Antecedents of students’ e-learning continuance intention during COVID-19: An empirical study

Md Al Amin
Department of Marketing, Bangabandhu Sheikh Mujibur Rahman Science and Technology University, Gopalganj, Bangladesh

Md Razib Alam, PhD
Department of Marketing, University of Dhaka, Dhaka, Bangladesh

Mohammad Zahedul Alam, PhD
Department of Marketing, Bangladesh University of Professionals, Dhaka, Bangladesh

Abstract
This study aims at exploring the underlying determinants influencing students’ continuance intention to use an e-Learning platform during the COVID-19 pandemic. Based on the technology acceptance model and expectation-confirmation model, the study investigated the role of contextual (i.e., social isolation), psychological (academic year loss and cyberchondria), and student support-related (government and institutional supports) determinants on students’ continuance intention to use an e-Learning platform during the pandemic. The study collected data from 440 respondents and analyzed those with Structural Equation Modeling. The findings showed that an e-Learning continuance intention during the pandemic is affected by usefulness, ease of use, attitudes, and intention to use the e-Learning platform, while the behavioral intention is influenced by usefulness, ease of use, attitudes, contextual, psychological, and student support-related determinants, and attitudes are impacted by usefulness and ease of use. Moreover, usefulness is predicted by confirmation of expectation; e-satisfaction is forecasted by usefulness and confirmation of expectation, whereas, cyberchondria is influenced by social isolation; fear of academic year loss is influenced by cyberchondria. Finally, intention to use mediated the impact of usefulness, ease of use, attitudes, contextual, psychological, and student support-related determinants on continuance intention. The study contributes to e-Learning literature incorporating contextual, psychological, and student support-related determinants into the technology acceptance model and expectation-confirmation model, which guide policymakers to understand how all levels of students can be brought into the e-Learning platforms that eventually help to eliminate digital discrimination barrier in the academia during any emergency. The policymakers must be careful in designing eLearning platforms since students’ e-learning continuance intention may vary due to unprecedented crises, such as COVID-19.
Keywords
Fear of academic irregularity, government supports, institutional supports, cyberchondria, e-learning, digital discrimination, social isolation

Introduction
Digitalization touches all aspects of human life. The application of technologies in the education sector is continuously growing. Educational institutions across the globe have been accepting the different methods of online education systems (Al-Fraihat et al., 2020; Khan et al., 2017). Information and communication technology (ICT) has been contributing tremendously to the acceptance of the e-Learning ecosystem across all levels of academia (Hamid et al., 2016; Khan et al., 2017). As part of the development of the e-Learning environment, educational institutions across the globe have been adopting the learning management system (LMS), a powerful tool to facilitate the education system with reduced schooling costs, quality and timely content, flexible accessibility, and convenience. According to Dahlstrom et al. (2014), 99% of institutions have LMS in place, and 85% of the faculty members use LMS in the US. In the UK, 95% of higher education institutions have adopted LMSs to support their educational services (McGill and Klobas, 2009).

Bangladesh experiences the adoption of different forms of e-Learning systems by educational institutions during the COVID-19 pandemic. The education sector faces intense challenges due to the adverse impact of highly contagious Coronavirus. Academic institutions across the globe shut down their on-campus academic activities to minimize the risk of infection from the Coronavirus (Martinez, 2020). As a result, more than 20 million students in Bangladesh suffer from the closure of educational institutions consisting of schools, colleges, and universities (IAU, 2020). Consequently, the education sector has been fighting to survive the crises by adopting different e-Learning platforms since the teachers and students were forced to stay at home to avoid being infected by this most contagious virus (Jena, 2020). Thus, exploring the underlying contextual (i.e., social isolation), psychological, and student support-related determinants influencing e-Learning continuance intention during COVID-19 outbreaks is essential.

Social isolation, which is emerged as a result of the pandemic, impacts everyday life and students’ attitudes toward online platforms. Social isolation allows for limited physical interaction, which can reduce the possibility of coronavirus transmission (Al Amin et al., 2021b). Various types of e-Learning platforms have gained popularity during the social isolation period. Different types of anxiety may arise from social isolation. Since on-campus education has been halted during the pandemic, the education system is only continued with the online System’s help. Social isolation might result in students’ continuance intention to use e-Learning during the COVID-19 pandemic. Hence, it is imperative to discover the impact of contextual factors (i.e., social isolation) on students’ intention to use e-Learning systems.

