analysis technique was adopted for structural equation modelling. Results from a structural equation modelling revealed that performance expectancy, effort expectancy, facilitating conditions, and social influence, all determine tutors' voluntariness of use of LMS for blended learning in distance education. Additionally, voluntariness of use predicted actual LMS use behavior among tutors. On the basis of the results, recommendations were made to reflect theory, policy and practice of voluntary integration of LMS by tutors for blended learning in distance education.

Keywords: LMS, voluntariness of use, tutors, blended learning, distance higher education, generalized structural component analysis

INTRODUCTION

The outbreak of COVID-19 disrupted the academic activities of most educational institutions (Ansong-Gyimah, 2020; Bervell et al., 2021; Bonsu et al., 2021; Zagkos et al., 2022). This was primarily due to the lockdown situation that hindered face to face interaction. As a result, most institutions resorted to online teaching and learning or webagogy (Bervell et al., 2021; Ramlo, 2021; Razkane et al., 2022). Currently, after the lockdown period, educational institutions especially, tertiary or higher educational outfits are encouraged to implement the blended learning mode to reduce in-person interaction (Bervell et al., 2020; Bonsu et al., 2021). However, one of the technologies that fosters the utilization of online pedagogy/andragogy is the learning management system (LMS) (Bervell & Umar, 2017; Mtebe, 2020). As a result, most higher educational institutions in Africa and across the world have procured LMS for blended learning purposes (Zalat et al., 2021).

Nonetheless, during the lockdown period, mandatory use of LMS for online learning was enforced by most higher educational institutions (Alturki & Aldraiweesh, 2021; Zagkos et al., 2022). The challenge here is that, this mandatory use of technology approach, according to Rawstorne et al. (2000), hinders a person's will from performing at optimum levels of usage as well as possess a favorable attitude towards the technology. According to Pynoo et al. (2011), even with student users, perceived voluntariness of use was more important. The more they experienced that their use of a web-based course management system was voluntary, the higher their attitudes and intensity and frequency to use (Pynoo et al., 2011).

Furthermore, Hartwick and Barki (1994) opined that even in a mandated environment, technology use is still fundamentally volitional. That is users can still choose to use a technology or not, especially for stand-alone software applications that can have alternatives or substitutes for job performance (Brown et al., 2002). This is further explained by two situations of where there is necessity and integration into the general organizational operation vs. personalized technology or system substitution not directly integrated into the general organizational operation (Brown et al., 2002). This is normally the case with LMS technology integration, since instructors can still achieve their aim with traditional methods of instruction (Johnson et al., 2016).

Mandatory use of technology hinders a person's will from performing at optimum levels of usage as well as possess a favorable attitude towards the technology (Rawstorne et al., 2000). According to Yeung et al. (2012), mandating the use of digital technologies in educational settings may not be useful. This is seconded by Shin and Dai (2020) who pointed out that a customer's voluntary use of self-service technology results in positive service experiences. According to Chen (2022), amidst or after the global pandemic, one can be sure that online instruction should still be encouraged. Thus, the cultivation of voluntary usage of technology has become imperative in defining individuals use behavior of technology. In the view of Van der Heuval (2020), in these times of extremely restrictive measures, a person's behavioral intention may only play a limited role in explaining one's actual behavior. Therefore, voluntariness is likely to influence a person's use behavior directly and in this case tutors. According to Schlachter et al. (2018), voluntary ICT use appears to be predominantly relevant for knowledge workers whose works are dominated by non-manual routines, just like blended and online teaching that requires technology use.

Within the context of this study, distance education tutors or facilitators engaged students both synchronously and asynchronously through the use of LMS where video-conferencing (especially via Zoom and Google Meet), chats, uploading assignments, and receiving feedback as well as downloading instructional materials were the main activities. What is missing in contemporary literature is how voluntariness of use of such a technology, especially in higher education, can be promoted and by which factors? Based on the above, it becomes imperative to unravel the factors that determine tutors' voluntariness of use of LMS for blended learning in distance education. Additionally, this study fills the research gap of defining a voluntariness of use-based model for LMS-enabled blended learning in distance higher education. Accordingly, the study seeks to answer the following research questions:

1. What are the determinants of tutors' voluntariness of use of LMS for blended learning in distance education?

2. What is the relationship between voluntariness of use and use behavior of LMS by tutors for blended learning in distance education?
3. What is the total variance (R^2) explained by the proposed model on voluntariness of use of LMS by tutors based on their use behavior for bended learning in distance education?

LITERATURE REVIEW

Literature is reviewed based on two proposed categories of factors with their corresponding variables, which may influence voluntariness of use of LMS in distance education. Thus, factors inherent to the LMS system (performance expectancy and effort expectancy) as well as external factors to the LMS system (facilitating conditions and social influence) are opined to exert some influence or effect on voluntariness of use of LMS by tutors for blended learning in distance education delivery. Literature was reviewed based on the possible relationships that exist among facilitating conditions, performance expectancy, effort expectancy, social influence, and voluntariness of use of LMS for blended learning. Finally, the relationship between voluntariness of use of LMS and use behavior was established by both theoretical and empirical literature.

HYPOTHESES FORMULATION AND CONCEPTUAL MODEL

Relationship Between Facilitating Conditions and Voluntariness of Use

Facilitating conditions explain the extent to which organizational resources and support are put in place for the uptake of technological systems (Bervell & Umar, 2017). Contextually, we define facilitating conditions as tutors' believe that organizational resources and support are available for the use of LMS to carry out blended learning endeavors in distance education. This implies that prior to the actual use of novel technologies for organizational work, support availability and accessibility should be a benchmark (Bervell & Arkorful, 2020; Kamaghe et al., 2020). Providing such enabling environment in relation to the utilization of technology has a great tendency of promoting self-will usage of technology. Thus, when potential users of technology come to the awareness of the fact that organizational resources and support are at their disposal to assist them to use novel technologies, they will act as innovators and try out these technologies on their own volition without a centralized mandatory condition from authorities and vice-versa (Chiu & Ku, 2015). Their intrinsic and extrinsic motivation to use technology at will, promotes a better use outlook behavior and personalization of the said technologies. Even within mandatory environments, Hurst (2010) explained that

> "the influence of facilitating conditions on use behavior is a consideration in the design of any mandatory technology-based learning program" (p. 12).

