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Is blended learning the future of education? Students perspective using discrete choice experiment analysis

Adib Ahmed
Bangladesh University of Professionals, Bangladesh, adib.ahmed@bup.edu.bd

Sakib Bin Amin
North-South University, Bangladesh, sakib.amin@northsouth.edu

Grace McCarthy
University of Wollongong, Australia, gracemc@uow.edu.au

Abdul Mahidud Khan
Bangladesh University of Professionals, Bangladesh, mahidud.khan@bup.edu.bd

Rabindra Nepal
University of Wollongong, Australia, rnepal@uow.edu.au

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Abstract

This is the first study to use discrete choice experiment in exploring the stated choice preference of blended learning preference among the university students in the context of Bangladesh. As a pre-requisite in developing student engagement learning strategies, we investigate the choice preference of university students towards different types of blended learning to explore relevant concerns and challenges in order to plan for successful implementation of this option. Around 306 responses from the students belonging to Bangladesh University of Professionals (BUP) and North South University (NSU) are considered representing both public and private universities in Bangladesh. Conditional logit model is used to explore the choice preference of the respondents based on the attributes. We find that university students explicitly dislike recorded videos as the primary mode of instruction as there is minimum human interaction using this method. Students with mobile internet also prefer offline classes to online classes, whereas students with broadband internet prefer the opposite choices. The policy implications of these findings hold global relevance in devising student engagement strategies towards blended learning such as for other developing economies in South Asia which were forced to transition to online learning as an adaptation response to the COVID-19 pandemic.

Practitioner Notes

1. This is the first study to use discrete choice experiment in exploring the stated choice preference of blended learning preference of the university students in the context of Bangladesh.
2. We apply Conditional logit model is used to explore the choice preference of the respondents based on the attributes.
3. Our sample includes 306 responses belonging to Bangladesh University of Professionals (BUP) and North South University (NSU).
4. We find that university students explicitly dislike recorded videos as the primary mode of instruction as there is minimum human interaction using this method.
5. Students with mobile internet also prefer offline classes to online classes, whereas students with broadband internet prefer the opposite choices.

Keywords

choice experiment, blended learning, students perspective, COVID 19, pandemic

Introduction

Is online learning capable of bridging the global gap in educational resources? Educational policymakers were long being obsessed with such nature of educational inquiry before the COVID-19 pandemic. However, the rapid global transition to online learning in response to the pandemic and the increasing adoption of blended learning post-pandemic is changing the focus of the aforementioned pre-pandemic discourse. Educators and policymakers are now largely concerned with the effectiveness of online learning such as towards improving student engagement and thereby better academic performance. *How can the effectiveness of online learning be improved in developing economies by understanding the preference of university students towards online learning?* This study attempts to shed some light by studying the preference towards blended learning among the university students in Bangladesh – a South-Asian developing economy. Bangladesh has graduated from low-income to lower-middle-income country status since 2015, as per the categorization of the World Bank. In 2018, Bangladesh fulfilled the criteria of the first review to graduate from the least-developed country (LDC) status, and it is anticipated to graduate from this status by 2024 (Raihan & Bourguignon, 2020). Expanding the number of universities in a territory is conducive to more robust economic growth in that territory (Agasisti & Bertoletti,2020). In fact, the human capital theory asserts that formal education is highly instrumental and necessary to improve the productive capacity of an economy (Mincer, 1984). The tertiary education sector in Bangladesh has seen phenomenal quantitative growth in the last three decades regarding the number of student enrollments, subjects taught, and the number of universities (UGC, 2019). As one of the rapidly growing economies of the world, improvement in the higher education sector can play a pivotal role to make the development sustainable and to emerge as a developed nation by the year 2041 as per the "Vision 2041" set by the present government of Bangladesh (Chowdhury et al., 2020). The Strategic Plan for Higher Education (SPHE) 2018–2030 has been framed in accordance with the higher education objectives of the United Nations Sustainable Development Goals (SDGs). The number of universities in Bangladesh currently stands at 154 in 2019 (46 public universities, 105 private universities, and three international universities) to offer higher education to 165 million people of this country (UGC, 2019).

