The Determinants and the Magnitude of their Effectiveness on Online Learning during Covid 19 Pandemic in Bangladesh

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Abstract

The purpose of this study is to investigate the factors and the extent of their effects on the effectiveness of online learning in Bangladesh during the COVID 19 pandemic. Moreover, this study intends to examine the mediating role of students' online learning motivation by observing and comparing information and communication technology infrastructure, competencies in information and communication technology, and students-teachers interaction as predictors of students' online learning motivation and effectiveness of online learning. Following the positivism research paradigm and cross-sectional design, the researchers adopt a quantitative approach using the survey method through a structured questionnaire covering 408 responses of undergraduate and graduate students from more than 23 public and private universities in Bangladesh. The 6-point Likert scale was used to measure the extent of effects of competencies in information and communication technology, competencies in information and communication technology, students-teachers interaction, and online learning motivation on the effectiveness of online learning using partial least squares based structural equation modeling. This study investigates three exogenous, one endogenous, and a mediating factor. This study finds significant effects of independent variables on effectiveness of online learning and a significant mediating role of online learning motivation between the independent variables and effectiveness of online learning apart from the direct effects of information and communication technology infrastructure on online learning motivation and competencies in information and communication technology on effectiveness of online learning. In addition, this study finds non-significant direct effects of competencies in information and

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communication technology on effectiveness of online learning but the mediating role of online learning motivation makes this effect significant. This study contributes to the knowledge of literature. From the managerial perspective, this study helps the responsible bodies to develop and design online learning-based curriculums and course content, which will allow sufficient interaction and collaboration among the students and the teachers. Moreover, this study recommends that the concerned authorities address issues and take initiatives to enhance teachers and students' online learning motivation and make online learning effective. This study will not be free from limitations that lead to pay attention to address for future research initiatives such as, this study is designed to conduct as cross-sectional in nature but further longitudinal study needs to conduct after the COVID-19 context to spot the changes in the level of impressions of teachers regarding online classes. Moreover, the results of this study might not explain the same problem from a different perspective even in the same context in a different country. Therefore, in the future, cross-country studies may be conducted.

Keywords: ICT infrastructure, Competencies in ICT, Students-teachers interaction, Internet of things, Smart devices, Online learning effectiveness.

1. Introduction

The Corona Virus Disease (COVID)-19 was rapidly spreading all through the globe and within seven days after its first identification in Wuhan, South China in December 2019, the World Health Organization (WHO) confirmed COVID-19 as a pandemic (Agunget al.2020). According to the guidelines of WHO, from March 15, 2020, the government of Bangladesh (GOB)emphasized social distancing and advised people of the country to work, study, and conduct religious practices from home (Shammi et al.2021). In such a situation, the GOB declared to close all educational institutes from 18th March 2020 to prevent the spread of this virus (Haqueet al.2020).Therefore, due to the closure of schools, colleges, and universities in the lockdown situation, face-to-face learning was interrupted and educational institutes across the country moved towards online learning to manage the adverse consequences on the education sector and students (Abbasiet al.2020). In managing such an adverse situation, GOB emphasized on online education like other countries (Hoq, 2020). The public and private universities of Bangladesh also attempted in adopting such online education (Haque et al.2020).Before 18th March in 2020, about 90% of students received their education in face-to-face classes. Since the COVID-19 situation created the reality of conducting online classes. Now it is important to know the effectiveness of online learning (Rahman et al.2021).

Now, smart devices become essential in our lives, a number of applications for Windows and iOS operating systems can be used for interfacing sensors measuring various parameters, which implies that the use of IoT has become smooth in our daily life (Gubbiet al.2013). These new means help the students and the teachers to manage educational tasks using smart devices via Information and Communication Technology (ICT), particularly at any adverse time (Benahmed & Douli, 2014).Bao et al.(2020) argues that there are some important factors that educational institutions must address which are highly integrated into the effectiveness of IoT-based learning or online learning. A study by Muthuprasad et al.(2021) showed that in operating virtual classes and learning, some basic requirements must be arrangement arranged for the participants. They also mentioned three primary requirements in online learning i.e. digital devices (desktop computer, laptop, or at least a smartphone), internet (uninterrupted high-speed internet), and a platform (Google Classroom, Zoom, Moodle, etc.). Moreover, Auma and Achieng (2020) and Rahman et al. (2021) have pointed out studies that to make effective online learning (EOL) in educational institutions particularly public and private universities the students and the teachers must have proper Information Communication Technological Infrastructure (ICTI), they need to have Competencies in Information and Communication Technology and also to have Instructor-Learner Interaction. Chenet al.(2020) found in their studies that the availability of Information and Communication Technology Infrastructure and its competencies on it are the most important factors that influence the Effectiveness of Online Learning of students. Since the accomplishment of online education depends on students' ability, readiness, and acceptance to use this system (Almaiah & Alismaiel, 2019), a shortage of online education system usage hinders the apprehension of well-being (Almaiah et al. 2019; Almaiah & Al-Khasawneh, 2020). In addition, Rahman et al. (2021) showed that the merit of communication between teachers and students; ICT-based infrastructure, and competencies in the use of Information and Communication Technology affect online learning. They further stated that the motivation of the students in joining online learning stems from its simple access, convenience, and agility. Mishra et al.(2020) argued that to keep hold of participants in online classes, their online learning platform usage, needs to be retained.