As the use of LMS-enabled blended learning has become a necessary option for both instructors and students in this COVID-19 era, the provision of facilitating conditions has a consequential effect on both voluntary and mandatory use environments of online learning. This suggests that facilitating conditions influence both voluntary and non-voluntary technology use environments for learning. The relationship between facilitating conditions and voluntariness of use of LMS has been theorized by Chiu and Ku (2015) and Venkatesh et al. (2003, 2008); but empirically proven by Bervell and Arkorful (2020). Against this backdrop, we postulate in this study that:

H1: Facilitating conditions have a positive predictive relationship with voluntariness of use of LMS by tutors for blended learning in distance education.

Relationship Between Performance Expectancy and Voluntariness of Use

Performance expectancy is the degree to which individuals believe that using technological systems will help them obtain or achieve better gains in job performance (Venkatesh et al., 2012). In the context of blended learning in distance education, this variable is explained as tutors' believe that using LMS to provide blended distance education will help them to deliver better andragogical practices and services to promote effective distance learning. Such positive expectations by tutors towards LMS usage in delivering blended distance education has a propensity to instill self-will usage of LMS without any force from a central administration. Tutors will not feel that an authority is pressurizing them to use LMS but rather have personally envisioned that the use of LMS technology is beneficial for their distance education practices and even enhances their performance of such responsibilities or tasks. Accordingly, Margahana and Garaika (2019) indicated empirically that voluntariness of use is influenced by performance expectations of potential users of learning technological systems. Theoretically, Brown et al. (2002) expressed that in a volitional setting, when perception of usefulness (performance expectation) is low, the result is simply not to adopt such technologies and vice-versa. This renders usefulness or performance expectation of technology as an important variable in voluntary technology use environments. According to Johnson et al. (2016), if teachers do not expect new technologies to be useful, they will be unwilling to use such technologies voluntarily. They will rather persist using more traditional methods. This presupposes that, tutors will go for LMS if they find it useful to their distance educational activities. This will further promote their voluntariness in choosing and using the technology. Although not much studies have been conducted on this relationship, the above literature provides a basis to hypothesize that:

H2: Performance expectancy has a positive predictive relationship with voluntariness of use of LMS by tutors for blended learning in distance education.

Relationship Between Effort Expectancy and Voluntariness of Use

Effort expectancy or ease of use denotes the degree to which individuals believe that using a particular information system will be easy to use or of limited use efforts (Venkatesh et al., 2012). Within this study, we explain the variable to be the degree to which tutors in distance education believe that the use of LMS for delivering blended distance learning will require little or no effort. This indicates that novel users of technologies will be eager to have information on the ease of use of such systems to ascertain if their usage will be devoid of complexity or excessive difficulty. Conversely, they will be hesitant to use it if the novel technology is too difficult as compared to their traditionally existing methods of carrying out their job-related activities (Richardson, 2011; Vaportzis et al., 2017). Within this study, it is envisaged that tutors of distance education will use LMS voluntarily to discharge their distance education duties if the technology usage is easy. The easiness or otherwise of LMS technology has the likelihood of promoting volition in use or vice-versa (Shi & Dai, 2020). This generates a kind of positive relationship between effort expectancy and voluntariness of use. According to Lwoga and Komba (2015) and Pynoo et al. (2011), ease of use or effort expectancy significantly relates to voluntary usage which later results in frequency and intensity of usage. This suggests that tutors' expectations of how easy LMS technology will be in utilizing it for blended distance learning, could directly influence their volition in using LMS and even how copious they will use it. Thus, if LMS usage requires very scanty or little effort, it will create in tutors a favorable affection towards its usage (Bervell & Umar, 2017) and eventually induce a non-mandated use behavior in tutors for blended distance education delivery. On this basis, the study postulates that:

H3: Effort expectancy will have a positive predictive relationship with voluntariness of use of LMS by tutors for blended learning in distance education.

Relationship Between Social Influence and Voluntariness of Use

Social Influence or subjective norm reflects the extent to which individuals believe that important referent others want them to use technology systems for job-related tasks (Venkatesh et al., 2012). In this study, it is tutors' believe that their peers and important others suggest that they use LMS to discharge their distance educational tasks other than a compulsion by a central authority. The influence of social norm has been a key determinant in the use of systems and other online behaviors such as online shopping, online advertisement, electronic services, etc. (Celik, 2011; Srinivasan, 2015). The same is prevalent when it comes to online learning or technology adoption. For instance, all authors (Kim & Park, 2011, Taiwo et al., 2012; Tarhini et al., 2014) expressed the influence of peers, role models, referent others, etc. in determining technology use. This is because conformity to group behavior is critical for realizing self-identity (Abrams et al., 2001; Kim & Park, 2011). Individuals are inclined to behave or model their actions around a group for belonginess (Kim & Park, 2011; Lascu & Zinkhan, 1999; Shin & Dai, 2020). Hence, the tendency to feel accepted and be defined with a group that is important to them, causes them to voluntarily accord or submit to group behaviors. Kim and

Park (2011) suggested a re-examination of the social influence factor when it comes to voluntary use of technology based on group recommendation. The authors indicated that when group members promote and prompt other members of usefulness of technology, they tend to adopt it at will to either gain the benefits from the technology or possess the group's new technology use identity. In addition, Shin and Dai (2020) indicated that individuals are more willing to use technology when they observe that others find it easy to use. However, apart from the empirical findings from Kim and Park (2011) on the effect of social influence on voluntary adoption of 'Gifticon' mobile service, very little is known on how this relationship is significant or otherwise in LMS usage research. Accordingly, we leverage on the above literature and postulate that if tutors find their peers using LMS for blended distance learning, their inclination to conform to the group norm will lead them to also adopt the technology willingly. Against this backdrop, we formulate the hypothesis:

H4: Social influence will have a positive predictive relationship with voluntariness of use of LMS by tutors for blended learning in distance education.