The COVID-19 pandemic has drastically altered the higher education system worldwide (Alghamdi, 2021., Crawford, 2021; Kefalaki et al. 2021), including Bangladesh, with a forced shift to online instruction (Islam et al. 2021). It has also created concern among faculties and students as unstable internet access, disruption in electricity connection, and limited electronic devices are crucial challenges in smoothly conducting online classes in a developing country like Bangladesh (Amin et al., 2021a). The closure of educational institutions has also affected many students around the world (Tice et al. 2021., Sumer et al. 2021., Khan et al. 2021., Koris and Pal, 2021., Diez-Guiterrez and Espinoza, 2021). From March 11, 2020, to February 2, 2021, around half of the scheduled classroom instruction was hampered globally, and around 36.8 million school students in Bangladesh have missed almost all in-person classroom instruction within this period (UNICEF, 2021). Nevertheless, COVID-19 has triggered educational institutions worldwide to pursue creative approaches on relatively short notice. Globally around 90 percent of education ministries have adopted remote learning approaches that involve radio, television, and/or the internet (Dreesen et al., 2020).

Amid this pandemic situation, technological innovations have brought about several innovations in the education system. Many higher education institutions have shifted from the traditional undergraduate classroom to virtual online education. Indeed, online learning has unlocked new opportunities in

Bangladesh, according to Al-Amin et al. (2021b). Most universities have shifted to online mode using Blackboard, Microsoft Teams, Moodle, Zoom, or some combination of other online platforms during this time. Faculty members have also adjusted their teaching and assessment methods (Muthuprasad et al., 2021). Although online classes were mainly treated as an elective medium of education before the pandemic; the pandemic forced online delivery to become the primary mode of learning during this period. Therefore, online platforms are currently used by educational institutions worldwide to support the learning process of students (Mulyanti et al., 2020**).**

Due to the prolonged pandemic, experts believe that the adoption of online distance learning will persist even after the pandemic, and a new blended learning model of education is expected to emerge as a future medium of classroom instruction (El Said, 2021). Blended learning is the thoughtful synthesis of offline and online learning experiences which integrate technology and online learning materials with traditional offline classroom activities (Garrison and Kanuka, 2004; Graham, 2006; Garrison & Vaughan, 2008). This method is also recognized as a hybrid, mixed-mode or flexible learning method introduced about a decade ago worldwide (Saboowala & Mishra, 2021). Building strong student engagement in face-to-face and technological environments is critical for effective blended learning (Lam et al., 2018). This learning method is widely adopted in higher education to enhance learning and create a learning space with more freedom for the learners (Smith & Hill, 2019). Several studies have already been conducted to explore the efficacy and implementation of this method in the post-pandemic circumstances (Orji et al., 2021; Saboowala & Mishra, 2021).

Currently, due to the closure of educational institutions, blended learning is not available to the students of Bangladesh. Since blended learning is likely to be the most viable future medium of education instruction for many universities and groups of students, investigating the choice preference of university students will allow us to explore relevant issues and challenges in order to plan for successful implementation of this option. Therefore, this study has used the stated preference method to explore the preferences of university students for different types of blended learning. Capturing the preferences of the university students towards blended learning will be important in identifying and designing appropriate learning strategies to foster student engagement in the blended learning mode. We rely on discrete choice experiment as choice experiment is a leading methodology in non-market valuation and finding consumer preferences (Scarpa & Rose, 2008). This method is used extensively in health, transportation, marketing to find out the preference of users or consumers. It can be distinguished from standard regression models by the explicit incorporation of a defined set of choices, some of which were not selected. The discrete choice method is one of the best-suited methods to reveal the preferences of the respondents while choosing among alternatives that have different levels of attributes (Hauber et al., 2016).

The study has taken 306 respondents from the students of Bangladesh University of Professionals (BUP) and North South University (NSU) as representative of public and private universities in Bangladesh. Conditional logit model has been used to explore the choice preference of the respondents based on the attributes. Also, marginal willingness to pay for the students has been calculated for non-monetary attributes using the parametric bootstrap method. To the best of our knowledge, this paper is the first paper using the discrete choice experiment (DCE) to explore the stated choice preference of blended learning preference of the university students in the context of Bangladesh. Our study identified student preferences relating to online and face-to-face instruction and assessment. The findings of our study are equally relevant to other South Asian economies in the region such as Afghanistan, Bhutan, India, Maldives, Nepal, Pakistan and Sri Lanka where blended learning can be expected to be the most viable mode of future education delivery. The remainder of the paper is organized into three sections. Section 2 presents the methodology of the study; Results and discussion are presented in Section 3. Finally, the conclusion and policy recommendations are presented in Section 4.

