Education Tech Research Dev (2023) 71:767–792
https://doi.org/10.1007/s11423-022-10165-1

CULTURAL AND REGIONAL PERSPECTIVES

Students' acceptance of online learning in developing nations: scale development and validation

Mehdi Rajeb[1] · Yurou Wang[2] · Kaiwen Man[3] · Laura M. Morett[4]

Accepted: 9 October 2022 / Published online: 10 November 2022

Abstract
Most education systems were severely impacted by the COVID-19 pandemic, and as a result, learning shifted from face-to-face to online in higher education institutions. This unprecedented shift in the learning environment caused substantial challenges for students. The situation was more severe in developing nations such as Bangladesh, which lacked available resources and knowledge of online education to support their students. Recent studies suggest that students resisted online learning in various developing nations. To support online learning in developing nations, this study develops the Acceptance of Online Learning (AOL) scale comprised of both institutional and student-related factors. To validate the AOL scale, the study collected data from 441 students across 30 higher education institutions in Bangladesh to determine the factors explaining students' acceptance of online learning using AOL measurements. The results showed that institutional factors, such as technological sufficiency, instructor efficiency, and technical assistance play significant roles in students' acceptance of online learning in developing nations. These findings will help education policymakers and administrators in developing nations to assess the needs of students with respect to online learning, and the AOL scale will assist in the evaluation of students' acceptance of online learning in these nations.

Keywords Online education · Student acceptance · Assessment · Structural equation modeling · Developing nation

Introduction

According to the United Nations (UN, 2020), approximately 1.6 billion students worldwide were affected by the COVID-19 pandemic. Moreover, the International Association of Universities (Marinoni et al., 2020) reported that 1.54 billion university students experienced negative impacts of the pandemic, and many universities across the world have suffered extensively. Situations are far worse in developing countries, in which students often lack computer accessibility, technical infrastructure, and competency in distance learning (Alibudbud, 2021). Online learning was rarely a regular component of Higher Education

✉ Mehdi Rajeb
mrajeb@crimson.ua.edu

Extended author information available on the last page of the article

Institutions (HEI) in developing nations; however, due to COVID-19, HEIs had to provide it on short notice. This study explores students' acceptance of online learning practices implemented in response to the COVID-19 pandemic in Bangladesh, a developing country in South Asia.

In many cases, online learning was adopted by HEIs due to the public health crisis caused by COVID-19, which prevented students from safely gathering to learn in person. Even developed nations with relatively better technological infrastructure suffered from these sudden changes, and developing nations demonstrated even less capacity to cope with the situation (Marinoni et al., 2020). Many students in developing nations have slow internet access, limited digital skills, insufficient technological infrastructure and support, instructors insufficiently trained in providing online instruction, and other socio-economic issues (Adnan & Anwar, 2020; Agormedah et al., 2020; Muthuprasad et al., 2021; Shrestha et al., 2021; Simamora, 2020). The context of higher education in developing nations is significantly different from developed nations in terms of the student population, recourses, and instructor abilities. Several studies suggest that the impact of COVID-19 on higher education was severe in developing countries such as Sri Lanka (Rameez et al., 2020), India (Jena, 2020), Pakistan (Adnan & Anwar, 2020), and Bangladesh (Saha et al., 2021; Shrestha et al., 2021).

Similar to the rest of the world, Bangladesh observed an instantaneous shift in the higher education system brought on by the large-scale adoption of online learning in response to COVID-19. This study attempted to use Bangladesh's scenario to demonstrate the difficulties many developing countries faced and propose a potential online learning evaluation model. Bangladesh has a population of more than 164 million (World Bank, 2020) and steady economic growth (Andaleeb et al., 2012). Currently, 130 universities are operating in Bangladesh (Chowdhury & Sarkar, 2018), enrolling 7.1 million students (UGC, 2018). Similar to other developing countries, Bangladesh has a high economic vulnerability, a low human asset index, and low per capita income (Davidson et al., 2014).

With the background in mind, many students in Bangladesh are unfamiliar with online education compared to students in developed countries, leading to resistance to online learning. A student survey in Bangladesh, conducted in June 2020 (3 months after the official closure of academic intuitions), indicated that 40% of university-level students were engaged in online teaching and learning and that a majority of these students were skeptical of several aspects of it (Islam et al., 2020). Moreover, another study identified an array of problems (e.g., adaptation to online learning, internet issues, lack of digital knowledge) associated with online teaching practices in Bangladesh (Al-Amin et al., 2021). Hence, to alleviate issues related with online learning, research is needed to explore how students are accepting the online learning processes implemented by the HEIs in developing nations.

Purpose of the study

Considering students' opinions as a valid measure of the effectiveness of online learning (Gatian, 1994; Srinivasan, 1985; Tai et al., 2019), this study aims to (a) develop the Acceptance of Online Learning (AOL) scale, a comprehensive evaluation tool to assess students' online learning acceptance, (b) test the reliability and validity of AOL scale, and (c) identify factors influencing the efficacy of online education in Bangladesh based on the measures obtained by the AOL scale. The findings provide empirical evidence on how to evaluate online teaching and learning effectiveness, especially in developing countries.

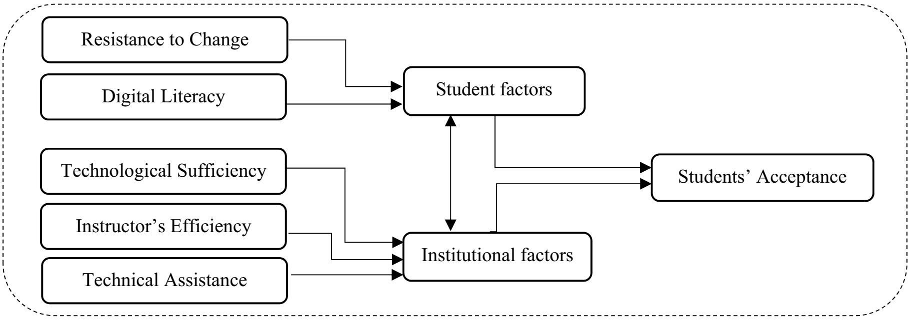

Fig. 1 Theoretical framework for AOL scale in developing nations

Literature review

This study proposes an integrated theoretical framework combining both student-related factors and institutional factors to measure students' acceptance of online learning in HEIs in developing nations (see Fig. 1). The study was initiated due to students' resistance to online learning in Bangladesh. Students in Bangladesh were utterly dissatisfied with online learning and unwilling to engage in it (Islam et al., 2020; Saha et al., 2021). Hence, this study attempts to develop an assessment scale to identify crucial components contributing to students' acceptance of online learning.

Most studies assessing students' acceptance of online learning focused on one type of factor and rarely considered more than one dimension of students' acceptance. Previous studies have emphasized the importance of students' acceptance of online learning (Aguilera-Hermida, 2020; Pal & Vanijja, 2020) and focused separately on institutional factors (e.g., facilitating conditions, support system, instructional quality), student-related factors (e.g., self-efficacy, motivation, experience), and socio-cultural factors (e.g., culture, demography) (Abbasi, 2011; Alenezi et al., 2011; Nichols, 2008; Priatna et al., 2020; Tarhini et al., 2016). However, institutional factors and student-related factors are dependent on each other as some student-related factors are heavily influenced by institutional interventions, and student-level efficacies also affect the perceived efficiency of institutional factors. For instance, perceived usability of the online learning process is explained by Lee (2010), relating both student-level characteristics and institutional factors. Furthermore, to enhance students' acceptance of online learning, students need both individual and institutional-level support (Lee, 2010). Several studies considered different institutional factors and various student-related factors to explain students' acceptance of online learning (Alenezi et al., 2011; Hong & Kim, 2018; Valencia-Arias et al., 2019). Also, Tarhini et al. (2016) emphasized how socioeconomic and cultural differences affect online learning acceptance.

A number of studies focused solely on institutional factors explaining students' acceptance of online learning. For instance, Teo (2010) developed an E-Learning Measurement (ELAM) scale consisting of instructor quality, perceived usefulness, and facilitating conditions. Larmuseau et al. (2019) have explained students' acceptance of online learning through instructional quality, and Alenezi et al. (2011) have focused extensively on institutional support.

On the other hand, several studies focused solely on student-related factors to explain online learning acceptance. For example, Hong and Kim (2018) proposed a Digital

Readiness for Academic Engagement (DRAE) scale conceptualizing the user's individuality considering the students' behavioral traits. Similarly, Shen et al. (2013) focused on user characteristics (i.e., self-efficacy) to explain online learning experience and acceptance. Moreover, several other studies have considered socioeconomic, demographic, and psychological factors affecting acceptance of online learning (Francis et al., 2019; Tarhini et al., 2016; Tsai et al., 2020; Tzafilkou et al., 2021).

Above all, a multidimensional perspective is needed to evaluate and improve online learning. Moreover, research on students' acceptance of online learning in developing nations is quite limited (Ayodele et al., 2018). Such research is necessary, as education infrastructure and academic culture are different in developing compared to developed nations (Asabere, 2013). Thus, attitudes toward online learning could also be utterly different, and are still going through a transformation (Phutela & Dwivedi, 2020) in developing nations.

Research on online learning is extremely limited in Bangladesh; hence, this study is conceptualized based on online learning acceptance studies conducted in other countries (please see Table 1). Moreover, opinions from students and experts were sought, and six factors were identified to be included in the study based on their relevance, applicability, and necessity. Hence, this study will introduce a measurement scale of online learning acceptance for developing nations exploring six aspects (see Fig. 1 for theoretical framework): (a) student factors: students' acceptance, digital literacy, resistance to change; (b) institutional factors: technological sufficiency, instructor efficiency, and technical assistance. Secondly, the context of online education in developing nations will be discussed, especially current conditions in Bangladesh relating to the six factors stated above.