There are many facets of online learning that could be considered but the researchers are interested in examining the relationships between the antecedents of online learning andeffective online learning. Moreover, the extent of mediating effect of students', Online Learning Motivation (OLM) also needs to be studied because Wei and Chou (2020) stated that effective learning tends to inspire for arranging effective online learning. ICT provides opportunities and assistance in arranging online learning and therefore the use of ICT Infrastructure is increasing day by day. Moreover, ICT Infrastructure provides real-time communication among the participants

(Kuoet al.2014).Martin and Bolliger (2018) found that the interaction between the students and the instructors eventually results ineffective learning. Wei and Chou (2020) found that participant' competencies in ICT (CICT) and motivation for learning bring an effective online learning atmosphere. To the best of the knowledge of the researchers, there is limited documentation in the context of Bangladesh that relates to examining the relationships among the antecedents of online learning with its effectiveness. Moreover, Rahman et al (2021) investigated the mediating role of online learning motivation in their research. In that research, they observed and compared the components of internet self-efficacy (ISE), learner-learner interaction, direct lectures, and instructor-learner interaction as predictors of OLM and effective online learning but there is no consensus on the relative importance of the mediation of OLM by observing and comparing ICT Infrastructure, competencies in ICT, and Students-Teachers Interaction (STI)in making online learning effectiveness. Therefore, in this study, the researchers intend to penetrate the gap in knowledge by examining the relative significance of ICT Infrastructure, competencies in ICT, and STI on the Effectiveness of Online Learning. Moreover, this study aims to scrutinize the OLM as the mediator in online learning effectiveness, which in turn has prompted the researchers to frame a new model of effective online learning. To achieve these purposes of this study, the researchers employed a positivist research paradigm using a quantitative approach.

2. Research model and hypotheses development

2.1. ICT infrastructure and online learning

The rapid propagation of ICT already changed everyday life from the perspective of social, cultural, and economic. ICT Infrastructure flourishes globalization and urbanization virtually and accelerate digital life (Auma & Achieng, 2020). The ICT Infrastructure provides participants with scopes in the study using technological innovation, particularly during COVID 19 pandemic when distance learning becomes mandatory (Ratheeswari, 2018). ICTs are by now intensifying the right to use high-quality learning objects, including books, remote instruction, and video material, and at a large amount minimum cost than earlier (Keeley & Little, 2017). Online education is an instance of the application by whichI CT Infrastructure assist educational methods whose exercise in educational institutions is ahead impetus with the way of time, particularly during pandemic situations (Maity et al.2021). A study by Kahn et al.(2012) have shown that ICT Infrastructure provides an effective educational atmosphere and it makes the teaching and learning practice in which participants acquire knowledge in a lively, self-directed, and practical manner. Goh et. al. (2017) mentioned that the eventual delivery of an online learning elucidationdepends on the ease of use of suitable and sufficient ICT Infrastructure. Previous studies on virtual learning in tertiary-level education have recurrently paid attention to the ICT Infrastructure by centering persons to employ the technology and information to resolve troubles and attain anticipated goals.The participants of online learning have confidence in the simplicity of exercising the ICT Infrastructure which has a noteworthy effect on online learning satisfaction and effectiveness (Wei & Chou, 2020).

2.2. CICT and online learning

It is widely recognized that during today's digital globalization virtual learning platform is bridging the gap between the face-to-face classroom and distance learning using communication technologies (Muthuprasadet al. 2021).Virtual learning is influenced by the ICT capacities and competencies of the teachers and students. Lim, Yan, and Xiong (2015) McFarlane (2000) and Zhao and Frank (2003) have highlighted the significance of ICT competencies in preparing teachers and students with the necessary skills to integrate ICT for effective online education program. Mims et al. (2006) assessed ICT competencies that could have a significant impact on the effectiveness of online learning. Mishra and Koehler (2006) identified CICT as one of the strongest constructs of participants' satisfaction and effectiveness in online learning. Moreover, competency in ICTis the main predictor of effective distance learning environments (Hew & Kadir 2016).

2.3. Students-teachers interaction and online learning

Students-Teachers Interaction is an essential component of learning in general and online learning as well. Interaction in learning is a mutual event between the participants that brings the learning participants closer to attaining an educational goal (Wagner, 1994).The goals of Students-Teachers Interaction are to deliver and share knowledge and information and also inspire learners by providing suitable responses and arranging appropriate associations. For making communication between the teachers and students during online learning, the reactions and feedback of the participants are vital (Kuo et al. 2014). Therefore, Students-Teachers Interaction as the essential element of online learning brings a satisfactory and effective experience for the learners (Burnettet al.2007). Ali and Ahmad (2011) stated thatStudents-Teachers Interactionisanimportant variable that has a noteworthyeffecton effective online learning. Proper, quality, and frequent interactions between the participants bring immense learning satisfaction and perceived learning rates.