Method

Theoretical background

Student engagement has been conceptualized in varied ways but three elements are universal in any definition of student engagement, namely, behavioral, emotional and cognitive (Fredericks, Blumenfeld and Paris, 2004). The behavioral, emotional and cognitive elements of student engagement are influenced by a vector of factors such as those pertaining to students, teachers, institutions and pedagogy as articulated by Kahu (2014). According to Kahu (2014), the conceptualization of student engagement needs to incorporate both its antecedents (structural and psychosocial) as well as the consequences (proximate and distal) while clearly distinguishing the state of engagement. For instance, a recent study by Mahadeo and Nepal (2021) show that pedagogical approaches such as adoption of case studies influences student engagement dimensions on cognitive and affective learning. Another recent study by Nepal and Rogerson (2020) concluded that behavioral factors stemming from students own attitude towards learning is a primary factor affecting student engagement in university education. Therefore, any strategies to foster student engagement first needs to consider the preference of the students towards learning which can be adequately captured through a choice experiment. This study used a discrete choice experiment, which is based on the random utility model (RUM), first introduced by Thurstone (1927) and popularized by McFadden (1974). This model is based on the assumption that an individual chooses an option using some observed variables and some unobserved variables. The researcher can only quantify the observed variables, whether these might be the socio-economic background of the respondents or the attributes of the option that the respondents chose. The random utility model used for this study is presented in the Appendix. Both conditional and multinomial logit models could be used in this regard. However, the Conditional logit model mainly used to quantify the preference of the attributes of the choice and the multinomial logit model is used to determine which socio-economic factors of the respondent, impacted the preference (Hauber et al., 2016).

As blended learning is not available to students of Bangladesh at the moment, it is not possible to observe their behavior to find out their preference in online education using the revealed preference method. Therefore, using the stated preference method, this study provided choices to respondents about different types of blended learning and asked about their preferences in relation to those choices. To find out the preference when respondent chooses among options which have different attributes and levels, a discrete choice experiment is the standard methodology.

Sample selection

This study was conducted in Dhaka city, the capital of Bangladesh. To take into account the heterogeneity of private and public-funded universities, a University from each category has been selected, namely. North-South University, a private university, and Bangladesh University of Professionals, a public university. Another criterion for choosing these universities is that students of both universities have experienced at least two semesters of an online class and final exam. NSU, a leading private university of Bangladesh, moved to full online education on March 28, 2020. BUP is one of the few public universities with functional online education and semester final exams since March 24, 2020.

This study has surveyed 306 students yielding (306*12 = 3672) observations. A rule of thumb to yield respondent numbers in DCE can be found using the following formula by Orme (2010).

$$n_m \geq \frac{500 * L_m}{C_Q * A} \tag{10}$$

Here, n_m is the minimum number of respondents needed for DCE, L_m is the maximum number of levels that any attributed has in the model, C_Q The number of choice questions for each respondent and A is the number of alternatives per choice question. Therefore, according to equation 1, our sample size for each University should not be less than 55.

Survey questionnaires were mailed to 520 students of NSU and BUP, with 316 responding. Hence, the response rate is 63%, which is above average for an online mail survey where the mean response rate is around 10- 25% (Sauermann & Roach, 2013). The survey included a consent form to assure students about the confidentiality and anonymity of their given information. Also, students were at liberty to stop any point of the survey and not to finish the survey if they did not want to. This study randomly selected eight classes of 40 students in NSU and four types of 50 students from BUP where there were no overlapping students in those classes.

Attributes and levels

Students were presented with two hypothetical learning systems with different levels of attributes of each choice set in our choice experiment. To make the choice sets user-friendly and comprehensible for the students, we only used three attributes. These attributes and levels are listed in Table 1. To find out the most important attributes to include, a focus group discussion was conducted. In that focus group, five students from each University were selected. The learning method could be classified online, offline, or blended by the class conducting method and exam conducting method. Also, some students opined that fully online or blended education should not be exactly the same cost as offline education. From this discussion, we added three attributes of DCE.