Relationship Between Voluntariness of Use and Use Behavior

The nature of environment within which technology adoption takes place has been categorized into two (Venkatesh et al., 2003). This comprises mandatory and voluntary environments. Venkatesh et al. (2003) defined mandatory environment of technology adoption as an environment where adopters or users are obliged to use a technology system to perform job-related tasks. On the other hand, a voluntary environment is an adoption condition where individuals use technological tools at their free-will without any imposition by an authority or management (Bervell & Arkorful, 2020). However, the voluntariness of use variable was explained by Venkatesh et al. (2003) as the degree to which the use of an innovation is perceived to be voluntary or of free-will. The disparity within the condition prevailing in the two usage environments (mandatory or voluntary) influences the nature and extent to which users employ a technological innovation (Bervell & Arkorful, 2020; Donaldson, 2011; Venkatesh et al., 2003). For example, Van der Heuval (2020) explained that mandatory use of technology prevents personalization and positive internalization of technology, while voluntary usage promotes positive attitudes and use intensity (Pynoo et al., 2011). This implies that the mandatoriness or voluntariness of the usage condition of technology, has an effect on the pattern of use behavior of users. Within LMS research, two authors have empirically confirmed this relationship. For instance, Bervell and Arkorful (2020) justified this relationship among tutors in a distance education milieu while Donaldson (2011) revealed the significance of the relationship among both instructors and students in integrating mobile learning technology into conventional higher education. Intriguingly, earlier findings by Wu and Lederer (2009) did not support that of Donaldson (2011) as well as Bervell and Arkorful (2020). Owing to the aforementioned, there is the need to further validate this relationship. Hence, this study suggests a postulation that:

H5: Voluntariness of use of LMS has a positive predictive relationship with use behavior of LMS by tutors for blended learning in distance education.

Based on the reviewed literature on the hypothesized relationships among the variables for this study, the conceptual model in **Figure 1** is proposed.

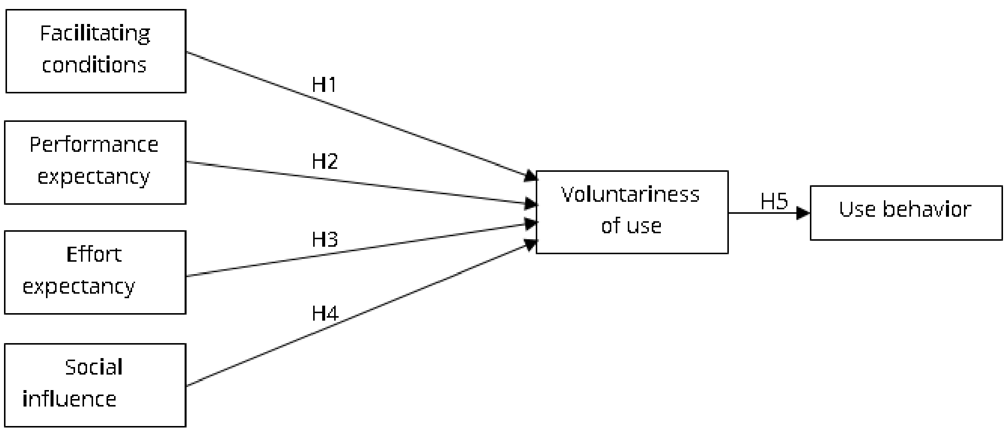

Figure 1. Hypothesized model for the study

MATERIALS AND METHODS

This study adopted a quantitative approach based on a survey design to collect data from a sample of 267 tutors out of a population of 400 tutors country-wide, who were engaged in tutoring online in distance education. Their consent was sought and had the will to fall out of the study at any time in order to fulfill ethical standards. The sampling technique was purposive, since it involved only tutors who were using the online system to teach. The 267 tutors were representative enough for the total population of 400, based on Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) (Kaiser, 1974) and Krejcie and Morgan (1970) sampling adequacy thresholds. Questionnaire adapted for this study was from Bervell (2018) and Venkatesh et al. (2003) and was anchored on a five-point Likert scale. The questionnaire consisted of two key sections: demographic and main data sections. The demographic section comprised gender, age, teaching experience, courses, program type, and location. The questionnaire was validated by experts' review and statistically verified for reliability through Cronbachs' alpha, composite reliability and Rho_A. The data collection period spanned three weeks and completed questionnaire responses were entered into SPSS for data cleaning. The refined data were converted into comma separated values (csv) file and exported into GSCA software for structural equation modelling (SEM) analysis.

ANALYSIS AND RESULTS

Demographic Data

Descriptive statistical analysis of demographic data revealed that there were 164 males and 103 females representing 61.4% and 38.6%, respectively. The general ages of tutors were between ≤35 to ≥56. However, those in the age bracket of 36-45 dominated the sample with 38.2% and a corresponding number of 102. The least age category of respondents comprised those tutors who were 56 years and above. In terms of teaching experience, majority of the tutors had taught between 6 and 10 years. This was represented by a frequency of 112 and a percentage of 42.0%. Few of the teachers had taught for more than 11 years. This is because only 57 of them had such an experience. On the type of courses tutors handled, more than half of the respondents taught education related courses, representing 50.9%. The remaining tutors belonged to business (69; 25.8%); and maths & science (62; 23.2%). On the level of programs, the diploma level had the majority of tutors with a percentage of 61.4%. The degree (undergraduate) and masters (postgraduate) tutors represented 87 and 14 with corresponding percentages of 5.2% and 33.3%, respectively. Finally, with respect to the location of tutors, 173 taught in an urban study center while 94 taught in a rural study center. Thus, more tutors were in the urban areas than that of the rural areas.