Student-related factors

Students' acceptance of online learning

Students' acceptance of online learning could be defined as an overall indicator of how comfortable students are in participating online learning process. The concept of students' acceptance of online learning is not new and can be defined as a strong indicator of usability of the online learning process (Casaló et al., 2008). Students' acceptance of online learning is assessed through widely used multidimensional components, including overall satisfaction (Casaló et al., 2008; Frøkjær et al., 2000; Lee, 2010), willingness to participate in the future (Beldad & Hegner, 2018; Lee, 2010; Tang & Chaw, 2016), user recommendations (Zhang et al., 2019), perceived convenience (Chang et al., 2012), and overall motivation to use the system (Venkatesh, 2000). Overall satisfaction is influenced by accumulated experiences with online learning (Parasuraman et al., 1994). Willingness to participate in the future is another indicator of acceptance of online learning (Beldad & Hegner, 2018). For instance, if a student is satisfied with the online learning process, the student will be more willing to participate in it. User recommendations are a strong indicator of satisfaction, as well. If students are willing to recommend an online learning system to other students, it reflects that students were satisfied and accepted the new learning process as an useful one (Lee, 2010; Singh et al., 2020). Perceived convenience is a measure of the usability of the online system. Specifically, if the new learning system is inconvenient, it is less usable (Chang et al., 2012), so the current study also considered students' perceived convenience. Based on self-determination theory, Chen and Jang (2010) have identified extensive implications of the motivation behind acceptance of the online learning process.

Table 1 List of studies reviewed to develop AOL scale

Authors	Name of the scale/major assessment area	Factors/constructs used	Assessment location
Tarhini et al. (2016), Teo (2010) and Teo et al. (2011)	E-learning acceptance measure (ELAM) scale	Tutor quality, perceived usefulness, and facilitating condition	England, Thailand, Lebanon
Hong and Kim (2018)	Digital readiness for academic engagement (DRAE) scale	Digital tool application, information-sharing behavior, information-seeking skills, digital media awareness, digital application usage	Korea
Lee (2010)	Online learning acceptance and student satisfaction	Perceived ease of use, perceived online education support service quality, online learning acceptance and satisfaction	USA and Korea
Valencia-Arias et al. (2019)	E-learning tools acceptance model (eLTAM)	Instructor's preparation, students' preparation, self-efficacy, learning autonomy, personal innovative-ness	Colombia
Larmuseau et al. (2019)	Students' acceptance of online learning	Perceived instructional quality and student accept-ance	Belgium
Alenezi et al. (2011)	Students' acceptance of e-learning	Facilitating conditions, training for students, institutional technical support, students' attitude, perceived usefulness of e-learning, intention to use e-learning system	Saudi Arab
Samsudeen and Mohamed (2019)	E-learning us behavior	Performance expectancy, effort expectancy, social influence, work life quality, hedonic motivation, internet experience, facilitating condition	Sri Lanka

Hence, this study also incorporated motivation as a contributing element to measure overall student acceptance.

Resistance to change

The sudden disruption of the traditional teaching system and shift towards online learning may incur resistance to change among students (Vivolo, 2016). Resistance to change is an essential concept in explaining the students' acceptance of online learning (Barak, 2018; Vivolo, 2016). Barak (2018) extensively reviewed students' resistance to change and explained how rigidity might affect key academic skills. Such skills are necessary for the practical implementation of knowledge. Due to the COVID-19 pandemic, resistance was apparent when HEIs initiated online learning in 2020. Therefore, institutions had to motivate their students to participate in online learning in Bangladesh (Majed et al., 2020; Saha et al., 2021). Resistance to change is critical factor to explain students' acceptance of online learning. A student's resistance to accept online learning may also be dependent on multiple aspects including academic culture, socioeconomic, and psychological conditions. In a developing nation, students' resistance to accept online learning may occur due to students' lack of adaptability, facilitating conditions, self-efficacy, or community (Dhawan, 2020; George & Camarata, 1996). In the theoretical model informing this study, resistance to change has been considered as one of the explanatory constructs behind students' satisfaction. It is assumed to be related to digital literacy, technological sufficiency, instructor's efficiency, and technical assistance.

Digital literacy

Digital literacy supports students' efficiency in using new technology. This study adopted digital literacy as a crucial factor behind students' acceptance of online learning, reasoning that if students can engage in online learning effectively, they will show greater acceptance of it (Holden & Rada, 2011). The impact of digital literacy may vary due to differences in target populations and technologies. Moreover, digital literacy relates to institutional factors as HEIs are playing an important role in mentoring young students (Reddy et al., 2021). Also, digital literacy may affect students' perceptions of technological conditions, technical support systems, instructor competency, and resistance towards online learning. As empirical measures of digital literacy vary (Lyons et al., 2019), the current study modified previous measurements and developed a new measure to explore digital literacy. This new measure is described in the Method section.

Institutional factors

Technological sufficiency

Alenezi et al. (2011) has emphasized technological sufficiency as a core institutional factor in implementing online learning. Technological sufficiency (i.e., availability of necessary hardware, software, and supporting infrastructure) is a primary issue affecting the acceptance of online learning (Tarhini et al., 2016; Teo, 2010). Technological sufficiency is a core concern in a developing nation such as Bangladesh. Lack of technological sufficiency may lead to perceived difficulty of use and may negatively impact the acceptance of the new technology. Moreover, technological sufficiency is critical for many students to successfully participate in online classes. Technological sufficiency is also a major component in explaining the digital divide in developing nations (Saha et al., 2021). Technological sufficiency influences the feasibility of online learning for students and affects digital literacy, technical assistance, and instructor efficiency. For instance, customized math learning software will aid instructors in communicating with students in online classes. In this study, technological sufficiency is measured through availability of hardware (Alshare et al., 2011; Blocher et al., 2002; Lee, 2008), availability of software (Almaiah et al., 2019; Lee, 2008; Ohliati & Abbas, 2019), and quality of internet access (Dhawan, 2020; Nugroho et al., 2021).

Instructor efficiency

Instructor efficiency is often mentioned as a major institutional factor affecting acceptance of online learning (Arghode et al., 2018; Ouyang & Scharber, 2017; Rios et al., 2018). Ouyang and Scharber (2017) extensively discuss instructor influence of online learning and conclude that instructors' lesson plans and facilitation significantly influence acceptance of online learning. Moreover, instructor efficiency is a multi-dimensional concept that depends on several factors, including communication, feedback, critical discourse, and building connections with learners (Arghode et al., 2018). Thus, instructor efficiency is a potent catalyst affecting both perceived ease of use and acceptance of online teaching in Bangladesh (Al-Amin et al., 2021).

Technical assistance

Technical assistance, a core institutional factor, is associated positively with perceived usefulness, and perceived support service quality affects online learning acceptance (Lee, 2010). Furthermore, the ideology of technical assistance is directly connected to the concept of perceived ease of use. A student will find online learning more accessible if the student receives technical assistance when needed (Cheng et al., 2012). This study investigates whether technical assistance influences students' acceptance of online learning. If technical support is overused, however, students will be underprepared and will be dependent on it.

Online learning in developing nations: current conditions

With increasing accessibility of communication technology in developing nations, online teaching offers certain advantages over traditional face-to-face teaching (e.g., access, cost, convenience). However, online learning may not be equally effective for all students in underdeveloped educational systems (Gulati, 2008). In developing nations, educational and communication infrastructure has yet to allow all students to participate in it (Jaffer et al., 2007). Indeed, multiple studies have noted obstacles related to online learning in developing nations. For instance, students in India lacked digital knowledge, access to high-speed internet, and necessary infrastructure and were unsatisfied with quality of learning and technical efficiency of teachers (Jena, 2020; Kumar, 2021; Muthuprasad et al., 2021). Moreover, online learning failed to produce desired results in Pakistan due to limitations in access to high-speed internet, technological infrastructure, and student finances (Adnan & Anwar, 2020). Furthermore, only a few educational institutions in Pakistan implemented effective online instruction during the COVID-19 pandemic (Ullah et al., 2021). Similar circumstances were evident in Sri Lanka (Haththotuwa & Rupasinghe, 2021; Howshigan & Nadesan, 2021). In Nepal, almost half of online classes were hampered by unreliable electricity and internet (Subedi et al., 2020). Students in Sub-Saharan developing countries such as Kenya, Ghana, and South Africa faced issues such as limited access to technological infrastructure, high cost and low reliability of internet service, and low digital proficiency (Pete & Soko, 2020). In sum, many developing countries have limited infrastructure, accessibility to digital devices, and digital proficiency of students and instructors. All of these may significantly influence the efficiency of online learning and students' acceptance of it.

As a developing nation, Bangladesh is facing similar obstacles. Prior to the COVID-19 pandemic, online learning was not institutionalized in Bangladesh. On May 7th, 2020, HEIs in Bangladesh were formally granted permission to deliver classes and examinations online (Abdullah, 2020). The transition from face-to-face to online learning was not easy; indeed, the Bangladeshi authority tasked with ensuring quality of education in HEIs in Bangladesh expressed concerns about the quality of academic activities in online learning (Riyasad, 2020). Moreover, students were stressed and started to express resistance (Kabir et al., 2021). At that point in time, the whole education system in Bangladesh was under tremendous pressure.