Table 1.
List of attributes and levels of the attributes

Attributes	Description	Levels
Class Conducting Method	The way faculties conduct classes	Live Online Class Only Recorded Videos Offline Class
Exam Conducting Method	How all the exams will be conducted	Live Online Exam Assignment Type Exam Offline Exam
Price Per Credit	Semester fees for per credit in BDT	5000 6000 7000 8000

Blended learning is a combination of online education and offline education, that is, some components of learning will be conducted online and some offline. Different models have existed before Covid-19, such as online class and offline exam systems. In some cases, there were recorded videos and live online exams. Considering these models, the class conducting method has been divided into three categories: online class, only recorded videos for classes, and offline classes. The first two cases can be considered as online-based learning. Similarly, the exam conducting method is divided into three-level, where the first two are online-based, and the third one is a traditional offline exam. Prices per credit are chosen from the average cost per credit in the private universities of Bangladesh.

Model estimation

From the**Table 1.** *List of attributes and levels of the attributes* Table 1 attributes and their levels can be substituted to equation 7 to find out the model this paper tries to estimate,

$$V_{ni} = \beta_0 + \beta_1 \text{Only Recorded Videos} + \beta_2 \text{Offline Class} + \beta_3 \text{Assignment Type Exam} + \beta_4 \text{Offline Exam} + \beta_5 \text{Price Per Credit}$$

Here, β_1 to β_4 are the coefficients of categorical attributes where these shows the strength of preference for each attribute level. β_0 shows alternative specific constant which provides the value of attributes if all other coefficients are zero. Live online class and live online exam are used for base attribute for class conducting method and exam conducting method respectively. β_5 represents the coefficient of continuous variable of price per credit which can be used to find out the marginal willingness to pay for each of the non-monetary attributes. Standard conditional logit model assumes a homogenous preference among the observations. Therefore, different CL models were estimated for different groups.

Results

This paper used ‘support.CEs’ function in R, developed Hideo Aizaki to design and implement choice experiment (Aizaki, 2012). Also, this paper used survival package by Terry M Therneau to analyse the results of conditional logit model (Therneau, 2021). Results of Conditional Logit (CL) model for all observations are estimated in Table, where ASC is Alternative Specific Constant. Also, in the case of class conducting method, the base is only the online class. It is clear that students' utility goes down for recorded videos only. From the focus group discussion, it was learned that students prefer human interaction in their classes. Furthermore, they like to ask questions instantly if they face any difficulties in understanding topics, which is not possible in recorded classes. Utility for offline classes is not statistically significantly different from online live classes. Therefore, human interaction plays the most important role in students’ preference for how classes are conducted. In the case of exam conducting method, the base level is live online classes. Here, students are getting more utility from assignment type exams and offline exam, and they are significantly different from live online exams. A live online exam where students have to keep their cameras on creates extra pressure for the students whereas assignment type exams give students a flexible schedule which is very important when everything is online. Also, students prefer offline exams which they find less stressful than online live examinations. However, this result is different according to group as stated below. Also, semester fee or per credit cost has negative utility on students’ learning choice which is expected.

Table 2:
Conditional logit model coefficient estimates of total observations

	Conditional Logit Coefficient Estimates
ASC	2.719^{***}
	(0.149)
Class Conducting Method	
Recorded Videos Only	-0.787^{***}
	(0.069)
Offline Class	-0.069
	(0.059)
Exam Conducting Method	
Assignment type Exam	0.635^{***}
	(0.061)
Offline Exam	0.230^{***}
	(0.057)
Price Per Credit	
Price per credit	-0.0003^{***}
	(0.00002)
Note:	*probability (p)<0.1; **p<0.05; ***p<0.01

The numbers in ( ) reports the standard errors for the respective coefficients.

This study has compared the utility of these choices in different groups of students. First of all, differences in preference in the students of NSU and BUP are shown in Table 3. Here, ρ^2 is 0.18 which shows the goodness of fit test for this model. However, ρ^2should not be confused with R^2[1] of OLS

[1] R^2 assesses the goodness of fit in a regression model. It shows what percentage of variation of dependent variable can be explained with the model. A model is considered good as it approaches 1.

method. ρ^2 is known as McFadden's pseudo R^2. If a model has ρ^2 of 0.2 to 0.4 it is considered a good fitted model (McFadden, 1978).