During the outbreak, students search online excessively to receive more information regarding the pandemic since they are concerned about their health. The students’ this kind of behavior is known as Cyberchondria (CRD). Moreover, closure of the on-campus classes due to lockdown affects the students psychologically, which includes worrying about the fear of academic year loss (FAYL) (i.e., Fear of Academic Irregularity) that eventually may affect their future careers (Alam, 2020; Bao, 2020; Hasan and Bao, 2020). Thus, it is necessary to comprehend how psychological factors (i.e., cyberchondria and fear of academic year loss) influence students to cope with e-Learning platforms during the outbreaks.

The students may negatively perceive the online learning system (Rohman et al., 2020) due to e-Learning platform affordability, technophobia, network unavailability, etc. Moreover, the
e-Learning system increases digital discrimination due to the adverse financial condition of many students (Jæger and Blaabæk, 2020). Adam et al. (2020) mentioned that due to digital discrimination and lack of access to up-to-date technology, students of lower-income families face difficulties accessing online classes. As almost all institutions are accepting one of the e-Learning platforms, concern ascended about the participation of unprivileged students, who may be deprived to access to the e-Learning system due to their challenging financial situation that limits their ability to have related devices and location of their residence where the internet is not available (Yen, 2020; Zhou et al., 2020). Government support (GS) and institutional support (InS) can play a crucial role in solving the discrimination of e-learning opportunities. For example, in the context of Bangladesh, University Grants Commission (UGC) and different universities are providing different supports (e.g., free internet connections, devices support, student loans, tuition fee off, etc.), which might influence students’ intention to use e-learning platforms (Dhaka Tribune, 2021). Hence, it is imperative to examine the influence of supports from government and educational institutions on students’ intention to use e-learning platforms during the COVID-19 pandemic.

This study aims at exploring the underlying success factors influencing students’ e-Learning continuance intention as a promising operational alternative to on-campus education and provides a solution to learning opportunity discrimination to afford e-Learning platform’s expenses by poor students during COVID-19. Few recent studies have examined the impact of the COVID-19 pandemic on students’ attitudes and technology adoption behavior (Alqudah et al., 2020; Raza et al., 2020; Shahzad et al., 2020; Sukendro et al., 2020). The previous studies mainly emphasized adoption and its influence on student’s intention to use technology (Al-Gahtani, 2016; Al-Okaily et al., 2020; Chang et al., 2020; Cheng and Yuen, 2018; Gan and Balakrishnan, 2017; Joo et al., 2018; Wang et al., 2019); success factors of e-learning adoption (Mohammadi, 2015; Mtebe and Raphael, 2018); the ubiquity of education from anywhere and at any time (Jou and Wang, 2013; Lin et al., 2014); and students’ psychological distress during COVID-19 on the acceptance of e-learning (Hasan and Bao, 2020). However, to the best of our knowledge, all these studies have ignored the influence of contextual (i.e., social isolation), psychological (i.e., Cyberchondria and fear of academic year loss), and supports related variables (i.e., the government support and institutional support) on students’ intention to use e-learning platforms.

The study has developed and tested an integrated theoretical model (i.e., e-Learning Continuance Model-eLCM) based on technology acceptance model (TAM, Davis et al., 1989) and expectation-confirmation model (ECM, Bhattacherjee (2001) along with five new dimensions (i.e., social isolation, Cyberchondria, fear of academic year loss, the government support and institutional support) that might contribute to the knowledge gap and help policymaker to make the appropriate decision when adopting the e-Learning platform during any emergencies. From the findings of the study, policymakers may understand how contextual variables such as social isolation, psychological variables such as Cyberchondria, and various support from a government and respective institution may impact the students’ continuance intention to use e-Learning platforms during a pandemic. Government and institutional supports are essential to minimize students’ digital discrimination barriers. Existing literature ignored the impact of these supports on students’ e-Learning use intention. The proposition regarding students’ negative perception of e-Learning behavior analogized by Rohman et al. (2020) has already been obsolete as e-Learning is considered the only promising alternative to on-campus education with its timely advantages during COVID-19 outbreaks.