Main Data

In order to analyze the main data based on the specified model of this study, we conducted a two-level analysis comprising measurement model analysis and structural model analysis. The measurement model analysis was to measure the internal consistency (validity and reliability) of the instrument used. Indices used included factor loadings, Cronbach's alpha, Rho_A, average variance extracted (AVE), heterotrait-monotrait ratio (HTMT), variance inflation factor (VIF), and total variance explained (R^2). **Figure 2** and **Table 1** depict the GSCA algorithm interface and statistical results, respectively.

Internal Consistency Measures

Table 1 shows all the factor loadings across the various constructs as well as Cronbach alpha, Rho_A, and AVE values obtained.

From **Table 1**, all the factor loadings were higher than the 0.701 threshold recommended by Hair et al. (2017). This is because all the loadings were between a minimum value of 0.707 to a maximum of value 0.882. This implies that all the items adequately measured the constructs within the model (Kline, 2015). Cronbach's alpha values were all higher than 0.7 as suggested by Cronbach (1990). The Rho_A, which is a more reliable and stable reliability coefficient, also recorded values of between 0.827 to 0.924 confirming that all the values were higher than 0.701 (Hair et al., 2017). Finally, AVE values are supposed to be equal or higher than 0.5 (Hair et al., 2017; Kline, 2015).

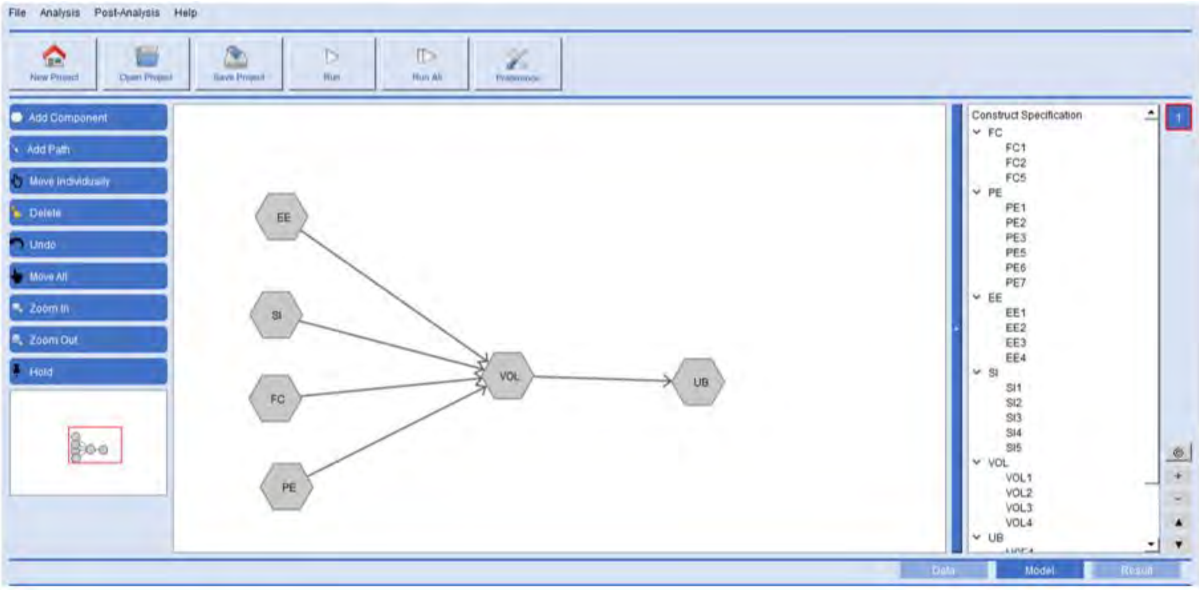

Figure 2. GSCA interface for model analysis (EE: Effort expectancy; PE: Performance expectancy; FC: Facilitating conditions; SI: Social influence; VOL: Voluntariness of use; UB: Use behavior)

Table 1. Validity and reliability indicators

Variables	Factors	Loadings	Cronbach's alpha	Rho$_A$	AVE
FC	FC1	0.775			
	FC2	0.808	0.701	0.829	0.618
	FC5	0.773			
PE	PE1	0.801			
	PE2	0.805			
	PE3	0.826	0.901	0.924	0.670
	PE5	0.831			
	PE6	0.836			
	PE7	0.810			
EE	EE1	0.807			
	EE2	0.835	0.842	0.894	0.678
	EE3	0.841			
	EE4	0.810			
SI	SI1	0.781			
	SI2	0.802			
	SI3	0.817	0.840	0.886	0.611
	SI4	0.794			
	SI5	0.707			
VOL	VOL1	0.589			
	VOL2	0.794	0.719	0.827	0.549
	VOL3	0.804			
	VOL4	0.756			
UB	USE1	0.842			
	USE3	0.882	0.881	0.918	0.738
	USE4	0.861			
	USE5	0.849			

From **Table 1**, the minimum AVE value was 0.549. This means that the threshold for AVE was also met by the measurement model. Based on the above-mentioned indices and their corresponding thresholds, the estimated model for this study met the reliability standards.

Discriminant Validity

For each factor or construct within the model, there should be uniqueness of measurement. Thus, discriminant validity measures how each variable within the model is different from each other to ensure the elimination of construct redundancy (Henseler et al., 2015). This is measured by the HTMT figures obtained in **Table 2**. According to Henseler et al. (2015), all corresponding values between variables should be less than 0.85 in the stricter sense. From **Table 2**, the HTMT values ranged between 0.123 to 0.574. This means that all the values were lower than the strict criterion of 0.85. Thus, discriminant validity was achieved.

Table 2. HTMT

Construct	HTMT values	Construct	HTMT values	Construct	HTMT values
FC <-> PE	0.506	PE <-> EE	0.734	EE <-> VOL	0.225
FC <-> EE	0.563	PE <-> SI	0.401	EE <-> UB	0.535
FC <-> SI	0.574	PE <-> VOL	0.299	SI <-> VOL	0.106
FC <-> VOL	0.123	PE <-> UB	0.450	SI <-> UB	0.283
FC <-> UB	0.473	EE <-> SI	0.475	VOL <-> UB	0.312

Structural Model Analysis

The second step of the analysis procedure is the paths modelling for significance testing of the hypothesized paths. The results of the paths analysis are indicated in **Table 3**.