Table 3:
University Wise comparison in utilities of learning methods

	Conditional Logit Coefficient in accordance with University	
	NSU	BUP
	(1)	(2)
ASC	3.545^{***}	2.018^{***}
	(0.207)	(0.232)
Class Conducting Method		
Recorded Videos Only	-0.999^{***}	-0.539^{***}
	(0.089)	(0.115)
Offline Class	-0.256^{***}	0.106
	(0.077)	(0.100)
Exam Conducting Method		
Assignment type Exam	0.422^{***}	0.895^{***}
	(0.081)	(0.093)
Offline Exam	0.046	0.430^{***}
	(0.079)	(0.083)
Price Per Credit		
Price per credit	-0.0004^{***}	-0.0002^{***}
	(0.00003)	(0.00004)
Observations	6,552	4,464
Note:	*probability (p)<0.1; **p<0.05; ***p<0.01	

The numbers in ( ) reports the standard errors for the respective coefficients.

NSU students get more disutility from only recorded classes than BUP students and in both cases the results are statistically significant. However, in the case of offline classes, NSU students significantly prefer online live classes to offline classes while BUP students prefer offline classes, even though results are not statistically significant. Therefore, for BUP students, live online class and offline class give the same utility. The exact reason for this result is unknown but it may be attributed to differences in how classes are conducted in public universities and private universities. Also, there are different results in preferences relating to the exam conducting method between NSU students and BUP students. Here, both groups of students prefer assignment types of exam to live online exams, although the degree of preference is different. In the case of offline exams, NSU students are indifferent and online live exam as coefficient is not statistically significant. On the other hand, BUP students prefer the offline exam method to online live exams and this result is statistically significant. This result can be explained through the exam-taking method of BUP where live proctored examinations and keeping cameras on for examinees even in case of slow internet connection create extra pressure for the students. This is different for students for NSU. Therefore, this study has revealed that a simple online vs offline exam taking method is not the issue, rather the issues for students are more subtle in each choice.

Family income can be an important factor in students' preference for different learning methods as presented in Table 4. In the class conducting method, if the family income is more than 75k taka per month, then they prefer online classes to offline classes. This is due to the opportunity cost for time spent for offline class which considerably higher than that of online education. However, if income is less than this, preference is not statistically significant. In the case of exam conducting method, preference is the same across all the groups, the only difference is degree of preference.

Finally, Table 5, shows the coefficients of CL model for type of internet each student uses. Here, for class conducting method, students with only mobile internet prefer offline class to online class while students who have broadband or both broadband and phone, are the opposite, even though both cases are statistically insignificant.

Table 4:
Student's preference of learning methods in accordance to family income

	Conditional Logit Coefficient in accordance with Income Group		
	Less than 45k	45k to 75k	More than 75k
	(1)	(2)	(3)
ASC	2.643^{***}	2.743^{***}	2.791^{***}
	(0.308)	(0.274)	(0.222)
Class Conducting Method			
Recorded Videos Only	-0.827^{***}	-0.823^{***}	-0.759^{***}
	(0.148)	(0.125)	(0.100)
Offline Class	-0.020	0.180^{*}	-0.268^{***}
	(0.126)	(0.106)	(0.087)
Exam Conducting Method			
Assignment type Exam	0.739^{***}	0.346^{***}	0.782^{***}
	(0.124)	(0.110)	(0.092)
Offline Exam	0.252^{**}	0.229^{**}	0.221^{***}
	(0.112)	(0.104)	(0.085)
Price Per Credit			
Price per credit	-0.0002^{***}	-0.0003^{***}	-0.0003^{***}
	(0.00005)	(0.00004)	(0.00003)
Observations	2,592	3,384	5,040
Note:	*probability (p)<0.1; **p<0.05; ***p<0.01		

The numbers in ( ) reports the standard errors for the respective coefficients.