The difficulty of transitioning to online learning in Bangladesh was due to several reasons. Firstly, the country was never prepared for such a major technological shift in higher education. Secondly, almost no research on online learning in Bangladesh had been conducted before its implementation there. Also, most of the HEIs in Bangladesh used synchronous general online meeting and conversation platforms such as WhatsApp, Facebook messenger, and Zoom to deliver online classes. Saha et al. (2021) concluded that the remote instruction implemented by HEIs in Bangladesh was unsatisfactory, creating a digital divide among students. Moreover, Shahriar et al. (2021) concluded that students' and teachers' lack of digital literacy created inertia in online classes. In addition, several studies have reported that issues such as poor technological infrastructure and limited access to devices and internet accessibility caused substantial obstacles for HEIs in operating online classes in Bangladesh, similar to other developing countries (Islam et al., 2020; Shahriar et al., 2021). However, few studies have discussed how to improve the quality of online teaching to promote students' acceptance of it in developing nations such as Bangladesh.

Hence, along with identifying factors affecting online learning acceptance, it is necessary to assess how to support online learning in developing countries. Supporting and enhancing the quality of online learning in developing nations may seem difficult as the process requires sizable investments in technology and other related sectors. On the other hand, if HEIs in developing nations start to assess their respective online learning process, it will provide necessary indications regarding what needs to be improved. Some online learning factors (e.g., facilitating condition or technological sufficiency) may not be improved instantly, but other factors, such as instructor efficiency or digital literacy, could be systematically improved with a reasonable amount of time and effort. Technological insufficiency is the main reason behind the digital divide in developing nations (Saha et al., 2021) and may require national level interventions to ensure digital fairness among students in developing nations. However, technological innovations in designing online learning delivery may reduce resource requirements for students to participate in online learning process in developing nations. For instance, Zhang et al. (2017) have discussed the possibility of customization in mobile phone-based curriculum integration for online learning, which could be a breakthrough for developing nations to overcome technological insufficiencies.

Need for an integrated scale for online learning acceptances in developing nations

The need for an integrated multidimensional framework of online learning acceptance is supported by previous research. First, recent studies indicate that acceptance of online learning is not a unidimensional construct (Larmuseau et al., 2019; Sivo et al., 2018). Secondly, the perspectives of students from developing nations should be considered when constructing an instrument to assess online learning acceptance. At present, however, there are only a few established online learning assessments appropriate for use in developing nations. Moreover, studies measuring acceptance of online learning in developing nations vary widely in number, focus, and conceptualizations of relevant constructs. Third, online learning is often implemented in conjunction with traditional face-to-face learning; thus, context-specific assessment processes for online learning are more important than ever. Fourth, most extant scales and questionnaires related to online learning (see Table 1) were constructed for developed nations, whose circumstances differ from those of developing nations. In developed nations, online learning has been implemented for decades and evolved as an accepted learning system. For instance, student enrollment in online education in the U.S. has been steadily increasing for last 14 years (Palvia et al., 2018). Similar growth in online student enrollment was observed in Australia during the same time frame (Greenland, 2011). Over the years, institutions in developed nations amassed experience in online teaching and learning, which influenced HEIs in developed nations to develop curriculum, tools, and programs for online learning. Moreover, the facilitating conditions necessary for online learning are far better in developed nations compared to those in developing nations. On the contrary, online learning is hardly institutionalized by HEIs in many developing nations, and many HEIs in developing nations have little experience in developing online teaching and learning process Hence, the online learning capacities of developing nations are far behind those of developed nations. The uniqueness of these conditions in developing nations may require different resolutions when building and assessing online learning acceptance.

Lastly, socioeconomic, and cultural issues have crucial effects on online learning acceptance assessments. Students in developed nations have different socioeconomic and cultural norms compared to students in developing nations. For instance, the ELAM scale (Teo, 2010) was a good fit for British environment but was found inefficient for Lebanese environment (Tarhini et al., 2016). According to Tarhini et al. (2016), cultural differences and unknown factors may have caused goodness of fit issues with the ELAM scale in the Lebanese environment. Additionally, Aguilera-Hermida (2020) assessed students' attitude and motivation towards online learning in USA, Mexico, Peru, and Turkey, and concluded that both attitude and motivation differ from country to country. Moreover, item wording, item format and assessment perspectives may vary widely from one culture to another (Tarhini et al., 2016).

Hence, this study introduces a new scale formed from reframing and combining prior scales to measure institutional and student factors affecting online learning acceptance in developing nations.

Research method

To date, little systematic research has been conducted on online learning acceptance in Bangladesh. Hence, the initial theoretical framework guiding this study was developed based on studies conducted in other nations. In addition, opinions from students and experts were sought, and six factors were identified in this study for inclusion in the AOL scale based on their informational and applicability implications.

Research steps

Based on previous literature, this study (a) develops a multidimensional scale to measure students' acceptance of online learning in developing nations; (b) tests the reliability and validity of this assessment; and (c) uses it to characterize students' acceptance of online learning in Bangladesh. This assessment is entitled Acceptance of Online Learning (AOL).

The majority of studies of technology acceptance focus on system efficiency or acceptance and usability. This study argues that acceptance depends not only on the efficiency of the system, but also the individuals who use the system, their perceptions of it, and related issues. Above all, students' resistance to change may impede their acceptance of online learning, whereas students' digital literacy and technological sufficiency, instructor efficiency, and institutional technical support may promote acceptance toward online learning in Bangladesh. Moreover, socio-economic, and cultural norms may affect online learning acceptance, as well.

Measurements and item generation

Overall, online learning acceptance was measured using five items. Of these items, three items were conceptually reframed from Teo Gopal et al. (2021), Casaló et al. (2008), and Swan (2001). Technological sufficiency was measured using four items, of which two items were obtained from the instrument developed by Sultana and Khan (2019). Instructor efficiency was measured using eight items, of which three items were adopted from instruments developed by Gopal et al. (2021), Chen and Chen (2007), and Swan (2001). Digital literacy was measured using four items, of which three items were obtained from Tang and Chaw (2016). Resistance to change was measured using two items obtained conceptually from the conclusions of Barak (2018). Technical assistance was measured using three items motivated by the work of Green and Denton (2012). Item formatting was changed to optimize acquisition of information from students in Bangladesh. All items utilized a 7-point Likert scale in which 1 represents strongly disagree and 7 represents strongly agree.

Scale development and pre-testing

The AOL scale was developed using a total of 35 questions, of which nine were demographic questions and 26 were items contributing to different constructs, such as overall acceptance, technological sufficiency, instructor efficiency, resistance to change, and digital literacy. These items were initially developed based on available literature reviews and issues identified in focus group discussions. To improve the quality of the items developed for the AOL scale, a small pilot test was conducted to ensure clarity and conciseness. A group of 15 students were given the AOL instrument and requested to complete the survey. Students were then interviewed about the clarity of each question in the survey. The wording, length and format of the items were further adjusted based on the responses acquired in the pilot test. The items of the AOL scale were developed in English as the respondents are usually taught in English. These items are given in Table 2.

Table 2 Item pool for AOL scale

Constructs	Items/questions
Technological sufficiency	Sufficient hardware is available to use for online learning (T1r)
	Sufficient software is available for the use of online learning (T2r)
	Internet access is reasonably fast and constant in your region (T3r)
	Downloading online learning content is easy for online learning education (T4r)
Instructor's efficiency	Instructor can stimulate interests in online classes (E1r)
	Instructor was efficient in handling web technology (E2r)
	We are usually invited to ask questions in online classes (E3r)
	Instructor encouraged student interaction (E4r)
	Instructors are friendly towards individual students (E5r)
	I find it difficult to communicate effectively with my teacher in online classes (E6r)
	I can ask relevant questions to clarify my confusion in online classes (E7r)
	The instructor frequently asks questions to students (E8r)
Digital literacy	I have necessary skillset to manage online classes (Cl1r)
	I have detail knowledge about functional software application for online learning process (Cl2r)
	How proficient are you in using a computer? (Cl3r)
	How frequently you search internet? (CL4r)
Technical assistance	Do you have sufficient and specific access to online facilities provided by your institution? (AoA1r)
	Does your university provide appropriate IT support for students? (AoA2r)
	Does your institute have dedicated IT department to support online education? (AoA3r)
Resistance to change	I don't think learning through online classes is a good idea (RC1r)
	I believe online learning is stressful for me (RC2r)
Students' acceptance	I am satisfied with the online teaching and learning activities (A1r)
	In future, I will be happy enroll in online classes (A2r)
	I will recommend my friends to enroll in online classes (A3r)
	Online classes are convenient for me (A4r)
	I am motivated to learn online (A5r)

Study design, sampling, and data collection

To conduct the study, a cross-sectional study design was implemented. Initially, the target population of this study was all university-level students in Bangladesh. At the time the survey was administered, however, only private universities in Bangladesh had implemented online learning. Hence, students from public universities were excluded as they were not exposed to online learning. There is no accessible student database for college or university students in Bangladesh; hence, this study adopted a convenience sampling procedure to collect data from 441 students of private HEIs in Bangladesh. Of the 105 private universities in Bangladesh (Hasan & Islam, 2020), this study collected data from students of 30 universities across four divisions,[1] i.e., Barisal, Chittagong, Dhaka and Rangpur.

[1] Bangladesh is geographically divided into eight divisions, and all HEIs are located in different divisions.

Table 3 Distribution of students' demographic characteristics in the sample (n = 441)

Students' academic year	Percentage (%)	Age	Percentage (%)
1st (1st–3rd semester)	28	18–22	44
2nd year (4th–6th semester)	37	22–26	43
3rd year (7th–9th semester)	11	26–32	11
4th year (10th–12th) and above	24	32 or more	2
Urbanization level of students' location		Gender	
Capital city	82	Female	45
Divisional city	5	Male	55
District city	7	Percentage of HEIs represented in the sample	29
Sub-urban city	5		
Rural region	1		

Table 3 contains sample characteristics. A similar sampling process is widely used in the current literature for scale development and validation (please see: Bhagat et al., 2016; Glassman et al., 2021; Sun & Rogers, 2021). Moreover, within the student population of Bangladesh, participants are heterogenous in nature and capable of providing multidimensional perspectives from students (see Table 3).