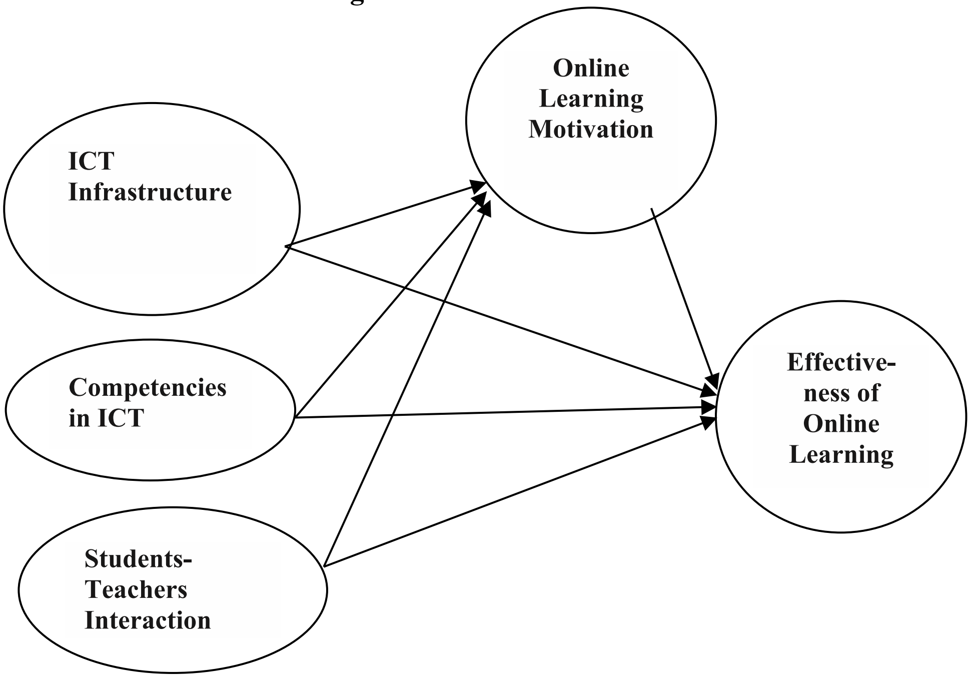
2.4. Students' motivation and online learning

The motivation relating to online learning is significantly connected to the desired outcomes. Lumsden (1994) describes the motivation for taking part in online learning that isthe willingness to take part in the learning process.Generally, motivation means the enticement that tends to do somethingof one's own volition. Earlier studies provide evidence that motivation plays a vital role in the learning process in both face-to-face and virtual (Hsu et al. 2020)Dörnyei (2020) stated motivation as the act that is closely associated with engagement and the assurance of motivation tends to the achievement of participants' engagement.Brooker et al. (2018) have pointed study that motivation is a prominent issue affecting learning outcomes. Moreover, Keskin and Yurdugül (2020) found that there is a strong significant relationship between the motivation to learn online and the success and attachment with the online learning settings. Thai, De Wever and Valcke (2017) studied and found that ICT Infrastructure impacts students' Online Learning Motivation. The competencies of ICT influence participants' motivation in the online learning process from both intrinsic and extrinsicaspects (Gohet al.2017) and a study by Kuo et al. (2014) reported that Students-Teachers Interactionboost participants' Online Learning Motivation. Simultaneously, online learning motivation directly influences online learning effectiveness.

2.5. Effectiveness of online learning

The means of online learning are the technological devices, which support conducting a distance mode of education and learning (Hartnett, 2016).By using the settings and systems of ICT Infrastructure, the participants get facilities of distance learning where learners are separated by time. In online learning, the communication between the teachers and students becomes a vital component to be effective. Before the introduction ofICT, distance learning had been common for a long time. Wan et al.(2008) in their study tested the effect of experience with ICT and online learning and found a positive impact between the ICT and the effectiveness of online learning. Moreover, they found theICTInfrastructure andcompetencies in it influenced online learning effectiveness. The study by Soffer and Nachmias (2018) indicated that online learning is effective and participants who log on to online classesbecome more contented. Such a situation motivated learners in creatinga cooperative learning atmosphere. They also argued that when there is proper ICTInfrastructure, when the participants are competent in Information and Communication Technology usage, when there is proper communication among the participants, and when the participants give significant feedback then it brings effective online learning. Accordingly, the following research model and hypotheses have been developed.