Table 5:
Student's preference for learning method in accordance with internet type

	Conditional Logit Coefficient in accordance with Internet type	
	Mobile Internet only	Broadband Internet or both type
	(1)	(2)
ASC	2.656^{***}	2.731^{***}
	(0.490)	(0.157)
Class Conducting Method		
Recorded Videos Only	-0.636^{***}	-0.801^{***}
	(0.224)	(0.072)
Offline Class	0.255	-0.101
	(0.194)	(0.062)
Exam Conducting Method		
Assignment type Exam	0.890^{***}	0.609^{***}
	(0.199)	(0.064)
Offline Exam	0.310^{*}	0.221^{***}
	(0.186)	(0.059)
Price Per Credit		
Price per credit	-0.0003^{***}	-0.0003^{***}
	(0.0001)	(0.00002)
Observations	1,080	9,936
Note:	*probability (p)<0.1; **p<0.05; ***p<0.01	

The numbers in ( ) reports the standard errors for the respective coefficients.

Now, the marginal willingness to pay for each of the attribute level is shown in Table 6. Here BUP students are willing to pay 663 taka per credit for offline classes whereas NSU students prefer live online classes. Also, for offline exam BUP students have a very high willingness to pay of 2681 taka in comparison to only 121 takas of NSU students. Also, students with lower income family are more willing to pay for offline exam than students with high income family. In the case of internet users, only those students who use mobile internet are willing to pay 778 takas for offline class whereas students who use broadband or both broadband and phone are not willing to pay any money for offline **classes.**

Table 6:
Marginal willingness to pay for attributes in accordance to different groups

	NSU	**BUP**	**Less than 45k**	**45k to 75k**	**More than 75k**	**Mobile Internet only**	**Broadband Internet or both**
ASC	9,232.153	12,578.500	11,973.950	9,293.339	9,796.074	8,108.217	10,266.470
Recorded Videos Only	-2,602.611	-3,360.217	-3,748.638	-2,787.178	-2,664.734	-1,941.613	-3,011.354
Offline Class	-666.868	663.175	-90.342	609.988	-940.275	777.723	-380.824
Assignment type Exam	1,098.485	5,576.681	3,348.825	1,171.082	2,745.604	2,716.919	2,289.269
Offline Exam	120.860	2,680.553	1,141.382	775.803	774.131	947.187	832.351

Conclusion

Higher education is experiencing a radical paradigm shift from traditional on-campus learning towards an online learning environment where blended learning mode is preferably on the rise. The study has examined the preferences of university students to explore the feasibility of the blended learning method for different groups of students as a future mode of education. Understanding the preference of university students towards blended learning is necessary in designing relevant student engagement strategies to foster student engagement in blended learning. Therefore, respondents from both representative public and private universities have been selected to conduct this study. Furthermore, the discrete choice method has been used to explore the respondents' preferences for different levels of attributes as student behavioral factors are significant in influencing their learning dimensions and attitudes such as those captured by student engagement.

Findings from the study have revealed that exclusively recorded video type class conducting method provide disutility to all groups of respondents. While other studies (Dodson and Binn, 2021) have shown that students value the opportunity to revisit lectures, it is important to include some synchronous time where educators and students can interact. Human interaction, either online or offline, is crucial for efficiently conducting classes. Although no substantial difference was found between online and offline classes in this study, this difference varies across different groups. Students from all segments have shown their preference for assignment-type exams compared with other forms of exam. This discrepancy is due to the flexibility and less stressful nature of the assignment-type exam method. This preference has also been noted elsewhere, e.g. in Australia (Sutton-Brady, 2021). Hence, it is crucial to devise a strategy to make the exam conducting method less hectic for students online and offline. The study has also revealed that students using mobile internet prefer offline classes to online classes. On the contrary, students with broadband internet have the reverse preference. In the context of Bangladesh, mobile network disruptions, costly mobile data, and lack of devices are the crucial issues behind this choice. Providing adequate infrastructure support and availing students of necessary resources will enable them to pursue their studies online and offline smoothly.

This study is the first attempt to explore the preference of tertiary education students by employing the discrete choice experiment method in the context of Bangladesh. The study clearly illustrated the viability and challenges of the blending learning method as a future medium of instruction from a developing country perspective. The findings from this study will assist in providing guidelines for the education-related authorities in comprehending the obstacles and feasibilities in implementing the blended learning method as a future learning method in the post-pandemic situation.