Due to restrictions on face-to-face data collection from the COVID-19 pandemic, data was collected via an online survey. This survey was sent to respondents via email, and they were requested to complete it outside of class and work. The survey response rate is approximately 25%. Students were informed that the survey was anonymous, and they were requested to ignore any questions that they did not feel comfortable answering and informed that they could withdraw at any time. Furthermore, students were informed that submission of the survey entails implied consent to participate in the study.

Missing value replacement

After data collection, it was observed that the data contained several missing values across different variables. For instance, item T1r had five missing values (out of 441 responses), items T2r, E3r, Cl1r, AOA1r, AOA3r and A4r had three missing values (out of 441 responses), item T3r had two missing values (out of 441 responses), and items T4r, E4r, AOA2r, A1r, and A3r had one missing value (out of 441 responses) (see item details in Table 2). To evaluate whether these missing values occurred randomly or not, a test of Missing Completely at Random (MCAR; (Little, 1988) was performed. The MCAR value was not significant, indicating that the missing values occurred at random. As SEM is sensitive to missing values, they were replaced with median values for respective items. A similar missing value replacement methodology was suggested by Maniruzzaman et al. (2018), Farrell (2010), and Gómez-Carracedo et al. (2014).

Table 4 Convergent validity measures for CFA model

Latent constructs	Composite reliability (CR)	AVE	Alpha	SQRT (AVE)
Technological sufficiency	.83	.55	.83	.74
Instructor's efficiency	.84	.52	.838	.72
Digital literacy	.82	.61	.817	.78
Technical assistance	.87	.7	.867	.83
Acceptance	.93	.73	.935	.85

Analysis

Analyses were conducted in IBM AMOS 20 and were divided into two parts. In the initial stage, the study employed Confirmatory Factor Analysis (CFA) to validate the AOL measurement scale. In the second stage, a Structural Equation Model (SEM) was developed to explore causal relations of each construct.

To validate the scale, a CFA approach was taken considering six constructs and 26 items to develop the AOL scale (see Table 2 for details). The first CFA model failed to meet the required goodness of fit measures. After careful consideration and stepwise deduction of each construct and respective items in the initial CFA model, one construct (i.e., resistance to change) and six items were dropped in the final model due to unsatisfactory factor loadings (<.6), as suggested by (Lopez et al., 2021). All items contributing to resistance to change (i.e., RC1r, RC2r) were dropped, as respective factor loadings failed to meet the cutoff point. Furthermore, one item (CL4r) contributing to the construct of digital literacy and three items (E6r, E7r, E8r) contributing to instructor efficiency were dropped due to unsatisfactory factor loadings. Therefore, the final CFA model was constructed using five constructs (i.e., overall acceptance, technological sufficiency, instructor efficiency, and digital literacy) and 20 items contributing to these constructs. Based on the covariance structure of the primary CFA model, errors for two items of Efficiency (i.e., E1r and E3r) and two items of Acceptance (i.e., A2r and A3r) are correlated. To constrain the effects of these correlated errors, the study allowed co-variation between the respective error terms of these items. These correlated items had similar wordings though their contents differed.

Results

The CFA model fit indices (CFI = .951, RMSEA = .06, NFI = .926, GFI = .912, χ^2_{158} = 439.2, $p < .01$) surpass their respective cut off points (Nunnally & Bernstein, 1994). Moreover, all standardized loadings for each item obtained in this model are high and positively significant. Furthermore, the composite reliability (i.e., internal consistency reliability) value for each construct exceeded the cutoff point of .7 (Nunnally & Bernstein, 1994). The study also obtained measures for convergent validity by using Average Variance Extracted (AVE) (see Table 4 for more details). Computed AVE values for each construct exceeded the threshold value of .50 (Bagozzi & Yi, 1988). Discriminant validity of the CFA model was assessed through comparisons between respective square root of AVE and correlations between constructs (Fornell & Larcker, 1981). The highest correlations

Table 5 Discriminant value (DV) for each factor and their bivariate correlations

	Technological sufficiency	Instructor's efficiency	Digital literacy	Technical assistance	Acceptance
Technological sufficiency	.74				
Instructor's efficiency	.59	.72			
Digital literacy	.73	.56	.78		
Technical assistance	.53	.68	.40	.83	
Acceptance	.64	.58	.54	.51	.77

between constructs were always less than the square root of the AVE of each construct (Farrell, 2010) (see Table 5 for detailed measures of discriminant validity). All available reliability and validity values for the measurement model indicate that the scale met acceptable psychometric criteria with sufficient validity and reliability. Standardized factor loadings as well as AVE and Composite Reliability values are presented in Table 6, and the estimated CFA model is provided in Fig. 2.

In the second phase of the analysis, a structural equation model was obtained, with student acceptance of online learning as the outcome variable. The structural model indicates sufficient fit of the data fit (CFI = .94, NFI = .92, RMSEA = .06, SRMR = .05, DF = 2.93, $p < .01$). The squared multiple correlation coefficient obtained from the model indicates that 48.9% of the variation in acceptance of online learning is explained by institutional and student related factors provided in Fig. 3. The Maximum Likelihood (ML) regression coefficient estimate for technological sufficiency is .51, $p < .01$, indicating that this factor had the strongest impact on students' acceptance of online learning in Bangladesh. The ML regression coefficient estimates for instructor efficiency is .305, $p < .01$, and for technical assistance is .157, $p < .05$. On the other hand, the ML regression coefficient estimate for digital literacy is statistically non-significant ($p > .05$) (see Table 7 for details). Hence, the model indicates that technological sufficiency, instructor efficiency, and technical assistance have a significant and positive impact on acceptance of online learning. In contrast, students' digital literacy failed to significantly affect acceptance of online learning. The fitted SEM model is available in Table 7 and Fig. 3. In summary, from CFA measures, this study concludes that the AOL scale developed in this study meets all major psychometric requirements, including internal consistency, composite reliability, convergent validity, and discriminant validity. Furthermore, the SEM model estimated the impacts of technological sufficiency, instructor efficiency, and technical assistance on students' acceptance of online learning in Bangladesh.

Discussion

Online learning will be a critical part of HEIs in Bangladesh, so students' acceptance of it has become immensely important. This study integrated both student and institutional factors to develop the Acceptance of Online Learning (AOL) scale to assess students' acceptance of online learning in Bangladesh. The AOL scale was examined and validated using confirmatory factor analysis. AOL is a five-factor (i.e., overall acceptance, technological sufficiency, instructor efficiency, technical assistance, and digital literacy) model and AOL constructs were developed focusing on online learning conditions in developing

Table 6 Constructs with items with standardized factor loadings, item means and standard deviations for AOL scale

Constructs (composite reliability-CR, average variance extracted-AVE)	Standardized factor loading	Mean rating	Standard deviation
Technological sufficiency for students (CR = .83, AVE = .55)			
Sufficient hardware is available to use for online learning (T1r)	.76	4.77	1.70
Sufficient software is available for the use of online learning (T2r)	.77	5.13	1.51
Internet access is reasonably fast and constant in your region (T3r)	.73	4.25	1.72
Downloading online learning content is easy for online learning education (T4r)	.72	4.53	1.71
Instructor's efficiency to conduct online classes (CR = .84, AVE = .52)			
Instructor can stimulate interests in online classes (E1r)	.74	4.41	1.62
Instructor was efficient in handling web technology (E2r)	.76	4.81	1.67
We are usually invited to ask questions in online classes (E3r)	.77	5.08	1.54
Instructor encouraged student interaction (E4r)	.72	5.17	1.55
Instructors are friendly towards individual students (E5r)	.65	5.15	1.61
Digital literacy level of students (CR = .82, AVE = .61)			
I have necessary skillset to manage online classes (Cl1r)	.80	5.13	1.54
I have detail knowledge about functional software application for online learning process (Cl2r)	.88	4.97	1.59
How proficient are you in using a computer? (Cl3r)	.66	5.37	1.44
Technical assistance for online activities (CR = .87, AVE = .70)			
Do you have sufficient and specific access to online facilities provided by your institution? (AoA1r)	.72	4.81	1.80
Does your university provide appropriate IT support for students? (AoA2r)	.94	4.59	1.89
Does your institute have dedicated IT department to support online education? (A0A3r)	.83	4.84	1.85
General acceptance level toward online learning activities (CR = .93, AVE = .73)			
I am satisfied with the online teaching and learning activities (A1r)	.88	4.27	1.79
In future, I will be happy enroll in online classes (A2r)	.86	3.90	1.93
I will recommend my friends to enroll in online classes (A3r)	.91	3.90	1.90
Online classes are convenient for me (A4r)	.88	4.17	1.83

Table 6 (continued)

Constructs (composite reliability-CR, average variance extracted-AVE)	Standardized factor loading	Mean rating	Standard deviation
I am motivated to learn online (A5r)	.76	4.46	1.85

