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Engineering Students' Readiness for Online Learning Amidst the COVID-19 Pandemic: Scale Validation and Lessons Learned from a Developing Country

Md Abdullah Al Mamun[1*], Md Akbar Hossain[2], Sayedus Salehin[3], Md. Shahadat Hossain Khan[1] and Mahbub Hasan[1]

[1]Department of Technical and Vocational Education, Islamic University of Technology, Bangladesh // [2]School of Business and Digital Technologies, Manukau Institute of Technology, New Zealand // [3]Department of Mechanical and Production Engineering, Islamic University of Technology, Bangladesh // a.mamun@iut-dhaka.edu // akbar.hossain@manukau.ac.nz // sayedus@iut-dhaka.edu // shkhants@iut-dhaka.edu // m.hasan@iut-dhaka.edu

[*]Corresponding author

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ABSTRACT: The recent outbreak of the COVID-19 pandemic forced education institutes to shift to an internet-based online delivery mode. This unique situation accelerates a long-standing issue of digital inequality among the students in education and warrants a concentrated study to investigate students' readiness for learning in online environment. This study developed an instrument to meticulously measure the students' readiness for online learning in a pandemic situation. The proposed model consists of (a) motivation, (b) self-efficacy, and (c) situational factors. The proposed model was validated with the engineering students (for pilot study N = 68 and main study N = 988) from several universities in Bangladesh. To validate the underlying relationships between the latent constructs, an exploratory factor analysis (EFA) was performed followed by structural equation modelling (SEM) for the construct validity of the measurement model and to assess the model fit. The findings showed that besides motivation and self-efficacy, the situational factors describing the contextual dynamics emerging from the COVID-19 significantly influenced the student's online readiness. We argue that digital inequality is an important factor influencing student readiness for online learning.

Keywords: Online learning readiness, COVID-19 pandemic, Bangladesh, Engineering education, Structural Equation Modelling, Situational factors, Digital inequality

1. Introduction

Bangladesh, being a high risk and country vulnerable to the COVID-19 pandemic (Hossain et al., 2020; Monjur & Hassan, 2020), took several measures to combat transmission of the virus. The most immediate measure introduced by the country was to regulate the practice of "social distancing" (Yeasmin et al., 2020) to flatten the curve of COVID-19 transmission. As a result, all educational institutions were closed across the country. Social distancing became the "new normal" for students and the usual comradeship of campus life disappeared. This has drastically impacted on Bangladesh's educational system, resulting in a loss of learning opportunities. Roughly 3.7 million students and a million teachers in the higher education sector are reportedly now stuck at home (Ahmed, 2020).

To minimize interruption caused by the COVID-19 pandemic, engineering universities in Bangladesh acted quickly to shift all face-to-face lectures to a home-based online distance learning mode using learning platforms such as Google classroom, Moodle, Zoom etc. Some universities even consider adopting flipped learning approach because of its effectiveness compared to traditional instructions reported in the recent literature (Chang et al., 2020; Galindo-Dominguez, 2021; Zheng et al., 2020). This paradigm shift from face-to-face learning to online distance mode creates two major complexities. Firstly, academic matters such as delivery, teachers' expertise, student preparedness, and engagement within this new virtual learning space must all be addressed (Ioannou & Ioannou, 2020; Khtere & Yousef, 2021). The second issue, perhaps more sensitive, relates to the physical and psychological wellbeing of the students. The absence of social and physical interaction has adverse effects on students' wellbeing (Twenge et al., 2019). Nevertheless, engineering universities are continuing to shift course delivery to fully-fledged online learning environments as no other viable solutions are available. Students get little time to cope with this "new normal" in their educational lives.

Therefore, an important question requires immediate attention: To what extent are the engineering students of Bangladesh ready for the online classes that are replacing face-to-face learning during the COVID-19 pandemic? Because the event is unique, research into understanding student readiness for online learning in a pandemic situation is only starting to emerge, and no reported research has been found in the context of engineering education in Bangladesh. Though several studies attempted to measure students' readiness for online learning (Arthur-Nyarko et al., 2020; Yu, 2018), none of them fully address the factors relating to an emergency. Chung et al. (2020) measured students' online learning readiness amidst the COVID-19 pandemic, nonetheless, they did not address the situational and context specific factors that emerged due to the pandemic. Thus, a careful understanding of the current pandemic situation and a reconceptualisation of the dimensions and constructs of the students' readiness for online learning is warranted.

For this reason, the current study develops and validates a more specific instrument that can be used to measure the students' readiness for online learning in a pandemic situation. Secondly, this study investigates how demographic factors influence the online learning readiness of engineering students of Bangladesh during the pandemic. Thus, this study sought to answer the following two questions in the context of the current pandemic caused by COVID-19:

- RQ1: What is the reliability, validity, and model fit evidence of the survey scale to assess engineering students' readiness for online learning?
- RQ2: To what extent are engineering students of Bangladesh (in terms of gender, level of study, place of living, and university type) ready to learn in online environments?

2. Reconceptualising the constructs of students' readiness in the pandemic situation

2.1. Motivation and self-efficacy: Two key constructs of students' online readiness

In previous literature, motivation was identified as the most crucial construct of students' readiness for online learning (Chung et al., 2020; Xiong et al., 2015; Yu, 2018). In the current pandemic situation, this has similarly become the primary factor for students to engage successfully in remote learning. The absence of social structure, close interactions, easy access to teachers and peers in online learning during COVID-19 pandemic may influence students' motivation and readiness to learn in this manner (Allam et al., 2020).