Table 3. Paths significance results

PR	SM (M)	SD (STDEV)	t-statistics (|O/STDEV|)	p-values	CI: LB 5%	UB 95%
PE -> VOL	0.243	0.049	6.527	0.001*	0.692	0.882
EE -> VOL	0.295	0.046	7.262	0.000*	0.691	0.875
SI -> VOL	0.233	0.023	5.241	0.004*	0.341	0.513
FC -> VOL	0.401	0.078	6.950	0.000*	0.014	0.313
VOL -> UB	0.241	0.093	6.313	0.002*	0.052	0.307

Note. PR: Path relationships; SM: Sample mean; SD: Standard deviation; CI: Confidence interval; LB: Lower boundary; UB: Upper boundary

From **Table 3**, the results of the bootstrapping sequence for paths' significance analysis indicate that performance expectancy (β=0.243; t=6.527; p=0.001 at p<0.01), effort expectancy (β=0.295; t=7.262; p=0.000 at p<0.01), social influence (β=0.233; t=5.241; p=0.004 at p<0.01) and facilitating conditions (β=0.401; t=6.950; p=0.000 at p<0.01), all determine tutors' voluntariness of use of LMS for blended learning in distance education. Finally, voluntariness of use of LMS predicted LMS use behavior at (β=0.241; t=6.313; p=0.002 at p<0.01). The significance of all the aforementioned paths is further validated by the unidimensional nature of the confidence intervals from the upper boundary and lower boundary values at a confidence level of 95% with a 5% margin of error. This implies that the significance of the paths is true and not spurious.

Total variance explained by the model

To further validate the model and determine the variance explained by the exogenous (independent) variables on the endogenous (dependent) variables, the coefficient of determination (R^2) was used. **Table 4** presents the results.

Table 4. Coefficient of determination (R^2)

R squared values of endogenous components in structural model					
FC	PE	EE	SI	VOL	UB
0	0	0	0	0.683	0.58529

Hair et al. (2017) suggested values of 0.25, 0.5, and 0.7 as small, medium, and large, respectively. Based on the R squared values from **Table 4**, the formulated model for this study explained close to large amount of total variance in tutors' voluntariness of LMS use and medium amount of explanation in tutors' LMS use behavior. This implies that other important variables are needed to sufficiently explain the total variance in both tutors' voluntariness of use of LMS, as well as their use behavior of LMS for blended learning in distance education.

Model fit

In structural model analysis, one of the key quality standards is that the model estimated fits with the data collected (Kline, 2015). This provides a solid basis to validate the results obtained by the model. In order to ascertain model fitness, indices such as FIT (Henseler, 2012), adjusted FIT (Hwang et al., 2007), GFI (Jöreskog, 1970), and SRMR (Hwang, 2008) are important measures for the overall model fit in GSCA (Ryoo & Hwang, 2017).

From **Table 5**, both FIT and AFIT had an estimate of 0.729 and 0.825, respectively. These estimates represent good fit parameters since Ryoo and Hwang (2017) recommend these values to be closer to 1 and should range between 0 to 1. Similarly, for GFI, the estimated model for this study obtained a value of 0.973, also closer to 1. In terms of validating a good SRMR, Ryoo and Hwang (2017) indicated that the closer the value to 0, the better the fit. From **Table 5**, the SRMR value was 0.058, which satisfies the criterion for good fit. The values of the fit indices obtained for the estimated model in this study implies that the model achieved good fitness.

Table 5. Model fit

Fit indices	Estimate	Fit indices	Estimate
FIT	0.729	GFI	0.973
AFIT	0.825	SRMR	0.058

DISCUSSION

To begin with, the study revealed a significant positive relationship between performance expectancy and voluntariness of use of LMS for blended learning for hypothesis one. This finding suggests that when tutors believe that using LMS will help them to accomplish their job demands in distance education, they will voluntarily use it. In other words, the tutors perceived that they have relative advantage in the use of LMS and thus, will use it out of their own will for online teaching. Empirical study on usage of educational technologies such as those from Margahana and Garaika (2019) as well as Johnson et al. (2016) have obtained a significant relationship between performance expectancy and voluntariness of use. The argument by Brown et al. (2002) that once users perceive LMS to be useful to their learning they will voluntarily use it to support their andragogical activities has been confirmed in this study. This relationship between performance expectancy and voluntariness of use has been consistent across most systems in the learning environment sector such as digital library system (Hamzat & Mabawonku, 2018) and LMS is no exception.

In terms of hypothesis two, another important finding of this study was that effort expectancy determined voluntariness of use of LMS for blended learning. This finding points out the fact that tutors will automatically use LMS based on its ease of use as well as other characteristics such navigation controls. Tutors are willing to use LMS when the activities on the LMS are insightful and effortless to navigate with little or no directions and support. The result of this study corroborates with that of Lwoga and Komba (2015) who suggested that friendliness of a system is a major factor that enhanced the voluntariness of use of an e-learning system in higher education. The finding also resonates with the opinion of Pynoo et al. (2011) that effort expectancy has an effect on voluntariness of use of LMS.

In the same vein, for hypothesis three we found social influence to be a strong predictor of voluntariness of use of LMS for blended learning. This implies that immediate social environment of the tutor in the learning environment has effect on tutors' perception to voluntarily use LMS to support their teaching in distance education. Within the teaching and learning environment, when tutors interact with other tutors who use LMS and receive positive feedbacks and recommendations from them, they are induced to also use the LMS due to group identity and use gains (Kim & Park, 2011; Shin & Dai, 2020). The finding is congruent with that of Kim and Park (2011) and also aligned with other studies that revealed that social influence determines voluntariness to use technology (Celik, 2011; Srinivasan, 2015).