**r indicates recoded variables went through general missing value analysis

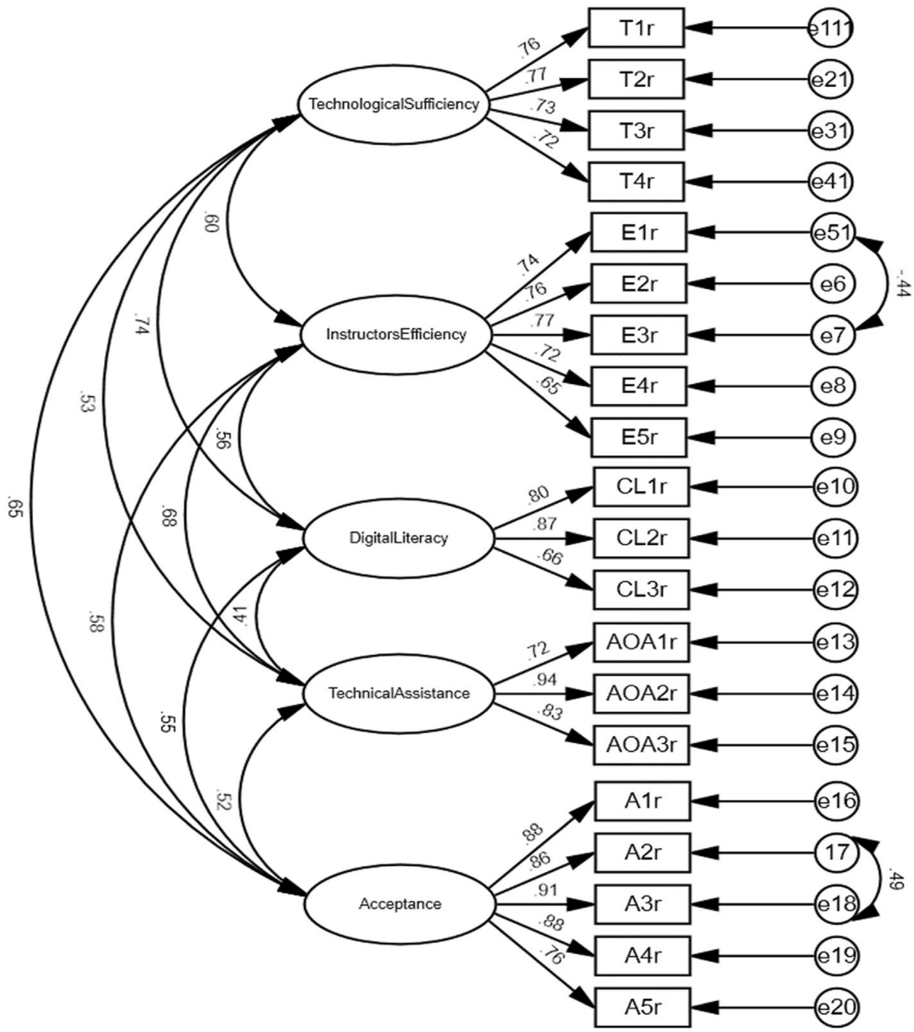

Fig. 2 Estimated five factor CFA model (item definitions are provided in Table 2)

countries. All constructs adopted by AOL are associated with each other, which indicates that online learning acceptance depends on an integrated combination of both institutional and student-related factors. For instance, technological sufficiency is highly correlated with digital literacy of students, $r = .73$, $p < .01$ (please see Table 5), which indicates that digital literacy of students is correlated with their access to digital equipment and internet facilities. Moreover, a student with better digital literacy will perceive online learning as more acceptable. Also, technical assistance for online education and instructor efficiency are strongly correlated, $r = .68$, $p < .01$ (see Table 5), which indicates that instructors may fail to provide efficient lessons in class unless institutions provide sufficient technical support. For instance, in absence of an appropriate learning management system, it is very difficult for a faculty member to provide resources to students, which in turn perceive the instructor

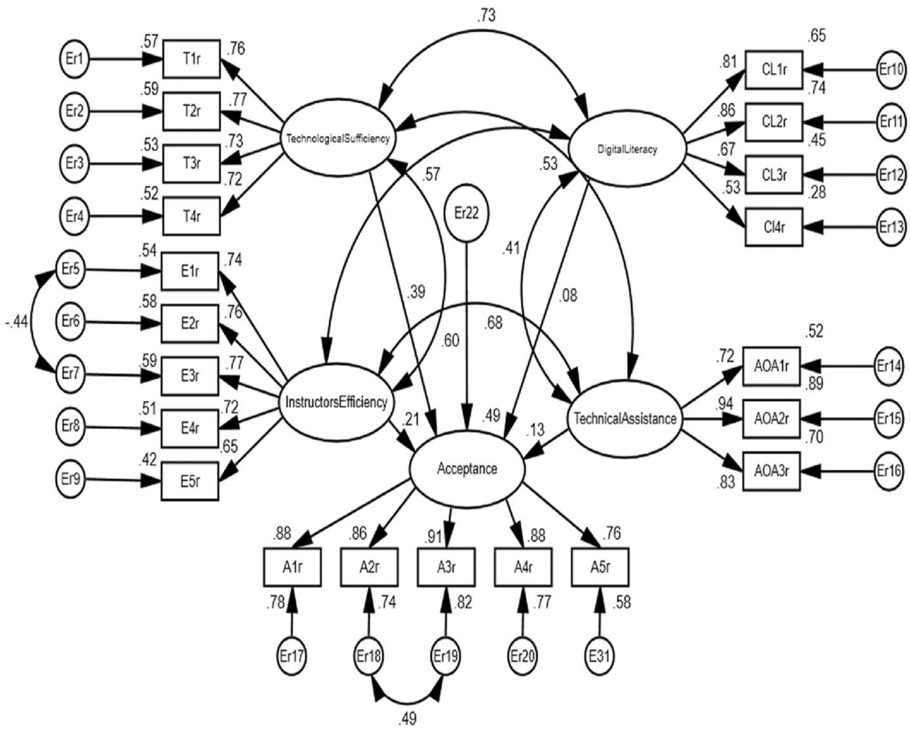

Fig. 3 Structural Model explaining students' acceptance towards online learning platforms (item definitions are provided in Table 2)

Table 7 Path co-efficient of different factors explaining effects on students' acceptance of online learning in Bangladesh

Factors	Unstandardized estimate	Standard error	Standardized estimate	*P*
Technological sufficiency	.51	.104	.395	.00
Instructors' efficiency	.305	.098	.215	.00
Digital literacy	.096	.093	.075	.30
Technical assistance	.157	.074	.129	.03

as less efficient. Furthermore, AOL is developed to assess the feasibility of online learning for students in developing nations and adopted a holistic approach to assessment.

AOL was used to explore critical factors affecting students' acceptance of online learning in Bangladesh using structural equation modeling (SEM). The results showed that three major factors had significant impacts on students' acceptance of online teaching and learning in Bangladesh: technological sufficiency, instructor efficiency, and technical assistance.

The findings were consistent with previous studies conducted in developing nations. For instance, Ambarwati et al. (2020) concluded that technological conditions affected online learning in Indonesia. In addition, institutional factors such as technological infrastructure, internet access, and access to supporting devices significantly impacted the behavioral intentions of online learners. In Malaysia, Goh and Blake (2021) revealed significant impacts of e-learning infrastructure on e-learning acceptance. Furthermore, in four countries in Southeast Asia, infrastructure, institutional service quality, and instructor efficiency contributed to e-learning success (Bhuasiri et al. (2012). These findings are aligned with those of other studies regarding instructor efficiency and technical assistance (Arghode et al., 2018; Chang et al., 2012; Larmuseau et al., 2019; Lee, 2010; Ouyang & Scharber, 2017; Rios et al., 2018; Teo, 2010).

However, the combination of AOL constructs is unique from current online learning acceptance scales for developing nations. Moreover, the items for each construct and the assessment dimensions of AOL differs from current scales. Also, some findings from Bangladesh measured using the AOL scale are not aligned with online learning acceptance scales or questionnaires developed in other developing nations. For instance, Al-Gahtani (2016) concluded that computer self-efficacy significantly affects students' intentions to use online learning, but in Bangladesh, digital literacy of students did not significantly affect online learning acceptance. This may indicate that the digital literacy levels of Bangladeshi students are similar. Bhuasiri et al. (2012) explored critical success factors behind e-learning in developing nations and revealed that changing learners' behavior plays an important role in successful e-learning implementation. The AOL scale failed to accommodate students' behavioral change even though resistance to change factor was incorporated in the initial theoretical model.

Conclusion and contributions

This study investigated students' perspectives towards online learning in a developing nation and integrated the findings of previous studies to develop a new assessment tool to evaluate online learning acceptance in developing nations. As this study is based on students' acceptance of online learning in Bangladesh, a developing nation, the multidimensional framework developed in this study is applicable to many similar developing nations.

The first contribution of this study is the development of a comprehensive scale to assess students' acceptance of online learning to support it in developing nations. The AOL scale will contribute to research and practice in two ways: (1) it will measure both feasibility conditions and overall student acceptance of online learning, and (2) it is developed for recurrent applications. The AOL scale can be used as a base by future researchers to add more dimensions to the theoretical framework of online learning acceptance. Even though the combination of factors incorporated in the AOL scale is unique, all factors included in it are grounded in similar previous scales, such as the ELAM scale (Teo, 2010), the DRAE scale (Hong & Kim, 2018), the measurement instrument developed by Shen et al. (2013), and the measurement instrument developed by Larmuseau et al. (2019).

Moreover, the AOL scale was designed and developed considering perspectives of students from Bangladesh, a developing nation, which are overlooked in the previous literature. At present, HEIs in Bangladesh are still at a very early stage of implementing online learning (Sarker et al., 2019). As online learning has not previously been considered a regular component of learning in developing nations such as Bangladesh, little research has assessed students' acceptance of online learning in these nations. Due the COVID 19 pandemic, many HEIs in Bangladesh and in other developing nations adopted online learning;

hence, a validated scale for assessing students' acceptance of it is needed to ensure achievement of learning outcomes in online learning environments.

Practically, the AOL scale and the findings from this study will aid academic administrators in implementing and maintaining an effective program of online learning. Acceptance of online learning can be assessed at regular intervals using the AOL scale. The overall acceptance score of the AOL scale indicates whether students are comfortable with online learning or not. Similarly, the AOL score for technological sufficiency indicates whether sufficient technological infrastructure is available for students to engage in online learning. Also, the AOL score for technical assistance indicates whether students are adequately supported to engage in online learning by respective HEIs. The AOL score for digital literacy indicates whether students are sufficiently digitally literate to accept online learning. Lastly, the AOL score for instructor efficiency indicates whether instructors are efficient enough to conduct online classes. Scores for each construct in the AOL scale indicates students' acceptance of online learning, as implemented by their respective HEIs. Moreover, the AOL scale is also suitable for longitudinal applications. This scale can be used as a base to customize and develop new scales according to the specific needs of different HEIs in developing nations such as Bangladesh.