Figure 1: Research model



(Source: Auma & Achieng, 2020, p. 22; Rahman et al. 2021, p. 5)

H1a: ICT Infrastructure has a positive relationship with the Effectiveness of Online Learning.
H1b: ICT Infrastructure has a positive relationship with Online Learning Motivation.
H2a:Competencies in ICT have a positive relationship with the Effectiveness of Online Learning.
H2b: Competencies in ICT have a positive relationship with Online Learning Motivation.
H3a: Students-Teachers Interaction has a positive relationship with the Effectiveness of Online Learning.
H3b: Students-Teachers Interaction has a positive relationship with Online Learning Motivation.
H4:Online Learning Motivation has a positive relationship with the Effectiveness of Online Learning.
H5:Online Learning Motivation will mediate the relationship between ICT Infrastructure and the Effectiveness of Online Learning.
H6:Online Learning Motivation will mediate the relationship between Competencies in ICT and the Effectiveness of Online Learning.
H7: Online Learning Motivation will mediate the relationship between Students-Teachers Interaction and the Effectiveness of Online Learning.

3. Research method

3.1. Study design and sample selection

This is a cross-sectional study following positivist paradigm employing quantitative approach. Data are collected from tertiary level (undergraduate and postgraduate) students. The sample of this study is the students of public and private universities in Bangladesh.Since it was not possible to conduct face-to-face interviews due to the COVID-19 pandemic, researchers used Google Forms. Moreover, data were collected following snowball sampling during April 2021 to December 2021.A structured questionnaire was developed based on the literature, then generated by Google Forms link, and sent to the teachers of different universities who shared the link with their students using Facebook, LinkedIn, Twitter, WhatsApp, and Messenger. According to BABIES, 2020, there are about 853267 students at the university level in Bangladesh. To have a representative sample size to conduct this study, a sample size calculator (RAOSOFT, 2020)was used to determine the minimum sample size by considering a 95% confidence level, ±5% margin of error, and 50% response distributionof the sample size calculator reached 384 respondents (Kumaret al. 2021). 416responses were collected from the students of 23 both public and private universities throughout the country from 15 July 2021 to 15 September 2021. From the collected 416 responses, 1.92% (N =8) responses were rejected because of missing values. Therefore, finally, 408 fully and correctly completed responses were used to conduct this study, which is satisfactory. A structural equation modelling (SEM) technique based on partial least squares (PLS) (Chin 1998a)was used to test both the measurement model and structural model because the PLS technique is more efficient in testing complex and sophisticated conceptual models. PLS-SEM is a causal modelling approach aimed at maximizing the explained variance of the dependent latent constructs (Hair, Ringle, and Sarstedt 2011).

3.2. Measurement tools

The structured questionnaire used for conducting this study consists of two parts, in which, the first part consists of the demographic profile of the respondents. The demographic part included gender, years of study, name of universitiesand faculties, residential area (urban or rural), using devices,and previous online learning experience. The second part of the structured questionnaire includedquestions with scale for getting the opinions of the respondents regarding the variables used for this study. This questionnaire was prepared using multi-item scales with a 6-point Likert scale. To measureICT Infrastructure, Competencies in ICT, and Students-Teachers Interaction, four, eight, and seven items respectivelywere used. Items for measuring ICT Infrastructure were adopted from Auma and Achieng (2020) and Rahman et al. (2021); items of competencies in ICTwere adopted from

Auma and Achieng (2020) and items of Students-Teachers Interactionwere adopted from Rahman et al. (2021). Moreover, to measure mediating variable of Online Learning Motivation 8 items were used, 5 of which were adopted from Chalak and Kassaian (2010), and the remaining 3 wereadopted from Saade and Kira (2007). The effectiveness of online learning was measured by 8 items, 6 of which were adopted from Abbasi et al. (2020), Augung et al. (2020), and Auma and Achieng (2020); the rest 2 items were adopted from Baczek et al. (2020) and Rahman et al. (2021) each.The option of an even point (6-point) Likert scale was used to survey because Nuruzzaman (2013) stated that Asian ethnicity participants seemed to prefer the middle score or to be non-partisan in their responses as this pattern was presumed to produce a research result that provided mean error. Since, this study is carried out in Bangladesh, which has an Asian population, therefore, this study used a 6-point Likert scale which has been anchored with 1 (strongly disagree) and 6 (strongly agree).

4. Analysis and findings

4.1. Respondent profile

The demographic profile of the respondents (N = 408) is as follows:

Table1: Respondent profile

Demographic Characteristics	Categories	%
Gender	Male	70.34% (N=287)
	Female	29.66% (N=121)
	Prefer not to say	0% (N=0)
Residential area	Rural	28.17% (N=115)
	Urban	71.83% (N=293)
Types of university	Public	74.26% (N=303)
	Private	25.74% (N=105)
Faculty	Agriculture	5.88% (N=24)
	Arts & Fine Arts	12.75% (N=52)
	Business Studies	13.97% (N=57)
	Engineering	9.31% (N=38)
	Law	5.39 (N=22)
	Life & Earth Science	11.03% (N=45)
	Science	19.12% (N=78)
	Social Science	22.55% (N=92)
Year of study	1st Year	16.18% (N=66)
	2nd Year	19.12% (N=78)
	3rd Year	20.83% (N=85)
	Final Year	20.59% (N=84)
	Masters	23.28% (N=95)
Previous experience in online learning	Yes	14.22% (N=58)
	No	85.78% (N=350)
Choice of gadget	Mobile	70.83% (N=289)
	Desktop	35.42% (N=17)
	Laptop	24.02% (N=98)