Motivation, as conceptualised in our study, delineates students' willingness to use online learning platforms during the COVID-19 pandemic. Guided by self-determination theory (Ryan & Deci, 2000), we considered students' intrinsic motivation i.e., interest or enjoyment, and extrinsic motivation i.e., perceived usefulness and reinforcement, to be the key aspects to evaluate students' motivation in our study. Self-determination theory further contends that students' connectedness with their teachers and peers are a vital component of student motivation. Previous literature also demonstrates the importance of engaging in human-human interactions and the sense of being part of a learning community for effective learning in online settings (Joksimović et al., 2015). Students get a feeling of connectedness to other students through online learning communities, and this contributes to meaningful learning experiences (Cho & Tobias, 2016).

COVID-19 also requires students to heavily depend on technology and to equip themselves with computer/internet literacy for successful online participation (Allam et al., 2020). COVID-19 entails students to have self-efficacy i.e., knowledge of and competencies in using modern technologies to achieve the educational objectives determined by their academic institutions (Lai, 2011). Even before the pre-COVID era, self-efficacy is considered as an important skill for learning in contemporary online settings (Hung et al., 2010). Early literature refers to self-efficacy as aspects which help students benefit from technology and its environment (Manganello et al., 2019). Self-efficacy is considered as a major driving factor in preparing students for online learning (Hung et al., 2010; Xiong et al., 2015) and that social and technical competency, two key dimensions of self-efficacy for student learning, are highly associated with online readiness and satisfaction (Yu, 2018; Yu & Richardson, 2015).

2.2. Situational factors: The emerging constructs for students' online readiness

Miglani and Awadhiya (2017) pointed out that the availability of digital resources and the ability to use and benefit from these are the key factors that characterize digital inequality. Based on the notion of digital inequality accelerated by the COVID-19 pandemic, several key dimensions with increased relevancy to students' readiness for online learning become apparent. In this study, we identified these dimensions under a common construct named "situational factors."

The first factor we conceptualise is the availability and access to the digital resources amidst a pandemic situation. Research shows that low-income families are suffering the most from the COVID-19 economic crisis because they have fewer and lower quality digital appliances (Fernandes, 2020). Bangladesh is not an exception here. Due to their low socio-economic status, many students in Bangladesh do not have the modern devices to readily adjust to the technology based “new normal” life. Instead, research shows that use of outdated devices, as is the supposed case for the majority students of Bangladesh, results in delays in connecting to online resources and an overall less satisfying experience (Beaunoyer et al., 2020). Also, the increased cost of internet data and poor connectivity remains a serious threat for technology adoption in Bangladesh (Ullah et al., 2021). As a result, students get fewer opportunities to access, engage with, and experience modern technologies.

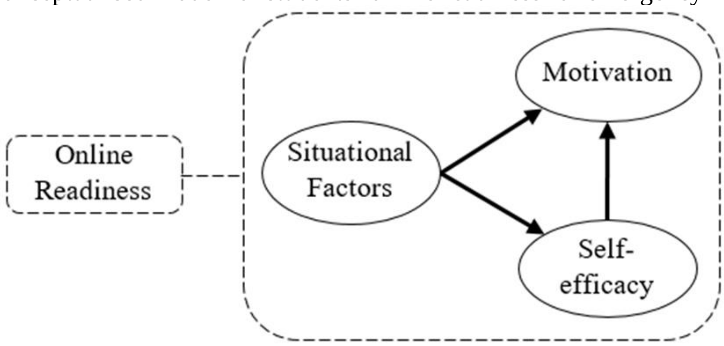
Second is the “learning atmosphere” in the home environment - a unique and unprecedented context emerging because of COVID-19 lockdown. Neuwirth et al. (2020) reasoned that some issues are exacerbated by underlying conditions of disparity of available resources triggered by the COVID-19 pandemic. These include the lack of a calm and peaceful study space within the home environment which can help students to learn in comfort and with privacy. However, a positive learning atmosphere is not simply silence: it is a complex-to-describe combination of sense experience and feelings shaped by underlying spatial organization, structures, social rules, and interactions governed by the environment (Cox, 2017). Often too, close proximities with other family members trigger disturbances, and students can be reluctant to use a webcam during classes which may expose their socioeconomic and living conditions (Neuwirth et al., 2020).

Leaning atmosphere at home are important sources for the development of positive self-efficacy which regulate students’ learning in online environment (Bonanati & Buhl, 2021). Research shows that factors within the home learning atmosphere can predict students’ self-efficacy (Bonanati & Buhl, 2021; Rohatgi et al., 2016). In contrast, when student experiences poor learning environments it affects their self-efficacy development and learning outcomes (Khine et al., 2020). For example, many students are facing difficulties in online assignment submission and tasks accomplishment during pandemic because of poor learning atmosphere (Bisht et al., 2020). In brief, the learning atmosphere is a crucial ingredient to stimulate student motivation (Pamungkas, 2019). Evidence indicates that a supportive learning atmosphere has a major influence on student self-efficacy and attitudes toward learning (Han & Ellis, 2021; Kokoç et al., 2021).

Third is the institutional support which can reduce the huge academic gap emerged due to remote learning. In fact, institutional support and quality education are linked in a significant way (Ullah et al., 2021). Educational institutions should facilitate student learning by providing emotional support and necessary information to help alleviate common challenges faced by online learners (Huang et al., 2020). The home confinement triggered by COVID-19 limits access to the faster networks readily available at educational institutions (Beaunoyer et al., 2020). When students are deprived of such facilities, educational institutions should subsidise the internet cost for students from low-income families. These types of supports can significantly help students to prepare themselves for online learning.