Limitation and future research

A limitation of the study is that data was gathered from students of private HEIs[2] in Bangladesh, as only they had implemented online learning at the time of data collection. Hence, it would be ideal for future studies to incorporate responses from students of public HEIs in Bangladesh and other developing nations. Moreover, this study did not examine causal relations between constructs. Lastly, measures were directly obtained from respondents through a self-administered online survey, as opposed to a trained data enumerator-administered survey. Despite these limitations, the AOL scale is expected to improve the feasibility and quality of online learning in HEIs in Bangladesh and other developing nations.

Availability of data and materials The data set analyzed in this study is available from the corresponding author upon request.

References

Abbasi, M. S. (2011). *Culture, demography and individuals' technology acceptance behaviour: A PLS based structural evaluation of an extended model of technology acceptance in South-Asian country context*. Unpublished doctoral dissertation. Brunel Business School.

Abdullah, M. (2020). UGC: Private universities can hold online exams with conditions. *Dhaka Tribune*. https://archive.dhakatribune.com/bangladesh/education/2020/05/07/ugc-issues-14-directives-for-private-universities-conducting-online-classes. Accessed on 21st December 2021.

Adnan, M., & Anwar, K. (2020). Online learning amid the COVID-19 pandemic: Students' perspectives. *Journal of Pedagogical Sociology and Psychology*, *2*(1), 45–51. https://doi.org/10.33902/JPSP.2020261309

[2] Private universities in Bangladesh have a similar academic structure to public universities but are administered by non-government entities.

Agormedah, E. K., Henaku, E. A., Ayite, D. M. K., & Ansah, E. A. (2020). Online learning in higher education during COVID-19 pandemic: A case of Ghana. *Journal of Educational Technology and Online Learning*, *3*(3), 183–210. https://doi.org/10.31681/jetol.726441

Aguilera-Hermida, A. P. (2020). College students' use and acceptance of emergency online learning due to COVID-19. *International Journal of Educational Research Open*. https://doi.org/10.1016/j.ijedro.2020.100011

Al-Amin, M., Al Zubayer, A., Deb, B., & Hasan, M. (2021). Status of tertiary level online class in Bangladesh: Students' response on preparedness, participation and classroom activities. *Heliyon, 7*(1), e05943. https://doi.org/10.1016/j.heliyon.2021.e05943

Al-Gahtani, S. S. (2016). Empirical investigation of e-learning acceptance and assimilation: A structural equation model. *Applied Computing and Informatics, 12*(1), 27–50.

Alenezi, A. R., Karim, A. A., & Veloo, A. (2011). Institutional support and e-learning acceptance: An extension of the technology acceptance model. *International Journal of Instructional Technology and Distance Learning, 8*(2), 3–16.

Alibudbud, R. (2021). On online learning and mental health during the COVID-19 pandemic: Perspectives from the Philippines. *Asian Journal of Psychiatry*. https://doi.org/10.1016/j.ajp.2021.102867

Almaiah, M. A., Alamri, M. M., & Al-Rahmi, W. (2019). Applying the UTAUT model to explain the students' acceptance of mobile learning system in higher education. *IEEE Access, 7*, 174673–174686. https://doi.org/10.1109/ACCESS.2019.2957206

Alshare, K. A., Freeze, R. D., Lane, P. L., & Wen, H. J. (2011). The impacts of system and human factors on online learning systems use and learner satisfaction. *Decision Sciences Journal of Innovative Education, 9*(3), 437–461. https://doi.org/10.1111/j.1540-4609.2011.00321.x

Ambarwati, R., Harja, Y. D., & Thamrin, S. (2020). The role of facilitating conditions and user habits: A case of Indonesian online learning platform. *The Journal of Asian Finance, Economics and Business (JAFEB)*, *7*(10), 481–489. https://doi.org/10.13106/jafeb.2020.vol7.no10.481

Andaleeb, S. S., Rahman, A., Rajeb, M., Akter, N., & Gulshan, S. (2012). Credibility of TV news in a developing country: The case of Bangladesh. *Journalism and Mass Communication Quarterly, 89*(1), 73–90. https://doi.org/10.1177/1077699011430060

Arghode, V., Brieger, E., & Wang, J. (2018). Engaging instructional design and instructor role in online learning environment. *European Journal of Training and Development, 42*, 366–380. https://doi.org/10.1108/EJTD-12-2017-0110

Asabere, N. Y. (2013). Benefits and challenges of mobile learning implementation: Story of developing nations. *International Journal of Computer Applications, 73*(1), 1.

Ayodele, S., Endozo, A., & Ogbari, M. E. (2018). A study on factors hindering online learning acceptance in developing countries. In *Proceedings of the 10th international conference on education technology and computers*. Tokyo, Japan.

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science, 16*(1), 74–94.

Barak, M. (2018). Are digital natives open to change? Examining flexible thinking and resistance to change. *Computers and Education, 121*, 115–123. https://doi.org/10.1016/j.compedu.2018.01.016

Beldad, A. D., & Hegner, S. M. (2018). Expanding the technology acceptance model with the inclusion of trust, social influence, and health valuation to determine the predictors of German users' willingness to continue using a fitness app: A structural equation modeling approach. *International Journal of Human–computer Interaction, 34*(9), 882–893. https://doi.org/10.1080/10447318.2017.1403220

Bhagat, K. K., Wu, L. Y., & Chang, C.-Y. (2016). Development and validation of the perception of students towards online learning (POSTOL). *Journal of Educational Technology and Society, 19*(1), 350–359.

Bhuasiri, W., Xaymoungkhoun, O., Zo, H., Rho, J. J., & Ciganek, A. P. (2012). Critical success factors for e-learning in developing countries: A comparative analysis between ICT experts and faculty. *Computers and Education, 58*(2), 843–855. https://doi.org/10.1016/j.compedu.2011.10.010

Blocher, J. M., De Montes, L. S., Willis, E. M., & Tucker, G. (2002). Online learning: Examining the successful student profile. *Journal of Interactive Online Learning, 1*(2), 1–12.

Casaló, L. V., Flavián, C., & Guinalíu, M. (2008). The role of satisfaction and website usability in developing customer loyalty and positive word-of-mouth in the e-banking services. *International Journal of Bank Marketing, 26*(6), 399–417. https://doi.org/10.1108/02652320810902433

Chang, C.-C., Yan, C.-F., & Tseng, J.-S. (2012). Perceived convenience in an extended technology acceptance model: Mobile technology and English learning for college students. *Australasian Journal of Educational Technology*. https://doi.org/10.14742/ajet.818

Chen, K.-C., & Jang, S.-J. (2010). Motivation in online learning: Testing a model of self-determination theory. *Computers in Human Behavior, 26*(4), 741–752. https://doi.org/10.1016/j.chb.2010.01.011

Chen, Y.-J., & Chen, P.-C. (2007). Effects of online interaction on adult students' satisfaction and learning. *The Journal of Human Resource and Adult Learning, 3*(2), 78–89.

Chowdhury, R., & Sarkar, M. (2018). Education in Bangladesh: Changing contexts and emerging realities. In R. Chowdhury, M. Sarkar, F. Mojumder, & M. M. Roshid (Eds.), *Engaging in educational research: Revisiting policy and practice in Bangladesh* (pp. 1–18). Singapore: Springer. https://doi.org/10.1007/978-981-13-0708-9_1

Davidson, E., Santos, A. D., Lee, Y., Martinez, N., Smith, C., & Tassew, T. (2014). *Inclusive growth diagnostic: Bangladesh*. USAID. https://www.usaid.gov/sites/default/files/documents/1865/Bangladesh%20Inclusive%20Growth%20Diagnostic%20-%20Final%20Report.pdf

Dhawan, S. (2020). Online learning: A panacea in the time of COVID-19 crisis. *Journal of Educational Technology Systems, 49*(1), 5–22. https://doi.org/10.1177/0047239520934018

Farrell, A. M. (2010). Insufficient discriminant validity: A comment on Bove, Pervan, Beatty, and Shiu (2009). *Journal of Business Research, 63*(3), 324–327. https://doi.org/10.1016/j.jbusres.2009.05.003

Fornell, C., & Larcker, D. F. (1981). *Structural equation models with unobservable variables and measurement error: Algebra and statistics*. Sage Publications.

Francis, M. K., Wormington, S. V., & Hulleman, C. (2019). The costs of online learning: Examining differences in motivation and academic outcomes in online and face-to-face community college developmental mathematics courses. *Frontiers in Psychology, 10*, 2054. https://doi.org/10.3389/fpsyg.2019.02054

Frøkjær, E., Hertzum, M., & Hornbæk, K. (2000). Measuring usability: Are effectiveness, efficiency, and satisfaction really correlated? *Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 345–352). The Hague, The Netherlands.

Gatian, A. W. (1994). Is user satisfaction a valid measure of system effectiveness? *Information and Management, 26*(3), 119–131. https://doi.org/10.1016/0378-7206(94)90036-1

George, G., & Camarata, M. (1996). Managing instructor cyberanxiety: The role of self-efficacy in decreasing resistance to change. *Educational Technology, 36*(4), 49–54.

Glassman, M., Kuznetcova, I., Peri, J., & Kim, Y. (2021). Cohesion, collaboration and the struggle of creating online learning communities: Development and validation of an online collective efficacy scale. *Computers and Education Open, 2*, 100031.