Demographic Characteristics	Categories	%
	Tablet	8.33% (N=4)
Online learning platform	Zoom app	83.33% (N=340)
	Google Classroom	4.11% (N=18)
	Microsoft teams	1.47% (N=6)
	Google Meet	5.88% (N=24)
	Others; Mzizi ERP	4.90% (N=20)

4.2. Measurement model

The convergent validity calculates the correlation degree of several agreed-upon measures of the same construct. In addition, it refers to the degree to which various measures designed to tap the same construct correlate with each other (Hair et al.2017a). The factor loading of the predictor, composite reliability (CR), and the average variance extracted (AVE) are considered to check the convergent validity of the collected data (Hair et al. 2014). The reliability of the indicator is the proportion of indicator variance described by the latent variable. Values differ between 0 and 1. According to Hair et al. (2014), the outer loading values should not be less than 0.60, and if the exclusion of the indicator with outer loadings between 0.40 and 0.60 leads to a rise in CR and AVE, it should be considered for deletion (Hair et al. 2014). The composite reliability instrument is used to evaluate the internal accuracy of the construction indicators of a study. At present researchers are using CR to measure the internal consistency of the indicators of construct by PLS-SEM (Hair et al.2017). The CR is determined in PLS-SEM by measuring the loading values of the indicators of constructs (Hair et al. 2017). During the years 2006 to 2010, 85 papers using PLS were published in four major journals. As proof of acceptable CR, the authors' most frequently cited cutoff values of the products are 0.70 (Fornell & Larcker, 1981). After measuring the internal consistency of the indicators of constructs it is needed to measure the validity of the indicators by using the AVE (Hair et al. 2014). As part of convergent validity, the indicators of AVE are considered and the loading value must be higher than 0.5, which will reflect at least 50% of the indicators explaining the construct (Hairet al.2011).

As shown in Table 2, to obtain the final loadings and AVE, three items of which one item (CI7) from the ICT Infrastructure, one (STI1) from Students-Teachers Interaction, and another (MV5) from Online Learning Motivationconstruct were deleted because of less than 0.60 loadings. Moreover, two items (EOL6 & EOL8) from the Effective Online Learning construct were deleted withthe same low loading. The AVEs of ICT Infrastructure, competencies in ICT, Students-Teachers Interaction, Online Learning Motivation, and Effective Online Learning were 0.659, 0.520, 0.618, 0.626,and 0.677, respectively are satisfactory as the values reflect more than 50% (.50) of the indicators explaining the construct.Moreover, table 2 shows the CR values ranging from 0.883 to 0.926, which were higher than 0.70 (Hair et al., 2017).Therefore, there was no problem with the collected data in respect of convergent validity.

Table 2: Internal consistency, reliability, and convergent validity

Construct	Measurement item	Outer loading	T Statistics	P Values	VIF	AVE	CR	CA α	rho_A
ICTI	II1	0.799	31.518	0.000	1.934	0.659	0.885	0.826	0.832
	II2	0.853	52.465	0.000	2.212				
	II3	0.852	47.621	0.000	2.000				
	II4	0.738	22.646	0.000	1.400				
CICT	CI1	0.624	16.142	0.000	1.409	0.520	0.883	0.844	0.850
	CI2	0.771	27.537	0.000	2.089				
	CI3	0.77	26.964	0.000	2.091				
	CI4	0.690	19.062	0.000	1.595				
	CI5	0.654	17.296	0.000	1.488				
	CI6	0.805	38.000	0.000	1.967				
	CI8	0.692	22.216	0.000	1.508				
STI	STI2	0.707	22.723	0.000	1.560	0.618	0.906	0.875	0.880
	STI3	0.783	29.959	0.000	1.918				
	STI4	0.718	21.98	0.000	1.703				
	STI5	0.780	32.351	0.000	2.273				
	STI6	0.848	56.356	0.000	2.867				
	STI7	0.829	45.268	0.000	2.380				
OLM	MV1	0.789	33.073	0.000	2.284	0.626	0.921	0.899	0.912
	MV2	0.643	16.979	0.000	1.549				
	MV3	0.866	51.876	0.000	3.001				
	MV4	0.767	27.36	0.000	1.930				
	MV6	0.679	18.067	0.000	1.685				
	MV7	0.862	64.748	0.000	3.247				
	MV8	0.862	51.621	0.000	3.087				
EOL	EOL1	0.852	53.733	0.000	2.731	0.677	0.926	0.903	0.909
	EOL2	0.847	45.676	0.000	2.614				
	EOL3	0.746	38.234	0.000	1.912				
	EOL4	0.841	47.978	0.000	2.779				
	EOL5	0.879	56.622	0.000	3.203				
	EOL7	0.720	24.403	0.000	1.682				

*CA α -Cronbach's alpha is a measure of internal consistency, that is, how closely related a set of items are as a group. ** The rho_A function calculates the rho_A reliability indices for each construct.