In contrast, the poor institutional support services may intensify these problems and affect student self-efficacy (Richardson et al., 2021). Irani et al. (2014) even claimed that institutions should consider multiple ways to support online students to mitigate the feeling of loneliness and separation from their peers and teachers. These supports can help online learners navigate important administrative, technical, financial, and other educational challenges while also increase students’ self-efficacy and improve student retention in online courses in the long run (Trespalacios et al., 2021). All these situational specific factors therefore signify the importance of students’ preparedness, motivation and their self-efficacy for online learning and their continuous intentions to use (Wang & Lin, 2021).

Figure 1. Reconceptualised model for students’ online readiness for emergency like COVID-19



Based on the understanding of different constructs of students' readiness amidst a pandemic situation, we therefore propose a reconceptualised model of students' readiness for online learning (Figure 1). This model consists of three key components: motivation, self-efficacy, and situational factors. Further, in this model we conceptualise situational factors as a combination of three sub-constructs: digital access, learning atmosphere and institutional support.

3. Research methods

3.1. Scale development

The scale development process was finalised in four different phases suggested by DeVillis (2016). First, we generated items based on related previous research employing a five-point Likert scale. Second, we modified and refined the items based on experts' feedback. Third, we conducted a pilot study with a sample of 68 students to check initial internal consistency and inter-item correlations of the items. Finally, we tested the reliability and validity of the survey scale using a larger student sample in the actual study.

Previous studies showed positive correlations between different motivational factors originated from self-determination theory such as interest, perceived usefulness, reinforcement, connectedness, and students' level of online readiness (Hung et al., 2010; Xiong et al., 2015). Therefore, we adapted seven items from Hung et al. (2010), Xiong et al. (2015) and *Intrinsic Motivation Inventory (IMI)* rooted in the self-determination theory (Ryan & Deci, 2000) to measure student interest; seven items from *IMI* and Xiong et al. (2015) to measure perceived usefulness; four items (two from Xiong et al. (2015) and two newly created) to measure reinforcement. Finally, we adapted eight items from *IMI* to measure students' relatedness in online learning.

To measure students' self-efficacy, we adapted four items from Yu and Richardson (2015) to measure students' technical competency and ten items from Hung et al. (2010) to measure social competency. The final constructs in our study are characterized as *situational factors* which describe the contextual dynamics emerging from the COVID-19 pandemic. We conceptualised this construct as the combination of three sub-constructs i.e., digital access, learning atmosphere and institutional support. Thus, we have created twelve new items under the situational factors (four items for learning atmosphere, four items for institutional support and four items for digital access). In total, there were 52 items in the initial survey instrument (see Appendix).

3.2. Research contexts and participants

The researchers started distributing the online survey during the peak of COVID-19 at the beginning of June 2020, when all the higher educational institutes of Bangladesh had already started online teaching. The survey was administered nationwide in a total of 23 universities. To achieve a representative sample for the study, participants were invited from all three types of universities: public (government funded), private, and international (funded by international donor agencies).

3.3. Data collection and preparation

Initially a total of 1038 responses were collected using Google form. After a rigorous data screening process, 988 responses were found to be valid. The data set had been scrutinized for missing values, normality, and outliers. The summary of the participants' demographic data can be found in the supplementary dataset at the end of the document. The reliability and descriptive statistics of the data set are shown below (Table 1).

Table 1. Reliability and descriptive statistics of the theoretical constructs

Constructs		Mean	Std. Deviation	Skewness	Kurtosis
Motivation	Interest	18.45	7.32	.319	-.757
α = 0.964	Usefulness	18.59	7.56	.311	-.856
	Reinforcement	11.58	4.18	.076	-.824
	Connectedness	21.67	6.94	.176	-.584
Self-efficacy	Technology competency	13.93	3.99	-.403	-.440
α = 0.926	Social competency	29.68	9.21	.101	-.608
Situational Factors	Learning atmosphere	12.81	4.06	-.043	-.769
α = 0.868	Institutional support	13.18	4.16	-.265	-.654
	Digital access	12.46	3.93	.038	-.610

Table 1 shows that the coefficient alpha values were well above 0.8 which showed very good internal consistency among the items (Blunch, 2008). Our data set also met assumptions of multivariate normality as both skewness (< 3.0) and kurtosis (< 10) are within the range (Kline, 2016).

3.4. Data analysis

To answer the RQ1, we first conducted an exploratory factor analysis (EFA) to determine the relationships between latent variables reflected in the items of the survey instrument (Hair et al., 2010). Table 2 shows the recommended index values for EFA analysis used in this study.

Table 2. Recommended index values for EFA used in this study

Indicators	Recommended value	Source
Kaiser-Meyer-Olkin (KMO)	> 0.70	Hutcheson and Sofroniou (1999)
Bartlett's test of sphericity	Significant at $p < 0.001$	Field (2013)
Satisfactory communalities values	> 0.50	Field (2013)
Total variance explained	> 50%	Podsakoff and Organ (1986)
The variance for the first factor	< 50%	Podsakoff and Organ (1986)
Factor loading for items	> 0.50	Hair et al. (2016)

Second, we conducted confirmatory analysis (CFA) to examine the reliability, convergent validity, and discriminant validity of our proposed model. Third, in the structural model, we assessed the model fit against several tests and fit indices recommended by literature (see Table 6 for details). Finally, to address RQ2, we ran a multivariate analysis of variance (MANOVA) to explore the students' readiness for online learning with regards to different demographic variables.

4. Results

4.1. Exploratory factor analysis

We used Monte Carlo software program for parallel analysis to identify the exact number of components to best reflect the underlying relationship among the variables. We kept only those components with the eigenvalues greater than the randomly generated data from parallel analysis (see supplementary dataset). For a cleaner solution, items with high communalities and factor loadings (greater than 0.5) were retained in EFA. In this process, a total of 39 survey items were retained for the EFA model. EFA suggested a four-factors model comprising motivation, self-efficacy, learning atmosphere and institutional support.