Goh, P. S. C., & Blake, D. (2021). E-readiness measurement tool: Scale development and validation in a Malaysian higher educational context. *Cogent Education, 8*(1), 1883829. https://doi.org/10.1080/2331186X.2021.1883829

Gómez-Carracedo, M., Andrade, J., López-Mahía, P., Muniategui, S., & Prada, D. (2014). A practical comparison of single and multiple imputation methods to handle complex missing data in air quality datasets. *Chemometrics and Intelligent Laboratory Systems, 134*, 23–33. https://doi.org/10.1016/j.chemolab.2014.02.007

Gopal, R., Singh, V., & Aggarwal, A. (2021). Impact of online classes on the satisfaction and performance of students during the pandemic period of COVID 19. *Education and Information Technologies*. https://doi.org/10.1007/s10639-021-10523-1

Green, L. S., & Denton, B. (2012). Examination of factors impacting student satisfaction with a new learning management system. *Turkish Online Journal of Distance Education, 13*(3), 189–197.

Greenland, S. (2011). Using log data to investigate the impact of (a) synchronous learning tools on LMS interaction. In *Proceedings of the Australasian society for computers in learning in tertiary education (ASCILITE) conference*.

Gulati, S. (2008). Technology-enhanced learning in developing nations: A review. *The International Review of Research in Open and Distributed Learning, 9*(1), 1–16.

Hasan, Z., & Islam, K. A. (2020). Academic, financial and administrative issues of online teaching during corona pandemic: The scenario of private universities in Bangladesh. *International Journal of Accounting and Finance Review*, *5*(1), 116–122. https://doi.org/10.46281/ijafr.v5i1.630

Haththotuwa, P., & Rupasinghe, R. (2021). Adapting to online learning in higher education system during the covid-19 pandemic: A case study of Universities in Sri Lanka. *Sri Lanka Journal of Social Sciences and Humanities, 1*(2), 147–152. https://doi.org/10.4038/sljssh.v1i2.46

Holden, H., & Rada, R. (2011). Understanding the influence of perceived usability and technology self-efficacy on teachers' technology acceptance. *Journal of Research on Technology in Education, 43*(4), 343–367. https://doi.org/10.1080/15391523.2011.10782576

Hong, A. J., & Kim, H. J. (2018). College students' digital readiness for academic engagement (DRAE) scale: Scale development and validation. *The Asia-Pacific Education Researcher, 27*(4), 303–312. https://doi.org/10.1007/s40299-018-0387-0

Howshigan, S., & Nadesan, T. (2021). Students' perceptions of online learning and teaching during COVID-19 pandemic: An empirical study in selected university in Sri Lanka. *Asian Journal of Economics Business and Accounting, 21*(8), 50–57.
Islam, M. S., Tanvir, K. M., Amin, M., & Salman, M. (2020). Online classes for university students in Bangladesh during the COVID-19 Pandemic—Is it feasible? *The Business Standard*. https://www.tbsnews.net/thoughts/online-classes-university-students-bangladesh-during-covid-19-pandemic-it-feasible-87454
Jaffer, S., Ng'ambi, D., & Czerniewicz, L. (2007). The role of ICTs in higher education in South Africa: One strategy for addressing teaching and learning challenges. *International Journal of Education and Development Using ICT, 3*(4), 131–142.
Jena, P. K. (2020). Impact of Covid-19 on higher education in India. *International Journal of Advanced Education and Research (IJAER), 5*(3), 77–81.
Kabir, H., Nasrullah, S. M., Hasan, M. K., Ahmed, S., Hawlader, M. D. H., & Mitra, D. K. (2021). Perceived e-learning stress as an independent predictor of e-learning readiness: Results from a nationwide survey in Bangladesh. *PLoS ONE, 16*(10), e0259281.
Kumar, A. A. (2021). Research note on online learning in India—Issues and challenges. *Prabandhan: Indian Journal of Management*, *14*(8), 40–46.
Larmuseau, C., Desmet, P., & Depaepe, F. (2019). Perceptions of instructional quality: Impact on acceptance and use of an online learning environment. *Interactive Learning Environments, 27*(7), 953–964. https://doi.org/10.1080/10494820.2018.1509874
Lee, J.-W. (2010). Online support service quality, online learning acceptance, and student satisfaction. *The Internet and Higher Education, 13*(4), 277–283.
Lee, Y.-C. (2008). The role of perceived resources in online learning adoption. *Computers and Education*, *50*(4), 1423–1438. https://doi.org/10.1016/j.compedu.2007.01.001
Little, R. J. (1988). A test of missing completely at random for multivariate data with missing values. *Journal of the American Statistical Association, 83*(404), 1198–1202.
Lopez, R., Ahmad, J., & Zarim, N. Z. A. (2021). The psychometric properties of authentic leadership measurement in school context: Confirmatory factor analysis approach. *Turkish Journal of Physiotherapy and Rehabilitation, 32*(3), 6975–6986.
Lyons, A., Kass-Hanna, J., Zucchetti, A., & Cobo, C. (2019). *Leaving no one behind: Measuring the multidimensionality of digital literacy in the age of AI and other transformative technologies*. https://hdl.handle.net/20.500.12381/332
Majed, N., Jamal, G. R. A., & Kabir, M. R. (2020, July 28, 2020). Online Education: Bangladesh Perspective, Challenges and Way Forward. *The Daily Star*. https://www.thedailystar.net/online/news/online-education-bangladesh-perspective-challenges-and-way-forward-1937625
Maniruzzaman, M., Rahman, M. J., Al-MehediHasan, M., Suri, H. S., Abedin, M. M., El-Baz, A., & Suri, J. S. (2018). Accurate diabetes risk stratification using machine learning: Role of missing value and outliers. *Journal of Medical Systems, 42*(5), 1–17. https://doi.org/10.1007/s10916-018-0940-7
Marinoni, G., Van't Land, H., & Jensen, T. (2020). The impact of Covid-19 on higher education around the world. *IAU Global Survey Report*.
Muthuprasad, T., Aiswarya, S., Aditya, K., & Jha, G. K. (2021). Students' perception and preference for online education in India during COVID-19 pandemic. *Social Sciences and Humanities Open, 3*(1), 100101. https://doi.org/10.1016/j.ssaho.2020.100101
Nichols, M. (2008). Institutional perspectives: The challenges of e-learning diffusion. *British Journal of Educational Technology, 39*(4), 598–609. https://doi.org/10.1111/j.1467-8535.2007.00761.x
Nugroho, Y. S., Anifah, L., Sulistiyo, E., Cahyaningtias, S., & Firmansyah, R. (2021). Analysis of learning quality with internet-based distance learning during the COVID-19 pandemic. *International Journal of Recent Educational Research*, *2*(1), 96–110. https://doi.org/10.46245/ijorer.v2i1.81
Nunnally, J. C., & Bernstein, I. (1994). *Psychometric theory*. New York: McGraw Hill.
Ohliati, J., & Abbas, B. S. (2019). Measuring students satisfaction in using learning management system. *International Journal of Emerging Technologies in Learning*. https://doi.org/10.3991/ijet.v14.i04.9427
Ouyang, F., & Scharber, C. (2017). The influences of an experienced instructor's discussion design and facilitation on an online learning community development: A social network analysis study. *The Internet and Higher Education, 35*, 34–47. https://doi.org/10.1016/j.iheduc.2017.07.002
Pal, D., & Vanijja, V. (2020). Perceived usability evaluation of Microsoft Teams as an online learning platform during COVID-19 using system usability scale and technology acceptance model in India. *Children and Youth Services Review, 119*, 105535. https://doi.org/10.1016/j.childyouth.2020.105535

Palvia, S., Aeron, P., Gupta, P., Mahapatra, D., Parida, R., Rosner, R., & Sindhi, S. (2018). *Online education: Worldwide status, challenges, trends, and implications* (Vol. 21, pp. 233–241). London: Taylor & Francis.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1994). Reassessment of expectations as a comparison standard in measuring service quality: Implications for further research. *Journal of Marketing, 58*(1), 111–124.

Pete, J., & Soko, J. (2020). Preparedness for online learning in the context of Covid-19 in selected sub-Saharan African countries. *Asian Journal of Distance Education, 15*(2), 37–47.

Phutela, N., & Dwivedi, S. (2020). A qualitative study of students' perspective on e-learning adoption in India. *Journal of Applied Research in Higher Education, 12*(4), 545–559. https://doi.org/10.1108/JARHE-02-2019-0041

Priatna, T., Maylawati, D., Sugilar, H., & Ramdhani, M. (2020). Key success factors of e-learning implementation in higher education. *International Journal of Emerging Technologies in Learning (iJET), 15*(17), 101–114. https://doi.org/10.3991/ijet.v15i17.14293

Rameez, A., Fowsar, M., & Lumna, N. (2020). Impact of Covid-19 on higher education sectors in Sri Lanka: A study based on south eastern university of Sri Lanka. *Journal of Educational and Social Research 10*(6), 341–349. https://doi.org/10.36941/jesr-2020-0132

Reddy, P., Sharma, B., & Chaudhary, K. (2021). Digital literacy: A review in the South Pacific. *Journal of Computing in Higher Education*. https://doi.org/10.1007/s12528-021-09280-4

Rios, T., Elliott, M., & Mandernach, B. J. (2018). Efficient instructional strategies for maximizing online student satisfaction. *Journal of Educators Online, 15*(3), n3. https://doi.org/10.9743/jeo.2018.15.3.7

Riyasad, N. (2020). COVID-19 and the conundrum of online classes. *New Age*. https://www.newagebd.net/article/104657/covid-19-and-the-conundrum-of-online-classes. Accessed 10 March 2022.