Discriminant validity guarantees that a measure of construction is empirically distinctive and reflects phenomena of interest that are not captured by other variables in a structural equation model (Hair et al. 2010). Two major measures are used for discriminant validity, firstly, the Fornell-Larcker criterion which assessescorrelational values among the constructs (diagonal elements denoting the square root of AVE) (Fornell & Larcker, 1981). Secondly, heterotrait-monotrait ratio of correlations (HTMT) as a new approach (Henseler et al.2015) to assess discriminant validity with the threshold value of 0.85 has been proposed by Kline (2015), while other researchers recommend a value of 0.90 (Goldet al. 2001; Hair et al.2019). Therefore, the HTMT value of this study satisfies the threshold of <0.90 as mentioned by Gold et al. (2001) and Hair et al. (2019). Table 3 and 4 shows the assessment of discriminant validity using the Fornell–Larcker and HTMT criterion. Hence, from the discriminant validity criteria,all the constructs of this study were found satisfactory. In summary, all the constructs demonstrate very strong reliability and validity.

Table 3: Discriminant validity of constructs Fornell-Larcker correlation check

Construct	CICT	EOL	ICTI	OLM	STI
CICT	**0.721**				
EOL	0.459	**0.823**			
ICTI	0.235	0.425	**0.812**		
OLM	0.514	0.844	0.344	**0.791**	
STI	0.508	0.808	0.356	0.847	**0.786**

Note: Diagonals (**in bold**) represent the squared root of the average variance extracted (AVE) while the other entries represent the correlations.

Table 4: Heterotrait-Monotrait ratio (HTMT) criteria

Construct	CICT	EOL	ICTI	OLM	STI
CICT					
EOL	0.516				
ICTI	0.279	0.488			
OLM	0.585	0.925	0.399		
STI	0.587	0.804	0.415	0.847	

Note: Criterion discriminant validity is established at HTMT0.90

4.3. Structural model evaluation

To estimate the structural model coefficients, a series of regression equationsis requiredfor assessment. In assessing structural relations, collinearity using variance inflation factor (VIF) must be inspected whichmeasures the existence of business problems in the collected data. According to the recommendations of Hasan et al.(2015) and Hair et al. (2014), the rule of thumb for multicollinearity tolerance level is less than 5.0. As such, the VIF values of each item of this study show below 5.0 indicating that there is no problem with the collinearity issue.To measure the statistical significance of the path coefficients, the bootstrapping technique needs to assessand inspect the underlying relationships between the constructs (Hair et al. 2017).Hair et al. (2014) suggest the minimum bootstrap sample should be 5000. They also mention that with a significance of 10%, 5%, and 1%, the t values are 1.65, 1. 96, and 2.58 respectively.To predict the dependent variable in a model, it needs to apply the Coefficient of Determination (R^2) which measures the predictive power of the independent variable(s). In general, R^2 values of 0.25, 0.50, and 0.75 can be expressed as being weak, moderate, and substantial (Hair et al. 2019).The values of effect size denoted by f^2 state the degree of contribution of the independentvariable to the R^2 of the dependent variable (Rahman et al., 2021).Chin,(1998) recognized a threshold of f^2values and recommended higher than 0.02, 0.15, and 0.35 represent small, medium, and high effect sizes. Q^2 represents a method for assessing the inner model's predictive relevance (Akter et al.2011).Particularly, when a Q^2 value is larger than zero for a particular dependent construct, it indicates the predictive relevance of the path model for that particular construct.The smaller the disparity between the predicted and the original values, the larger the Q^2 and hence the predictive accuracy of the model (Akter et al.2011). This study provides the result of 0.505 for endogenous construct and 0.450 for mediating construct, which is more than zero. The following table 5 and figure 2 show the evaluation of the structural model of the study.