Table 3. Inter factor correlation matrix and reliability of the EFA model[#]

Factors	1	2	3	4	Reliability (Cronbach α)
1. Motivation	1.000				0.971
2. Self-efficacy	.461	1.000			0.863
3. Learning atmosphere	.633	.488	1.000		0.860
4. Institutional support	.580	.333	.581	1.000	0.853
Sampling Adequacy					
KMO	0.980				
Bartlett's tests of sphericity	0.000***				
Total Variance Explained	62.62%				

Note. [#]Extraction Method: Principal Component Analysis; Rotation Method: Promax with Kaiser Normalization. ***Significant at $p < .001$.

Table 3 shows excellent internal consistency (Cronbach's alpha) of the items in the four factors EFA model. Discriminant validity is also ensured as no cross loading of the items are observed in more than one factor and inter factor correlations are below 0.70. Bartlett's tests of sphericity were found to be significant (0.000; $p < .001$) with excellent KMO value (.980), suggesting the suitability of factor analyses.

4.2. Measurement model

In validating the measurement model with confirmatory factor analysis (CFA), we found some problematic items and therefore, following suggested data-analysis practices (MacCallum et al., 1996), we retain 30 items for the final model. Table 4 shows excellent composite reliability, high factor loadings and standardized regression weights (greater than .05 at $p < .001$) which support the convergent validity of the model (Hair et al., 2010). The average variance extracted (AVE) (greater than .50) also confirm the convergent validity (Fornell & Larcker, 1981).

Table 4. Convergent and discriminant validity of the measurement model

Constructs	CR	AVE	MSV	1	2	3	4
1. Motivation	0.967	0.623	0.442	**0.790**			
2. Self-efficacy	0.824	0.540	0.528	0.665^{***}	**0.735**		
3. Learning atmosphere	0.831	0.555	0.528	0.659^{***}	0.727^{***}	**0.745**	
4. Institutional Support	0.856	0.600	0.425	0.652^{***}	0.607^{***}	0.533^{***}	**0.775**

Note. $^{***}p < .001$.

The correlations of the constructs and the square root of the AVE on the diagonal (in bold numbers) are shown in Table 4. As revealed, all square root of AVEs is greater than the inter factor correlations and all AVEs are greater than the MSVs (maximum shared variance) (Fornell & Larcker, 1981). Thus, our model met the criteria of discriminant validity. Further, the heterotrait-monotrait (HTMT) ratio of correlations in Table 5 are below .850 showing a strict discriminant validity between the factors (Fornell & Larcker, 1981; Henseler et al., 2015).

Table 5. HTMT Analysis

Constructs	1	2	3	4
1. Motivation	---			
2. Self-efficacy	0.687	---		
3. Learning atmosphere	0.671	0.757	---	
4. Institutional support	0.668	0.628	0.562	---

In sum, the evaluation of the measurement model suggested that all items are reliable and met the conditions of convergent and discriminant validity.

4.3. Structural model

Hu and Bentler (1999) state that a RMSEA value less than 0.07, and CFI and TLI values greater than 0.90 indicate good fit of a model. In our study, the value of the RMSEA coefficient is 0.063, and other indicators (CFI, TLI, IFI, and NFI) are all above 0.90 which indicate a good fit for the model. SRMR fit index is also smaller than 0.10, further confirming. Thus, we conclude that our model met all the recommended levels of fit indices (Table 6).

Table 6. Recommended values of the fit indices and the corresponding results of the proposed model

Fit Index	Admissibility	Source	Result	Fit
CMIN/DF	< 5.0	Hu and Bentler (1999); Kline (2016)	(1954.32/399) = 4.898	Yes
RMSEA	< 0.08	Hu and Bentler (1999)	0.063	Yes
CFI	> 0.90	Hu and Bentler (1999)	0.929	Yes
TLI	> 0.90	Hu and Bentler (1999);	0.923	Yes
IFI	> 0.90	Hu and Bentler (1999);	0.929	Yes
NFI	> 0.80	Bentler and Bonett (1980); Schumacker and Lomax (2010)	0.912	Yes
SRMR	< 0.10	Hu and Bentler (1999)	0.045	Yes

We also assessed for multicollinearity issue using variance inflation factor (VIF) and found that all the values are between 1.903 and 3.550. Thus, the VIF values met the criteria to support the structural model (Hair et al., 2016; Kline, 2016).

Table 7 shows the path coefficients and path significances revealing that all values are significant between the factors (at $p < .001$).

Table 7. Model path analysis

Path relationships			Unstandardized estimate	*S.E.*	*p*	Standardized estimate (beta coefficient)
Self-efficacy	<---	Learning atmosphere	.654	.050	***	.563
Self-efficacy	<---	Institutional support	.287	.034	***	.307
Motivation	<---	Institutional support	.373	.037	***	.349
Motivation	<---	Self-efficacy	.263	.053	***	.230
Motivation	<---	Learning atmosphere	.406	.058	***	.306

Note. $^{***}p < .001$.

Figure 2 shows that 58% variance (R^2 = 0.58) in motivation is explained by learning atmosphere, institutional support, and through the effect of self-efficacy. Likewise, learning atmosphere and institutional support have explained 60.0% of variance (R^2 = 0.60) in self-efficacy.