The limitations of the study include that the study only explored the student perspective and focused on the medium of instruction (live online/recorded online/off-line), the means of conducting examinations, and the price students were willing to pay. Further research is needed to assess the impact of other factors such as the expertise and teaching philosophy of the educator, the types of activity most suited to online and blended learning, and providing a range of engaging online and blended learning resources capable of being accessed even with poor internet connections. Also, as this study was done at the time of pandemic and forced online classes were conducted, results of this study should be use with caution.

Ethical approval

Dr. Sakib Amin from North South University, Bangladesh has obtained the ethical clearance to conduct the research from the NSU Institutional Review Board/ Ethics Review Committee (*Reference: 2021/OR-NSU/IRB/0801*). Mr. Adib Ahmed and Mr. Abdul Mahidud Khan has got the ethical permission for this research from the chairman of the Department of Economics, Bangladesh University of Professionals (*Reference: Ethical Permission Application.10/06/2021*). The authors are grateful to the comments from the editor-in-chief and the anonymous reviewers, which has immensely helped in improving the quality of the manuscript.

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Appendix: Random utility model

The discrete choice experiment is built on the random utility model (RUM). This model assumes that an individual would obtain a certain level of utility from selecting an option from a set of choices. Let's assume an individual n, receives utility from an alternative option j, and this can be denoted as U_{nj} where, $j = 1, \ldots, J$. Now the individual would choose an alternative option i, if and only if $U_{ni} > U_{nj} \forall_{j \neq i}$. Now, utility is only perceived by the individual who chooses an alternative option over others. Researchers can observe some attributes (x_{nj}) of the alternative options that a decision-maker faces and some characteristics (s_n) of the decision-maker. Therefore 'represented utility' can be derived by,

$$V_{nj} = V(x_{nj}, s_n) \forall_j \tag{1}$$

However, researchers cannot observe all aspects of utility of an individual, therefore $V_{nj} \neq U_{nj} \forall_j$. Therefore, utility of the individual can be divided into,

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{2}$$

Where, V_{nj} is the observable utility components and ε_{nj} is the part of utility that is not included in V_{nj}. Researchers do not know about $\varepsilon_{nj} \forall_j$, therefore it can be thought of as random.

Now, the probability that a decision maker chooses an alternative i can be written as,

$$Pni = Pr(U_{ni} > U_{nj} \quad \forall_{j \neq i}) \tag{3}$$

$$= Pr(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj} \quad \forall_{j \neq i}) \tag{4}$$

$$= Pr(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \quad \forall_{j \neq i}) \tag{5}$$

Now, assuming that, individual will choose from three or more alternative options and distribution of ε_{nj} is independent and identically distributed with type-I extreme values also known as Gumbel distribution by McFadden (1974), a conditional logit (CL) model can be derived,

$$P_{ni} = \frac{exp\, V_{ni}}{\sum_{j=1}^{J} exp\, V_{nj}} \tag{6}$$

Where, total probability for all the alternatives is equal to one; $\sum_{i=1}^{J} P_{ni} = 1$. Now, the observed utility can be converted into linear-in-parameter function such as,

$$V_{ni} = \beta_0 + \sum_{k=1}^{K-1} \beta_k X_{nki} \tag{7}$$

Where, β_0 is a constant and β_k is the coefficient of attributes of X_{nki} and k is the number of alternative options. This paper used log-likelihood functions to estimate the parameters by maximizing following functions,

$$ln\, L = \sum_{n=1}^{N} \sum_{i=1}^{J} d_{ni}\, ln\, P_{ni} \quad (8)$$

Here, N is the number of independent observations and d_{in} is equal to 1, if decision maker chooses i and it would be 0 in other cases.

Marginal willingness to pay(MWTP) in discrete choice experiment is the amount of money respondents are willing to pay for certain desirable categorical attribute. Marginal rate of substitution of any non-monetary attribute and monetary attribute can be found using the ratio of these parameter estimates.

$$WTP_k = \frac{\frac{\delta U}{\delta x_k}}{\frac{\delta U}{\delta x_p}} = \frac{\beta_k}{\beta_p} \quad (9)$$

There are different methods for estimating the intervals of MWTP and here the nonparametric bootstrapped method by Krinsky and Rob was used (Daly et al., 2012).