Table 5: Result of the structural model assessment for direct relations

H	Relation	Std. β	SE	t-values	p-values	f^2	Decision
H1a	ICTI→EOL	0.132	0.029	4.538	0.000	0.061	S
H1b	ICTI→OLM	0.042	0.03	1.409	0.159	0.006	NS
H2a	CICT→EOL	-0.006	0.033	0.178	0.859	0.000	NS
H2b	CICT→OLM	0.111	0.034	3.261	0.001	0.033	S
H3a	STI→EOL	0.300	0.056	5.338	0.000	0.100	S
H3b	STI→OLM	0.777	0.026	29.768	0.000	1.517	S
H4	OLM→EOL	0.548	0.058	9.489	0.000	0.337	S

* S=supported, NS=not supported

Figure 2: Structural model representing outer loading, path coefficients, and R^2

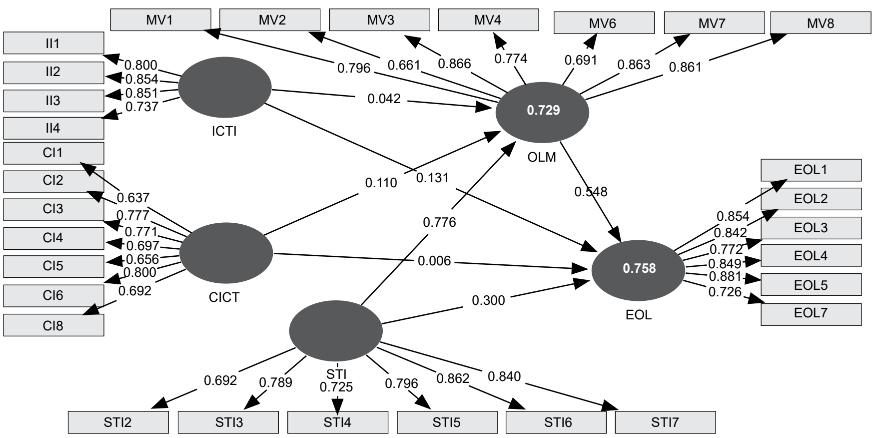


Table 5 and Figure 2 show the positive and statistically significant direct relationship between exogenous variablesand endogenous variables as hypothesized, except for hypotheses H1b (ICT Infrastructure→Online Learning Motivation) and H2a (Competencies in ICT→Effective Online Learning). Specifically, Information Communication Technological Infrastructure was not significantly directlyrelated to Online Learning Motivation (β = 0.042, t =1.409, p= 0.159) and competencies in ICT was not also significantly direct related to Effective Online Learning (β = 0.033, t =0.178, p= 0.859).

The following table 6 shows the mediating effect of Online Learning Motivation to establish whether it mediated the relationships between Information Communication Technological Infrastructure, Competencies in ICT, Students-Teachers Interaction, and Effective Online Learning. Online Learning Motivation (β = 0.061, t = 3.107, p=0.002) mediated the relationship between Competencies in ICT and Online Learning Effectiveness and Online Learning Motivation (β = 0.425, t = 9.156, p=0.000) also mediated the relationship betweenStudents-Teachers Interaction and Online Learning Effectiveness. But Online Learning Motivation (β = 0.023, t = 1.36, p=0.174) did not mediate the relationship between ICT infrastructure and Online Learning Effectiveness.

Table 6: Results of the structural model assessment for specific indirect effects

H	Relation	Std. β	SE	t-values	p-values	Decision
H5	ICTI → OLM →EOL	0.023	0.017	1.36	0.174	NS
H6	CICT → OLM →EOL	0.061	0.019	3.107	0.002	S
H7	STI → OLM →EOL	0.425	0.046	9.156	0.000	S

In order to describe the significance of the relationships between the exogenous and endogenous variables, it is required to report R^2 and f^2(Hair et al. 2017). This study found R^2 of Online Learning Motivationshown in figure 2 as 0.729 and Online Learning Effectivenessas 0.758, which emphasizes that the exogenous variables Information Communication Technological Infrastructure, Competencies in ICT, and Students-Teachers Interaction can describe 72.9% of the variability in students' Online Learning Motivationand 75.8% of the variability in their effective learning during the COVID-19 outbreak. From the f^2 perspective, all relationships indicate significant effects from the independent variables (H1a, H2b, H3a, H3b and H4: $f^2 > 0.02$) except the insignificant effects on the relationships between Information Communication Technological Infrastructure →Online Learning Motivation ($f^2 < 0.02$) and competencies in ICT→Effective Online

Learning ($f^2 < 0.02$). Moreover,this study employs the common method variance (CMV) to test the biasesusing Harman single-factor method which shows the first factor was responsible for only 34.021% of the variance, which was less than the threshold (<50%) and as such the values of CMV were satisfactory in this study (Podsakoff, Mackenzie & Lee, 2003).