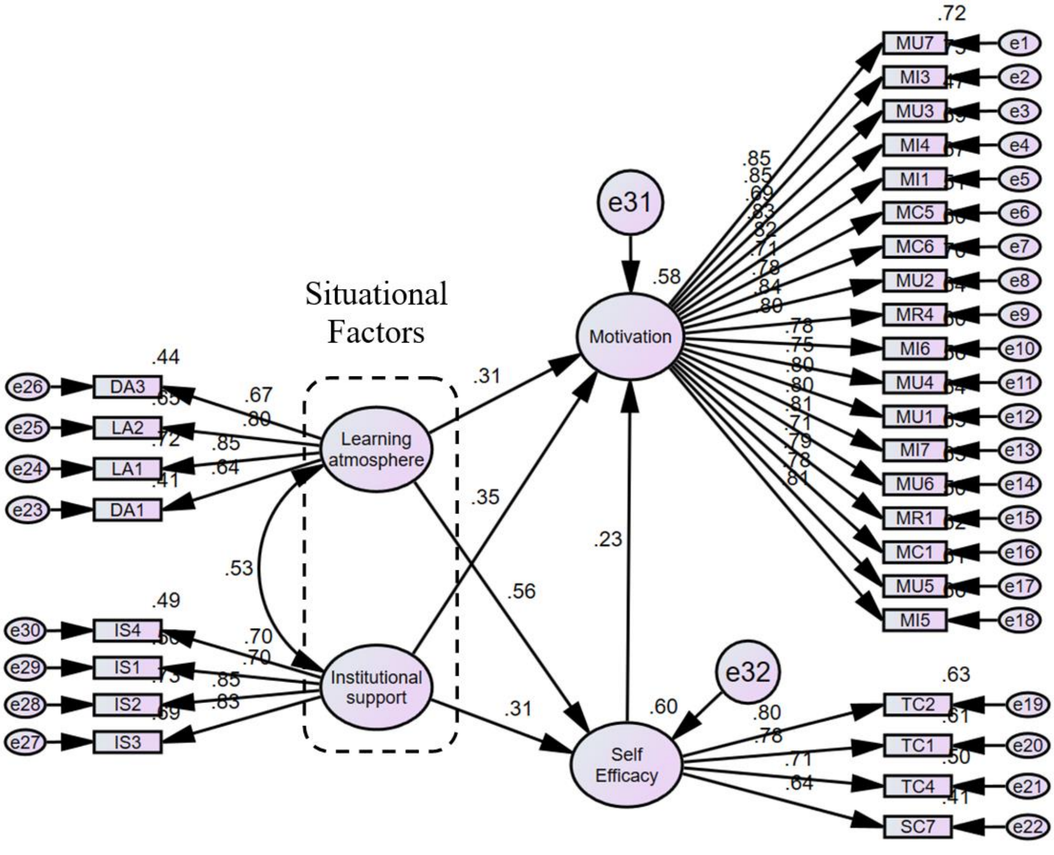
Finally, using bootstrapping we found that both the relationships between learning atmosphere and motivation, as well as institutional support and motivation are partially mediated by self-efficacy. In both the relationships, mediation effect is found significant at p < .001 (Table 8).

Table 8. Mediation effect in the structural model

Relationships	Direct effect	Indirect effect	Result
Institutional support --> self-efficacy --> motivation	.373***	.071***	Partial Mediation
Learning atmosphere --> self-efficacy --> motivation	.406***	.130***	Partial Mediation

Note. $^{***}p < .001$.

Figure 2. Final model of students' readiness for online learning

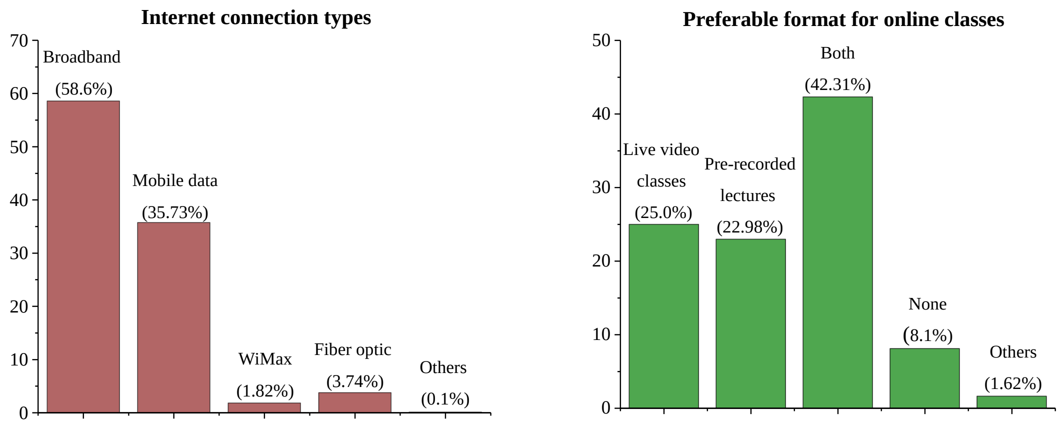


4.4 Student readiness for online learning

As discussed in the literature, the availability and speed of internet connection become important indicators of students' readiness. A significant portion (35.73%) of the students depend on mobile data (see Figure 3) which provides slower speed compared to the other internet connections in Bangladesh.

When asked about their preferred method for online class engagement, 22.98% of the students were in favour of pre-recorded lectures. Interestingly, 8.10% of the students do not like to participate in any form of online classes. This clearly indicates that a significant portion (22.98% and 8.18%) of the students is uncomfortable engaging in live online classes.

Figure 3. (a) Available internet connection; (b) Students' preferable mode of online classes



(a) (b)

Further, we conducted MANOVA test to examine the effect of demographic variables on students' readiness (i.e., motivation and self-efficacy). The results of the MANOVA (Table 9) analysis suggest a statistically significant effect of all demographic variables on student readiness.