Saha, A., Dutta, A., & Sifat, R. I. (2021). The mental impact of digital divide due to COVID-19 pandemic induced emergency online learning at undergraduate level: Evidence from undergraduate students from Dhaka City. *Journal of Affective Disorders, 294*, 170–179. https://doi.org/10.1016/j.jad.2021.07.045

Sarker, M. F. H., Al Mahmud, R., Islam, M. S., & Islam, M. K. (2019). Use of e-learning at higher educational institutions in Bangladesh: Opportunities and challenges. *Journal of Applied Research in Higher Education, 11*(2), 210–223. https://doi.org/10.1108/JARHE-06-2018-0099

Shahriar, S. H. B., Arafat, S., Sultana, N., Akter, S., Khan, M. M. R., Nur, J. E. H., & Khan, S. I. (2021). The transformation of education during the corona pandemic: Exploring the perspective of the private university students in Bangladesh. *Asian Association of Open Universities Journal, 16*(2), 161–176. https://doi.org/10.1108/AAOUJ-02-2021-0025

Shen, D., Cho, M.-H., Tsai, C.-L., & Marra, R. (2013). Unpacking online learning experiences: Online learning self-efficacy and learning satisfaction. *The Internet and Higher Education, 19*, 10–17. https://doi.org/10.1016/j.iheduc.2013.04.001

Shrestha, S., Haque, S., Dawadi, S., & Giri, R. A. (2021). Preparations for and practices of online education during the Covid-19 pandemic: A study of Bangladesh and Nepal. *Education and Information Technologies*. https://doi.org/10.1007/s10639-021-10659-0

Simamora, R. M. (2020). The Challenges of online learning during the COVID-19 pandemic: An essay analysis of performing arts education students. *Studies in Learning and Teaching*, *1*(2), 86–103. https://doi.org/10.46627/silet.v1i2.38

Singh, N., Sinha, N., & Liébana-Cabanillas, F. J. (2020). Determining factors in the adoption and recommendation of mobile wallet services in India: Analysis of the effect of innovativeness, stress to use and social influence. *International Journal of Information Management, 50*, 191–205. https://doi.org/10.1016/j.ijinfomgt.2019.05.022

Sivo, S. A., Ku, C.-H., & Acharya, P. (2018). Understanding how university student perceptions of resources affect technology acceptance in online learning courses. *Australasian Journal of Educational Technology*. https://doi.org/10.14742/ajet.2806

Srinivasan, A. (1985). Alternative measures of system effectiveness: Associations and implications. *MIS Quarterly, 9*(3), 243–253.

Subedi, S., Nayaju, S., Subedi, S., Shah, S. K., & Shah, J. M. (2020). Impact of e-learning during COVID-19 pandemic among nursing students and teachers of Nepal. *International Journal of Science and Healthcare Research, 5*(3), 68–76.

Sultana, T., & Khan, R. H. (2019). Investigating university students' satisfaction on online class: Bangladesh perspective. *Bangladesh Education Journal, 18*(2), 23–64.

Sun, Y., & Rogers, R. (2021). Development and validation of the online learning self-efficacy scale (OLSS): A structural equation modeling approach. *American Journal of Distance Education, 35*(3), 184–199. https://doi.org/10.1080/08923647.2020.1831357

Swan, K. (2001). Virtual interaction: Design factors affecting student satisfaction and perceived learning in asynchronous online courses. *Distance Education, 22*(2), 306–331. https://doi.org/10.1080/0158791010220208

Tai, J.H.-M., Bellingham, R., Lang, J., & Dawson, P. (2019). Student perspectives of engagement in learning in contemporary and digital contexts. *Higher Education Research and Development, 38*(5), 1075–1089. https://doi.org/10.1080/07294360.2019.1598338

Tang, C. M., & Chaw, L. Y. (2016). Digital literacy: A prerequisite for effective learning in a blended learning environment? *Electronic Journal of E-Learning, 14*(1), 54–65.

Tarhini, A., Elyas, T., Akour, M. A., & Al-Salti, Z. (2016). Technology, demographic characteristics and e-learning acceptance: A conceptual model based on extended technology acceptance model. *Higher Education Studies, 6*(3), 72–89. https://doi.org/10.5539/hes.v6n3p72

Teo, T. (2010). Development and validation of the e-learning acceptance measure (ElAM). *The Internet and Higher Education, 13*(3), 148–152. https://doi.org/10.1016/j.iheduc.2010.02.001

Tsai, C.-L., Cho, M.-H., Marra, R., & Shen, D. (2020). The self-efficacy questionnaire for online learning (SeQoL). *Distance Education, 41*(4), 472–489. https://doi.org/10.1080/01587919.2020.1821604

Tzafilkou, K., Perifanou, M., & Economides, A. A. (2021). Negative emotions, cognitive load, acceptance, and self-perceived learning outcome in emergency remote education during COVID-19. *Education and Information Technologies, 26*, 1–25. https://doi.org/10.1007/s10639-021-10604-1

UGC. (2018). *Higher education achievements*. Retrieved from http://www.ugc.gov.bd/sites/default/files/files/ugc.portal.gov.bd/publications/8e681540_daa9_4844_a09c_a8b269364912/Higher%20Education%20Achivement%202018.pdf

Ullah, A., Ashraf, M., Ashraf, S., & Ahmed, S. (2021). Challenges of online learning during the COVID-19 pandemic encountered by students in Pakistan. *Journal of Pedagogical Sociology and Psychology, 3*(1), 36–44.

UN. (2020). *Education during COVID-19 and beyond*. United Nations. https://www.un.org/development/desa/dspd/2020/04/social-impact-of-covid-19. Accessed 30 December 2021.

Valencia-Arias, A., Chalela-Naffah, S., & Bermúdez-Hernández, J. (2019). A proposed model of e-learning tools acceptance among university students in developing countries. *Education and Information Technologies, 24*(2), 1057–1071.

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research, 11*(4), 342–365. https://doi.org/10.1287/isre.11.4.342.11872

Vivolo, J. (2016). Understanding and combating resistance to online learning. *Science Progress, 99*(4), 399–412. https://doi.org/10.3184/003685016X14773090197742

Zhang, J., Cai, Z., Zhao, Z., & Ji, K. (2017). Cell phone-based online biochemistry and molecular biology medical education curriculum. *Medical Education Online, 22*(1), 1374135.

Zhang, S.-N., Li, Y.-Q., Liu, C.-H., & Ruan, W.-Q. (2019). Critical factors in the identification of word-of-mouth enhanced with travel apps: The moderating roles of Confucian culture and the switching cost view. *Asia Pacific Journal of Tourism Research, 24*(5), 422–442. https://doi.org/10.1080/10941665.2019.1572630

Mehdi Rajeb is an Assistant Professor (on leave) in the ULAB School of Business, the University of Liberal Arts Bangladesh. He is also a doctoral student, and Graduate Council Fellow in the department of educational studies in Psychology, Research Methodology, and Counselling at The University of Alabama. He served in several research positions in Center for Enterprise and Society and served as research consultant in several projects initiated by Bath University, UK/Dutch Funding Agency, USDA, and IFC-SEDF (World Bank Group). His research interest is focused on Bayesian approach in psychometric analysis, educational research methodology, statistical predictive modeling, and statistical applications in educational research and social science.

Dr. Yurou Wang, Ph.D. is a Clinical Assistant Professor of Educational Psychology and Residential M.A. in Educational Psychology Program Coordinator at the University of Alabama (UA). She received her Ph.D. in Educational Psychology (Learning and Development) from the University of Kansas in 2019. She endeavors to help disadvantaged and low-motivation students. Her research agenda coalesces around self-determination theory, achievement emotions, and academic persistence. She has amalgamated technology into the exploration of academic motivation and emotion by building the Micro-facial Expression Tracking (MET) Lab.

Dr. Kaiwen Man, Ph.D. was appointed as an Assistant Professor in the Department of Educational Studies in Psychology, Research Methodology, and Counseling at the University of Alabama. Also, Kaiwen has held many positions as Researchers including at the Association of American Medical College, at the Educational Testing Service, and at the Charted Financial Analyst. His research explores questions on the boundaries and interactions of the educational statistics, biometrics, and behavioral research literature with particular attention to models for eye-tracking data, responding process data, Bayesian statistics, and data mining. His works has been published in many peer-reviewed flagship quantitative journals such as Educational and Psychological Measurement, Journal of Educational Measurement, Journal of Educational and Behavioral Statistics, and Applied Psychological Measurement. Furthermore, his projects have been externally funded by the ETS Harold Gulliksen Psychometric Research Fellowship program.

Dr. Laura Morett, Ph.D. is Assistant Professor of Educational Psychology at the University of Alabama. Dr. Morett uses research approaches from cognitive neuroscience, educational psychology, and developmental science to investigate how the neurobiological organization of language develops and how it contributes to learning, with a particular focus on gesture and its relationship to speech.

Authors and Affiliations

Mehdi Rajeb[1] · Yurou Wang[2] · Kaiwen Man[3] · Laura M. Morett[4]

Yurou Wang
ywang329@ua.edu

Kaiwen Man
kman@ua.edu

Laura M. Morett
lmorett@ua.edu

1 Department of Educational Studies in Psychology, Research Methodology, and Counseling, College of Education, The University of Alabama, Carmichael Hall, Tuscaloosa, AL 35401, USA

2 Department of Educational Studies in Psychology, Research Methodology, and Counseling, College of Education, The University of Alabama, 310 Carmichael hall, Tuscaloosa, AL 35401, USA

3 Department of Educational Studies in Psychology, Research Methodology, and Counseling, College of Education, The University of Alabama, 313 Carmichael hall, Tuscaloosa, AL 35401, USA

4 Department of Educational Studies in Psychology, Research Methodology, and Counseling, College of Education, The University of Alabama, Box 8700, Tuscaloosa, AL 35487, USA