Hypothesis four that emphasized the effect of facilitating conditions, has also been revealed by this study to be another predictor of voluntariness to use LMS for blended learning. This shows that provided there is the presence of both technological and administrative support towards LMS use, tutors will automatically use LMS if they own or have access to the technology and application that allow them to access the system. The psychological awareness that resources are available and accessible for LMS use in distance education promotes a positive drive towards LMS usage as suggested earlier by Chiu and Ku (2015) and Taiwo et al. (2012). It is important to note that the availability and accessibility of resources for LMS uptake propels the extrinsic motivation of tutors to try out LMS at will for their distance education endeavors (Bervell & Arkorful, 2020). With such motivation, the eagerness to personalize usage of LMS is high and positive. Though this outcome is not anticipated in the original, UTAUT (Radovan & Kristl, 2017; Venkatesh et al., 2003) we can suspect that this outcome is influenced by the resources put in place and the proliferation of low cost of access technology (laptops, smart phones, desktops, 4G internet) by the respondents.

Finally, in relation to hypothesis five, voluntariness of use of LMS turned out to positively predict use behavior of LMS for blended learning in distance education. Implicit of this finding is that, rolling out LMS usage for tutors to use at will, encourages self-usage for job performance among tutors. The positive relationship between the two variables suggests that as usage of LMS is made more voluntary, it will have a corresponding high use behavior of LMS for blended learning, which will also result in positive usage experience. This confirms the earlier stands of authors such as Pynoo et al. (2011) and Shin and Dai (2020). Interestingly, the positive relationship contradicts with earlier findings by Bervell and Arkorful (2020) who identified an inverse significant relationship between voluntariness and LMS usage behavior. However, the significant relationship also differs from earlier findings by Wu and Lederer (2009) assertion that "usage is determined by facilitating conditions" and that voluntariness has no effect on use behavior.

Implications on Theory

This study has pioneered the investigation into possible factors that could influence or determine voluntariness of use of LMS for blended learning in distance education. It has redefined existing theories on technology acceptance and adoption by proving that, antecedents such as performance expectancy, effort expectancy, facilitating conditions and social influence are pertinent in defining novel users' voluntariness to use LMS for blended learning. This is very insightful as it deviates from previous studies on technology acceptance that emphasizes the above predictive factors as only determining behavioral intentions towards technology use.

The implication of the theoretical and verified model used in this study is that, we can also measure voluntariness of use of technology systems to determine their factors other than behavioral intentions.

Implications for Policy and Practice

Higher education institutions who want to promote voluntariness of use of LMS for blended learning should:

1. Make it easy to use for tutors/lecturers through the necessary training and support.
2. Explain the affordances (usefulness) of LMS to tutors/lecturers prior to LMS-enabled blended learning implementation.
3. Allow tutors/lecturers to explore with LMS initially to ascertain its usefulness to their academic
4. Provide the necessary facilities required for LMS usage for blended learning.
5. Promote the collaborative platform for tutors/lecturers to share ideas on their positive usage experiences as well as how they have navigated through challenges in using LMS for blended learning.

Limitations

1. The study did not test for any moderating effects such as gender, age group, teaching experience, course taught or location of study center on the significant predictive relationships to ascertain the incidence of effects.
2. The study did not consider the effects of personality factors such as attitude, self-efficacy, anxiety and experience towards LMS for blended learning.
3. The study did not consider an in-depth analysis of the types of engagement between tutors and students according to individual courses they offered.

Suggestions for Future Research

1. Future studies can test for moderating effects such as gender, age group, teaching experience, course taught or location of study center on the significant predictive relationships to ascertain the incidence of effects.

2. Future studies can consider modelling the effects of personality factors such as attitude, self-efficacy, anxiety and experience towards technology, on voluntariness of LMS use for blended learning.
3. An in-depth analysis of the types of engagement between tutors and students on the various individual courses they offered can be considered by future studies.

CONCLUSION

This study has provided an important insight into the factors that influence tutors' voluntariness to use LMS for blended learning in distance education. It proposed a model and verified it through structural equation modelling based on GSCA analyses. Both the measurement and structural model analyses validated the estimated model for this study. Additionally, all model fit indices produced acceptable values that confirmed the fitting of the data to the model, rendering the results obtained in this study substantiated. The verified model explained a 68.3% variance in voluntariness of use of LMS for blended learning purposes. The study has opened up academic discourse and contributed immensely to literature on how voluntary use of LMS can be achieved by higher educational institutions that will want to adopt LMS technology to support their pedagogical and andragogical practices if factors such as performance expectancy, effort expectancy, facilitating conditions and social influence are carefully considered.

Author contributions: All authors were involved in the concept, design, collection of data, analysis, interpretation, writing, and critically revising the article. All authors approved the final version of the article.

Funding: This work was supported by the sponsorship of University of Cape Coast research grant (TDS/109/V.2/97).

Compliance with Ethical Standards: This study was approved by the Registry, College of Distance Education, University of Cape Coast (CoDE/P/162/37) with human subjects. This approval includes language related to consent to participate and consent for publication.

Acknowledgements: The authors would like to gratefully thank all the distance education tutors for serving as respondents for data collection.

Declaration of interest: Authors declare no competing interest.

Data availability: Data generated or analyzed during this study are available from the authors on request.

REFERENCES

Abrams, D., Wetherell, M., Cochrane, S., Hogg, M. A., & Turner, J. C. (2001). Knowing what to think by knowing who you are: Self-categorization and the nature of norm formation, conformity and group polarization. In M. A. Hogg, & D. Abrams (Eds.), *Intergroup relations: Essential readings* (pp. 270-288). Psychology Press.

Alturki, U., & Aldraiweesh, A. (2021). Application of learning management system (LMS) during the COVID-19 pandemic: A sustainable acceptance model of the expansion technology approach. *Sustainability, 13*(19), 10991. https://doi.org/10.3390/su131910991

Ansong-Gyimah, K. (2020). Students' perceptions and continuous intention to use e-learning systems: The case of Google Classroom. *International Journal of Emerging Technologies in Learning, 15*(11), 236-244. https://doi.org/10.3991/ijet.v15i11.12683

Bervell, B. (2018). *Distance education tutors' acceptance of learning management system for blended learning in Ghana* [Unpublished doctoral thesis]. Universiti Sains Malaysia.