Table 9. MANOVA analysis showing the impact of demographic variables on students' readiness

Demographic variables	Wilk's lambda (λ)	F	Hypothesis df	Error df	p	Partial eta squared
Gender	.987	6.560	2.0	985.0	$.001^{***}$	.013
University	.910	23.873	4.0	1968.0	$.000^{***}$	.046
Study Level	.983	2.130	8.0	1964.0	$.030^{*}$	.009
Place of living	.951	8.338	6.0	1966.0	$.000^{***}$	.025

Note. $^{*}p < .05$; $^{***}p < .001$.

We ran a separate analysis of variance (ANOVA) test to examine the statistical significance of the demographic variables on motivation and self-efficacy. We further conducted a multiple-comparison analysis (post hoc) to show exactly where the differences existed between three or more group means (Table 10).

The results indicate statistically significant impact on student readiness as follows:

- Gender showed a statistically significant impact on students' readiness for online learning, F (1, 986) = 12.96, p = .000, partial eta squared = .013, with male (M = 48.66) scoring higher than female (M = 43.38) in motivation; and F (1, 986) = 6.35, p = .012, partial eta squared = .006, with male (M = 13.69) scoring higher than female (M = 12.94) in self-efficacy.
- University type revealed a statistically significant influence on students' readiness in motivation, F (2, 985) = 45.965, p = .000, partial eta squared = .085, with public university (M = 52.37) scoring higher than international university (M = 40.55), and private university (M = 51.65) also scoring higher than international university (M = 40.55).
- Likewise, F (2, 985) = 8.065, p = .000, partial eta squared = .016, with public university (M = 14.09) scoring higher than international university (M = 12.93), and private university (M = 13.82) again scoring higher than international university (M = 12.93) in self-efficacy.
- Study level showed a statistically significant impact on students' readiness for online learning, F (4, 983) = 3.750, p = .005, partial eta squared = .015, with postgraduate students (M = 56.68) scoring higher than year 1 (M = 45.54) and year 2 (M = 45.50) students in motivation; and F (4, 983) = 2.611, p = .034, partial eta squared = .011, with postgraduate students (M = 15.22) scoring higher than year 1 (M = 13.22) students in self-efficacy.
- Living place showed a statistically significant impact on students' readiness, F (3, 984) = 7.255, p = .000, partial eta squared = .022, with village students (M = 51.95) scoring higher than both city (M = 45.64) and district town (M = 46.38) students in motivation.
- No statistically significant differences were found for living places in self-efficacy.

Table 10. F test results for demographic variables on students' readiness for online learning

Demographic variables	Student readiness	Category	*M*	*SD*	*df*	Error	*F*	*p*	Partial eta squared	Post hoc
Gender	Motivation	1. Male	48.66	19.14	1	986	12.96	.000***	.013	---
		2. Female	43.38	17.24						
	Self-efficacy	1. Male	13.69	3.84	1	986	6.35	.012*	.006	---
		2. Female	12.94	3.80						
University	Motivation	1. Public	52.37	19.80	2	985	45.965	.000***	.085	1>3, 2>3
		2. Private	51.65	18.38						
		3. International	40.55	16.74						
	Self-efficacy	1. Public	14.09	3.73	2	985	8.065	.000***	.016	1>3, 2>3
		2. Private	13.82	3.83						
		3. International	12.93	3.83						
Study Level	Motivation	1. Undergraduate Year 1	45.54	18.78	4	983	3.750	.005**	.015	5> 1, 2
		2. Undergraduate Year 2	45.50	18.92						
		3. Undergraduate Year 3	48.36	19.02						
		4. Undergraduate Year 4	49.09	18.56						
		5. Postgraduate	56.68	17.99						
	Self-efficacy	1. Undergraduate Year 1	13.22	3.83	4	983	2.611	.034*	.011	5>1
		2. Undergraduate Year 2	13.27	4.03						
		3. Undergraduate Year 3	13.47	3.95						
		4. Undergraduate Year 4	13.83	3.57						
		5. Postgraduate	15.22	3.78						
Place of living	Motivation	1. City	45.64	18.57	3	984	7.255	.000***	.022	4>1, 2
		2. District Town	46.28	18.09						
		3. Thana Town	51.28	18.50						
		4. Village	51.95	19.42						
	Self-efficacy	1. City	13.70	3.78	3	984	1.043	.373	.003	---
		2. District Town	13.12	3.62						
		3. Thana Town	13.52	3.70						
		4. Village	13.31	4.14						

Note. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

5. Discussion

In this study, we have developed and proposed a model for measuring engineering students' readiness for online learning in the COVID-19 situation. In developing this context-specific model, we have combined three well-known constructs: motivation, self-efficacy, and situational factors. Considering the unique situation of the COVID-19 pandemic, we have proposed the context-specific construct "situational factors" which constitute information on (i) learning atmosphere, and (ii) institutional support. We have assessed the reliability, validity, and model fit evidence of the proposed survey scale using structural equation modelling (SEM). The developed model was validated and found to be reliable for use in similar scenarios.

Situational factors, the key findings of this study, play a significant role in determining student readiness during pandemic situations, as the coefficient of determination, R^2, indicates a high percentage of variance to explain motivation and self-efficacy (see Figure 2). In this article we argue that learning atmosphere has a pronounced impact on the extent to which engineering students are ready for online classes. Study shows that engineering students seem to be more engaged in a learning environment that offers practical-oriented, interactive, and team-based activities in an online learning environment (Kebritchi et al., 2017; Radianti et al., 2020). Boosting students' intrinsic motivation (Ryan & Deci, 2000) by offering appropriate pedagogical modes and learning activities is likely to improve students' readiness for online classes (Hasan et al., 2016).

We also argue that institutional support plays a vital role in student motivation towards online learning and therefore their readiness learning online. If institutions provide timely IT support and a synchronized and reliable communication platform, students are likely to engage in online classes. Even if institutions provide support for online theory classes, however, more practical aspects of learning need to be included for effective online learning, especially for engineering students whose study involves practical concepts (Naji et al., 2020).