5. Findings and discussion

From the statistical results and analysis of this study, it can be seen that competencies in ICT and Students-Teachers Interaction have noteworthy impacts on Online Learning Motivation. Students think thatCompetencies in ICT and Students-Teachers Interaction are significant motivators and students like to take part in online learningas they are used to online classes. Previous researches also support that as the motivator Competencies in ICT and Students-Teachers Interaction have positive and significant effects on online learning (Auma & Achieng, 2020; Rahman, et al.2021). The researchers also found that Students-Teachers Interaction has a positive and significant influence on the Effectiveness of Online Learning, which is supported by the findings of the studies by Rahman, et al. (2021) and Yukselturk and Yildirim (2008). According to them, Effective Online Learning is one of the most important variables for the success or failure of distance learners, which depends on the Students-Teachers Interaction. On the other hand, according to the results of this study,Competencies in ICT has anegative and insignificant direct effect on Effective Online Learning but in the case of a specific indirect effect between Competencies in ICT and Effective Online Learning, Online Learning Motivation mediates such relations and gets a significant positive relationship. Therefore, students' learning motivation is strongly mediating the Competencies in ICT construct as a positive and significant effect on Online Learning Effectiveness, which is the new finding investigated in this study. In the case of online learning, such learning depends on the ICT Infrastructure (Auma & Achieng, 2020; Ratheeswari, 2018)and as such, this study finds a positive and significant direct relationship between ICT Infrastructure with Effective Online Learning but insignificant relation with Online Learning Motivation. Moreover, the specific indirect relationship of ICT Infrastructure with Effective Online Learning in the mediation of Online Learning Motivation, a weak mediating relationship, has been found which is not supported by the previous studies by Abbasi et al.(2020) and Wei and Chou (2020). Therefore, students are de-motivating in making effective online learning because of lack of devices, weak internet connection, and costly internet data and such reasons bring the insignificant direct relation between ICT Infrastructure and Online Learning Motivation as well as indirect relation of ICT Infrastructure and Effective Online Learning with the mediation of students' motivation.

However, this study did find a very strong positive and significant relationship between Students-Teachers Interaction with Online Learning Motivationand a strong positive and significant relationship between Online Learning Motivation and Effective Online Learning. Earlier studies by Chen and Jang (2010) and Rahman, et al. (2021) emphasized motivation as the issue of having priority in online learning. This study did find a significant relationship between the overall Online Learning Motivation and Effective Online Learning.

6. Implications

This study did find the highest level of variability and lowest mean value in ICT Infrastructure, which means that participants do not have enough, and proper support for ICT Infrastructure for online classes and learning, therefore the level of their confidence varies greatly in such construct. The findings of the studies by Auma and Achieng (2020); Lee (2002); Ratheeswari (2018) and Rahman, et al. (2021) are also in line with the results of this study and suggest that online learning can be effective if significant attention is givento the arrangement of proper ICT Infrastructure. In this respect, concerned authorities i.e. departments, faculties, universities, University Grants Commission, and Education Ministry should take initiatives to provide proper support for ICT Infrastructure to the participants. Moreover, the excessive cost and weak connection tothe internet de-motivated participants to be attentive to the online classes or learning. The authorities should address these issues and such initiatives will enhance students' online learning motivation and makes effective online learning. Further, the findings of this study show that Competencies in ICT has insignificant effects on Effective Online Learning but the mediation of Online Learning Motivationcan change the effect and make it significant. For this, participants shouldbe provided necessary training on system infrastructure and how to conduct online classes. Moreover, the responsible bodies should develop and design online learning-based curriculums and course content, which will allow sufficient interaction and collaboration among the students-teachers.

7. Conclusions, limitations, and future research

This study examines the relationships between ICT Infrastructures, Competencies in ICT, Students- Teachers Interaction, and Online Learning Effectiveness of the students of universities in Bangladesh, particularly during the COVID-19 pandemic. This study also examines the mediating effect of Online Learning Motivation on the effectiveness of online learning. To examine such relationships and effects, the researchers of this study employed the PLS-SEM approach and found significant positive direct effectsof ICT Infrastructure, Students-Teachers Interaction, and Online Learning Motivation on Effective Online Learning, and a significant positive impact of Competencies in ICT and Students-Teachers Interactionon Online Learning Motivation. The study also found significant mediating roles of online learning motivation between Competencies in ICT, Students-Teachers Interaction, and the Effectiveness of Online Learning. The findings have significant implications for future researchers, the ministry of education, university grants commission, university authorities, faculties, departments, and other policymakers to integrate, prepare and execute proper platforms for online learning, including the concern of students' motivation, and make the available course of action of such implications to face the post-COVID-19 educational challenges. The researchers of this study recommend that ICT Infrastructure and competencies on in need to be enhanced and online-education-friendly curriculums are developed to motivate participants ensuring the highest level of online learning effectiveness.

This study is not free from limitations and needs attention to address for future research initiatives. Firstly, data were collected only from the university students and thus may not represent the actual context of the online education effectiveness of the country under study. In this regard, in further studies, the students of high schools and colleges should be included to generalize the results. Secondly, this study adapted three exogenous variables to investigate the extent of relations with the online learning effectiveness which may not be representative. To overcome such limitations further studies may use more variables i.e. students-student interaction, internet self-efficacy, direct instruction, etc. In addition, the inclusion of the nature of course curriculums and learning support as moderators could influence the Online Learning Effectiveness. Thirdly, this study was cross-sectional but further longitudinal study needs to be conducted after the COVID-19 context to spot the changes in the level of effectiveness of online learning. Finally, the results of this study might not explain the same problem from a different perspective even in the same context in a different country. Therefore, in the future, a cross-country study on online learning effectiveness may be conducted.

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