Bervell, B., & Arkorful, V. (2020). LMS-enabled blended learning utilization in distance tertiary education: Establishing the relationships among facilitating conditions, voluntariness of use and use behaviour. *International Journal of Educational Technology in Higher Education, 17*(1), 1-16. https://doi.org/10.1186/s41239-020-0183-9

Bervell, B., & Umar, I. N. (2017). Validation of the UTAUT model: Re-considering non-linear relationships of exogeneous variables in higher education technology acceptance research. *Eurasia Journal of Mathematics, Science and Technology Education, 13*(10), 6471-6490. https://doi.org/10.12973/ejmste/78076

Bervell, B., Kumar, J. A., Arkorful, V., Agyapong, E. M., & Osman, S. (2021). Remodelling the role of facilitating conditions for Google Classroom acceptance: A revision of UTAUT2. *Australasian Journal of Educational Technology, 38*(1),115-135. https://doi.org/10.14742/ajet.7178

Bervell, B., Nyagorme, P., & Arkorful, V. (2020). LMS-enabled blended learning use intentions among distance education tutors: Examining the mediation role of attitude based on technology-related stimulus-response theoretical framework. *Contemporary Educational Technology, 12*(2), ep273. https://doi.org/10.30935/cedtech/8317

Bonsu, N. O., Bervell, B., Armah, J. K., Aheto, S. P. K., & Arkorful, V. (2021). *WhatsApp use in teaching and learning during COVID-19 pandemic period: Investigating the initial attitudes and acceptance of students*. https://digitalcommons.unl.edu/libphilprac/6362/

Brown, S. A., Massey, A. P., Montoya-Weiss, M. M., & Burkman, J. R. (2002). Do I really have to? User acceptance of mandated technology. *European Journal of Information Systems*, *11*(4), 283-295. https://doi.org/10.1057/palgrave.ejis.3000438

Celik, H. (2011). Influence of social norms, perceived playfulness and online shopping anxiety on customers' adoption of online retail shopping: An empirical study in the Turkish context. *International Journal of Retail & Distribution Management, 39*(6), 390-413. https://doi.org/10.1108/09590551111137967

Chen, L. (2022). Designing online discussion for HyFlex learning. *International Journal of Educational Methodology, 8*(1), 191-198. https://doi.org/10.12973/ijem.8.1.191

Chiu, T. M., & Ku, B. P. (2015). Moderating effects of voluntariness on the actual use of electronic health records for allied health professionals. *JMIR Medical Informatics, 3*(1), e7.1-e7.10. https://doi.org/10.2196/medinform.2548

Cronbach, L. J. (1990). *Essentials of psychological testing*. Harper & Row.

Donaldson, R. L. (2011). *Student acceptance of mobile learning* [Unpublished PhD thesis]. Florida State University.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling*. SAGE. https://doi.org/10.15358/9783800653614

Hamzat, S. A., & Mabawonku, I. (2018). *Influence of performance expectancy and facilitating conditions on use of digital library by engineering lecturers in universities in south-west, Nigeria*. https://digitalcommons.unl.edu/libphilprac/1670/

Hartwick, J., & Barki, H. (1994). Explaining the role of user participation in information systems use. *Management Science 40*(4), 440-465. https://doi.org/10.1287/mnsc.40.4.440

Henseler J. (2012). Why generalized structured component analysis is not universally preferable to structural equation modeling. *Journal of the Academy of Marketing Science, 40*, 402-413. https://doi.org/10.1007/s11747-011-0298-6

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115-135. https://doi.org/10.1007/s11747-014-0403-8

Hurst, K. R. (2010). *Technology acceptance in a mandatory technology-based learning environment* [PhD thesis, The University of West Florida].

Hwang, H. (2008). VisualGSCA 1.0–A graphical user interface software program for generalized structured component analysis. In K. Shigemasu, A. Okada, T. Imaizumi, & T. Hoshino (Eds.), *New trends in psychometrics* (pp. 111-120). University Academic Press.

Hwang, H., DeSarbo S. W., & Takane Y. (2007). Fuzzy clusterwise generalized structured component analysis. *Psychometrika, 72*, 181. https://doi.org/10.1007/s11336-005-1314-x

Johnson, A. M., Jacovina, M. E., Russell, D. E., & Soto, C. M. (2016). Challenges and solutions when using technologies in the classroom. In S. A. Crossley, & D. S. McNamara (Eds.), *Adaptive educational technologies for literacy instruction* (pp. 13-29). Taylor & Francis. https://doi.org/10.4324/9781315647500-2

Jöreskog, K. G. (1970). A general method for estimating a linear structural equation system. In A. S. Goldberger, & O. D. Duncan(Eds.), *Structural equation models in the social sciences* (pp. 85-112). Seminar Press. https://doi.org/10.1002/j.2333-8504.1970.tb00783.x

Kaiser, H. (1974). An index of factor simplicity. *Psychometrika, 39*, 31-36. https://doi.org/10.1007/BF02291575

Kamaghe, J., Luhanga, E., & Kisangiri, M. (2020). The challenges of adopting m-learning assistive technologies for visually impaired learners in higher learning institution in Tanzania. *International Journal of Emerging Technologies in Learning, 15*(1), 140-151. https://doi.org/10.3991/ijet.v15i01.11453

Kim, J., & Park, H. S. (2011). The effect of uniform virtual appearance on conformity intention: Social identity model of deindividuation effects and optimal distinctiveness theory. *Computers in Human Behavior, 27*(3), 1223-1230. https://doi.org/10.1016/j.chb.2011.01.002

Kline, R. B. (2015). *Principles and practice of structural equation modelling methodology in the social sciences*. Guilford Publication.

Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement, 30*(3), 607-610. https://doi.org/10.1177/001316447003000308

Lascu, D.-N., & Zinkhan, G. (1999). Consumer conformity: Review and applications for marketing theory and practice. *Journal of Marketing Theory and Practice, 7*(3), 1-12. https://doi.org/10.1080/10696679.1999.11501836

Lwoga, E. T., & Komba, M. (2015). Antecedents of continued usage intentions of web-based learning management system in Tanzania. *Education+Training, 57*(7), 738-756. https://doi.org/10.1108/ET-02-2014-0014

Margahana, H., & Garaika, A. (2019. The influence of credibility and voluntariness toward technological use behavior: Entrepreneurial potential model approach. *International Journal of Entrepreneurship, 23*(2), 1-9.

Mtebe, J. S. (2020). Examining eLearning system self-efficacy amongst instructors at the University of Dodoma, Tanzania. *Open Praxis*, *12*(3), 343-357. https://doi.org/10.5944/openpraxis.12.3.1103

Pynoo, B., Tondeur, J., van Braak, J., Duyck, W., Sijnave, B., & Duyck, P. (2011). Assessing teachers' acceptance of educational technologies: Beware for the congruency between user acceptance and actual use. In T. Hirashima (Ed.), *Proceedings of the 19th International Conference on Computers in Education*. Ghent University, Department of Educational Studies. https://doi.org/10.1016/j.compedu.2011.12.026

Radovan, M., & Kristl, N. (2017). Acceptance of technology and its impact on teachers' activities in virtual classroom: Integrating UTAUT and CoI into a combined model. *Turkish Online Journal of Educational Technology*, *16*(3), 11-22.

Ramlo, S. (2021). The coronavirus and higher education: Faculty viewpoints about universities moving online during a worldwide pandemic. *Innovative HigherEducation, 46*, 241-259. https://doi.org/10.1007/s10755-020-09532-8

Rawstorne, P., Jayasuriya, R., & Caputi, P. (2000). Issues in predicting and explaining usage behaviors with the technology acceptance model and the theory of planned behavior when usage is mandatory. *Proceedings of ICIS 2000*. Association for Information Systems.

Razkane, H., Sayeh, A. Y., & Yeou, M. (2022). University teachers' attitudes towards distance learning during COVID-19 pandemic: Hurdles, challenges, and take-away lessons. *European Journal of Interactive Multimedia and Education, 3*(1), e02201. https://doi.org/10.30935/ejimed/11436

Richardson, J. W. (2011). Challenges of adopting the use of technology in less developed countries: The case of Cambodia. *Comparative Education Review*, *55*(1), 008-029. https://doi.org/10.1086/656430

Ryoo, J. H., & Hwang, H. (2017). Model evaluation in generalized structured component analysis using confirmatory tetrad analysis. *Frontiers in Psychology*, *8*, 916. https://doi.org/10.3389/fpsyg.2017.00916

Schlachter, S., McDowall, A., Cropley, M., & Inceoglu, I. (2018). Voluntary work-related technology use during non-work time: A narrative synthesis of empirical research and research agenda. *International Journal of Management Reviews, 20*(4), 825-846. https://doi.org/10.1111/ijmr.12165

Shin, H., & Dai, B. (2020). The efficacy of customer's voluntary use of self-service technology (SST): A dual-study approach. *Journal of Strategic Marketing*. https://doi.org/10.1080/0965254X.2020.1841269

Srinivasan, R. (2015). Exploring the Impact of social norms and online shopping anxiety in the adoption of online apparel shopping by Indian consumers. *Journal of Internet Commerce, 14*(2), 177-199. https://doi.org/10.1080/15332861.2015.1008891

Taiwo, A. A., Downe, A. G., & Mahmood, A. K. (2012). *User acceptance of eGovernment: Integrating risk and trust dimensions with UTAUT model* [Conference session]. 2012 International Conference on Computer & Information Science, Kuala Lumpur, Malaysia. https://doi.org/10.1109/ICCISci.2012.6297222

Tarhini, A., Hone, K., & Liu, X. (2014). Measuring the moderating effect of gender and age on e-learning acceptance in England: A structural equation modeling approach for an extended technology acceptance model. *Journal of Educational Computing Research, 51*(2), 163-184. https://doi.org/10.2190/EC.51.2.b

Van der Heuval, S. (2020). *COVID-19 beats current technology acceptance theories*. https://www.linkedin.com/pulse/covid-19-beats-current-technology-acceptance-theories-van-den-heuvel/

Vaportzis, E., Giatsi, C. M., & Gow, A. J. (2017). Older adults perceptions of technology and barriers to interacting with tablet computers: A focus group study. *Frontiers in Psychology, 8*, 1-11. https://doi.org/10.3389/fpsyg.2017.01687

Venkatesh, V., Brown, S.A., Maruping, L. M., & Bala, H. (2008). Predicting different conceptualizations of system use: The competing roles of behavioral intention, facilitating conditions, and behavioral expectation. *MIS Quarterly, 32*(3), 483-502. https://doi.org/10.2307/25148853

Venkatesh, V., Morris, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157-178. https://doi.org/10.2307/41410412

Wu, J., & Lederer, A. (2009). A meta-analysis of the role of environment-based voluntariness in information technology acceptance. *MIS Quarterly*, *33*(2),419-432. https://doi.org/10.2307/20650298

Yeung, A. S., Taylor, P. G., Hui, C., Lam-Chiang, A. C., & Low. E.-L. (2012). Mandatory use of technology in teaching: Who cares and so what? *British Journal of Educational Technology, 43*(6), 859-870. https://doi.org/10.1111/j.1467-8535.2011.01253.x

Zagkos, C., Kyridis, A., Kamarianos, I., Dragouni, K. E., Katsanou, A., Kou-roumichaki, E., Papastergiou, N., & Stergianopoulos, E. (2022). Emergency remote teaching and learning in Greek universities during the COVID-19 pandemic: The attitudes of university students. *European Journal of Interactive Multimedia and Education, 3*(1),1-9. https://doi.org/10.30935/ejimed/11494

Zalat, M. M., Hamed, M. S., & Bolbol, S. A. (2021). The experiences, challenges, and acceptance of e-learning as a tool for teaching during the COVID-19 pandemic among university medical staff. *Plos ONE, 16*(3),1-12. https://doi.org/10.1371/journal.pone