In essence, this study's most significant contribution is that it offers an instrument to measure student readiness during pandemic situations. While this study confirms the previous investigations about the influence of motivation and self-efficacy on student readiness in general (Chung et al., 2020; Hung et al., 2010; Xiong et al., 2015; Yu, 2018), additionally, it argues that situational factor is also an important phenomenon that plays a significant role on student readiness especially during a pandemic situation.

The difference between the standardized estimation values of the direct effect and the indirect effect in Table 8 confirms the mediation effect of self-efficacy between the situational factors and motivation. The higher standardized estimation values of direct effect also confirm that the situational factors' impact is higher than the impact of self-efficacy on motivation. As such, situational factors play a key role in student online readiness during a pandemic.

When a direct question was asked about the students' preferred online mode of participation, we found that approximately 30% of students did not like to engage in live online classes (see Figure 3b). This finding provides strong evidence of a low level of students' readiness for online learning during the emergency. Interestingly, students' unwillingness to engage in live online classes is commonly reported in the literature; for instance, in Handel's study (Händel et al., 2020), only 6% of students used live streaming. One potential reason for such unwillingness to attend the live classes during pandemic may be the increased number of online classes that were not usual for students, and hence difficult for them to adopt the sudden paradigm shift from full face-to-face to full online mode. Further research may explore the emerging causes of students' unwillingness to attend live classes during an emergency and normal situation.

Our data also suggest a digital inequality as a significant portion of students do not have adequate digital access in terms of internet connectivity (see Figure 3a). Using the Technology Acceptance Model (TAM) (Davis, 1989), as an investigation framework, Siron et al. (2020) argued that individuals with prior experience using computers and the Internet demonstrated higher scores in "perceived ease of use" of technology compared to new learners, and this claim is supported by the works of Lee et al. (2014) and Purnomo and Lee (2013). Because these 'at risk' or digitally-not-ready students tend to be vulnerable, a careful and deliberate instructional strategy for their online learning is required.

Our findings revealed that the differences in students' demographics (gender, university type, study level, living place) have a significant impact on student online readiness. For example, male students are likely to be more motivated and efficient than female students. This finding is supported by the study of Händel et al. (2020), however it contradicts the findings of Naji et al. (2020) and Chung et al. (2020) who reported no significant relationship between gender and student readiness. Further studies may result in better understanding of engineering students' readiness for online learning based on their gender.

Also, while differences were found among students of public, private, and international universities, the difference between public and private was not significant with respect to both motivation and self-efficacy. This may be due to some universal characteristic of students irrespective of their type of institution. Results also revealed that the junior cohort student (year 1 and year 2) is less likely to be ready than students in the senior cohort (year 3, year 4 and postgraduate). In both motivation and self-efficacy no significant differences were found among senior students. Young university students have been found to be motivated toward learning and to perform better than the senior students (Abdullah, 2011). In our case, it may be due to the pandemic that senior students become more serious about their learning to complete their study and gain employment quickly.

An interesting finding was observed when students' readiness was explored with respect to their place of living. Our data showed that village students were more motivated in online classes than city students, whereas urban students enjoyed better access to the internet than village students. The village students may believe that having less access to technology could impact negatively on their academic performance. As such, they became more motivated but also anxious about gaining access to technology and joining online classes.

5.1. Limitations and implications of this study

The survey used in this study employed convenience sampling for collecting data from the participants i.e., engineering students in Bangladesh. This sampling method can lead to unexpected or uncontrolled factors in the sample data which could potentially impact on the investigation and skew the results of the study (Emerson, 2015). However, a large sample group such as the current study may minimize the limitations posed by the convenience sampling (Etikan et al., 2016). Also, as the name indicates, convenience sampling is often used despite its limitations due to the expediency of recruiting participants (Sedgwick, 2013).

Another limitation of this study is to solely rely on self-reported survey data to measure students' readiness for online learning. We acknowledge that obtaining qualitative data through structured or semi structured interviews from some of the participants could help triangulate the data to further validate the results of this study. Future studies might consider the data triangulation approaches to gain a more comprehensive understanding of the factors that affecting students' readiness for online learning during the pandemic.

This study presented some stimulating observations which have both practical and theoretical implications for ensuring a proper learning environment for students. For example, the significance of this validated survey instrument lies in enabling institutions to assess students' readiness so they can make informed decisions about how to improve online learning, specifically, in relation to the situational factors (learning atmosphere and institutional support). These factors provide the underlying fundamentals for policy makers to design the learning context, assessment technique, etc., to prepare students for online learning. Support from educational institutes for students, in monetary or other form, would help foster a caring environment for learning too.

Informed by the insights presented, academic entities may consider establishing counselling units dedicated to supporting the students' psychological wellbeing during the pandemic as this should enhance student confidence in online learning. Institutions can consider various strategies where students with lower online readiness (i.e., motivation, self-efficacy, and situational factors) receive peer-to-peer support, guidance, or supportive intervention when they face problems or feel discouraged during the online learning. This in turn will increase student satisfaction with the education offered by their respective institutions.

Furthermore, policy makers in developing countries should consider important evidence when preparing policies for teaching in similar conditions - pandemic or otherwise - where students are required to shift to online learning due to some unwanted circumstances. Moreover, the findings will be applicable to other developing countries with similar sociodemographic conditions. Although this study focused on engineering students, some of the general findings can be applied to online learning for students from other disciplines as well.

This study revealed three key factors (motivation, self-efficacy, and situational factors) as the required conditions of student readiness for online learning. Since the current study found that computer/Internet self-efficacy and motivation for learning have direct effects on online readiness, institutions can create a simple, easy-to-use learning portal, especially where students can manage their learning resources. Such simplicity would help students feel more confident and perhaps feel less pressure to participate in the online classes.

Lessons from the study could also help teaching staff improve and customize their course teaching for such situations to improve the learning experience for students. Teaching staff should help students remain motivated since motivation is one of the important factors influencing student readiness. Students' intrinsic motivation can be increased by promoting the features of online learning i.e., creating more channels to interact with instructors and peers so that students feel a strong loving relationship among them. Rewards and extra grading can be provided to facilitate students' extrinsic motivation when students were actively engaged in online class activities, or their active participation has been recognized in any form.

6. Conclusion

The focus of this study was to investigate engineering students' readiness for online learning during the COVID-19 situation. For this, we conducted an online survey in different universities in Bangladesh and, after scrutiny, selected 988 responses out of 1038 initial responses. We collected engineering students' opinions on factors that influence students' readiness for online learning. Our study proposed a new model to measure student readiness for online learning considering the context of the COVID-19 situation. The reliability, convergent and discriminant validity of the proposed model was tested using EFA and CFA methods. Twenty-two items were removed from the original 52 items to achieve composite reliability greater than 0.7. Our study suggests that besides motivation and self-efficacy, situation and context-specific factors influence students' readiness for online learning. It is evident from the findings that students are not ready yet for online learning. Besides the usual student unwillingness (Händel et al., 2020), our study shows that student readiness towards online learning is hindered by digital inequality in a developing country due to lack of experience and access to relevant technologies. In developing countries like Bangladesh, the penetration of internet connectivity is widely varied; hence students lived in rural areas are seemly less accessed to the internet.

Moreover, it becomes more severe during the pandemic as students' need to move their home areas to stay with families. The proposed model can be helpful to improve the student learning experience in emergencies and address potential issues related to student online readiness. A longitudinal study may be performed in future to detect any changes in the relationship of the factors considered in this study. We also plan to extend this study by broadening the demographic distribution to include participants from different disciplines.

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Appendix

The initial "Student Online Learning Readiness" Survey

A. Motivation

Sub-constructs	**Items**
Interest	MI1. I think I enjoy learning very much in online environment.
	MI2. I think learning in online environment is a boring activity*.
	MI3. I would describe learning activity in online environment as very interesting.
	MI4. I think online learning activity is quite enjoyable.
	MI5. I am open to accept the online environment for my learning.
	MI6. I like to work with my classmates in an online environment.
	MI7. I like to work with my teachers in an online environment.
Perceived Usefulness	MU1. I believe it is effective to learn in online classes.
	MU2. I believe online classes can help my learning.
	MU3. I believe online classes help me to learn more complex topics than face-to-face classroom.
	MU4. I believe online classes allow many opportunities for discussion and sharing ideas among my classmates.
	MU5. I would be willing to learn in online classes again because it has some value to me.
	MU6. I think online learning is important because it can improve my learning.
	MU7. I believe online learning activity could be beneficial to me.
Reinforcement	MR1. Through online classes, I hope to achieve a good grade for the courses I attend.
	MR2. I hope my teachers and classmates will praise me if I can perform good in online classes.
	MR3. I hope my attendance in online classes will improve my course grade.
	MR4. I hope online classes will have a positive impact in my career.
Connectedness/ Relatedness	MC1. I like to connect with my teachers and classmates in the online learning environment.
	MC2. I feel like I can trust my teachers in the online learning environment.
	MC3. I prefer not to interact with my teachers and classmates in the online learning environment in future*.
	MC4. I feel disconnected from my teachers and classmates in the online learning environment*.
	MC5. I feel close to my teachers and classmates in the online learning environment.
	MC6. I feel I could develop friendship with my teachers and other students in the online learning environment.
	MC7. I would like to interact with my teachers and classmates more often in the online learning environment.
	MC8. I feel I could develop a good bonding with others through online learning environment.

**Item needs reverse coding*

B. Self-efficacy

Technology Competency	TC1. I feel confident in performing the basic functions of technology used in online learning. TC2. I feel confident in my knowledge and skills of how to manage software for online learning. TC3. I feel confident in using the internet to find or gather relevant information for learning. TC4. I feel competent at integrating computer technologies into my learning activities.
Social Competency	SC1. I feel confident to ask questions to my teachers in online classes. SC2. I feel confident to seek help from my teachers when needed. SC3. I feel confident to timely inform my teachers when unexpected situations arise. SC4. I feel confident to express my opinions to teachers respectfully. SC5. I feel confident to initiate discussions with my teachers in online environment. SC6. I feel confident to respect other students' social actions in online environment. SC7. I feel confident to apply different social interaction skills depending on situations. SC8. I feel confident to initiate social interaction with classmates. SC9. I feel confident to work in groups in online environment. SC10. I feel confident to develop friendship with my classmates in online environment.

C. Situational Factors

Learning atmosphere	LA1. I think my living environment is supportive to study in online environment. LA2. I think I can effectively study from my living place. LA3. I think my family members around me are helpful for my online study. LA4. I think it is difficult to study online from the place where I am living[*].
Institutional Support	IS1. I believe my institution is supportive for my online study. IS2. I believe I can get the necessary help from my institution to study online. IS3. I believe my institution makes necessary arrangements for effective online learning. IS4. I believe my institution can provide a favourable environment for my online study.
Digital access	DA1. I believe I have the necessary devices to participate in online classes. DA2. I believe I can afford the cost of internet to participate in online classes. DA3. I believe the internet connection and speed is reliable enough for the online classes. DA4. I think I do not have enough resources to study online[*].

[*]*Item needs reverse coding*

Supplementary dataset

Available from Mendeley data repository.