The next part of this paper will cover the literature review, conceptual framework, and hypotheses development. Then it includes the research methodology, followed by the empirical results and discussion on the theoretical contributions and practical implications. Finally, the paper concludes with limitations and future research directions.
E-Learning is a teaching or learning technique that depends on electronic devices (e.g., smartphones, laptops, computers) and technology through synchronous or asynchronous platforms with internet access rather than paper classroom-based teaching. Singh and Thurman (2019) defined e-learning as “learning experiences in synchronous or asynchronous environments using different electronic devices (e.g., mobile phones, laptops, etc.) with internet access. Under these environments, students can be anywhere (independent) to learn and interact with instructors and other students”. The e-Learning can be divided into two major types: i) the first is asynchronous type, time-independent (e.g., Google Classroom) by which students can learn and download course material, and ii) the other is real-time online learning, the synchronous (zoom, Google Meet, etc.) by which students can grab real-time learning opportunities with the capability to interact and chat with their instructors instantly in a live virtual class on a scheduled time (Dhawan., 2020). As a result, higher education institutions have adopted e-Learning systems to support their educational services (McGill and Klobas, 2009) due to the possible advantages (e.g., reduced schooling costs, quality, and timely content, flexible accessibility, the versatility of education for everyone’s convenience and convenience) (Hamid et al., 2016).

During the COVID-19 pandemic, e-Learning or distance learning has gained priority in the education sector in Bangladesh due to the longtime closures of educational institutes. As a result, the students and teachers started installing the e-Learning platforms as a promising operational alternative, including BLC (Blended Learning Center), SMS (School Management System), LMS, Open Sources (e.g., Google Classroom/Meet, Zoom Online Class, Skype, Wikis, etc.). Moreover, the University Grant Commission (UGC), Bangladesh signed an MoU with Zoom-BDREN to facilitate all public and private university teachers with premium BD-REN Zoom ID free of cost (UGC, 2020a) and with different mobile phone operators to reduce the cost of the internet (Dhaka Tribune, 2021). Moreover, the University Grant Commission (UGC), Bangladesh, signed an MoU with Zoom-BDREN to facilitate all public and private university teachers with premium BD-REN Zoom ID free of cost and with different mobile phone operators to reduce the cost of the internet (Dhaka Tribune, 2021).

Theoretical framework and hypotheses development. In the recent past, researchers showed a deep interest in exploring the adoption of e-Learning. The existing studies mainly emphasized adoption and its influence on students’ intention to use e-Learning using different theoretical frameworks. Among these models, Technology Acceptance Model (TAM; Davis, 1989) has been the most widely-used and reported model in the social science context (Teo et al., 2017). The TAM defines that the attitude: “people’s feeling, positive or negative, regarding the behavioral intention performance towards adopting a system is predicted by their perceived usefulness and ease of use” (Davis, 1989). In the original theory of TAM, perceived ease of use is also reported to predict perceived usefulness. Besides, behavioral intention to adopt a system is expected by the attitude and perceived usefulness. Finally, the actual use described as using a system is predicted by behavioral intention (Davis, 1989). Studies reported some external factors, contextual factors, or situation variables accompanying the original TAM constructs (Venkatesh and Bala, 2008; Venkatesh and Davis, 2000).

Moreover, TAM is also used in different e-Learning related studies. For example, Sukendro et al. (2020) revealed the student’s e-Learning usage intention during the COVID-19 pandemic-based TAM. Moreover, as antecedents to medical professionals’ continuance intention of the cloud-based
e-learning system have been examined by Cheng (2020). Saeed al-Marouf et al. (2021) show teachers’ and students’ perceived technology self-efficacy, ease of use, and usefulness are the main factors directly affecting the continuous intention to use technology”. Some other studies have considered TAM in e-learning integration reports in education (Cakır and Solak, 2015; Gan and Balakrishnan, 2017; Lee et al., 2009; Mohammadi, 2015; Wang et al., 2019; Zhang et al., 2008).

In addition, Expectation-Confirmation Theory (ECT) has also been considered by many studies to explore the underlying attributes that impact the continued IT usage intention in various contexts, such as confirmation, expectation, and satisfaction (e.g., Al Amin et al., 2021a, 2022b; Bhattacherjee, 2001; Ray et al., 2019; Qazi et al., 2017), ease of use and perceived usefulness (e.g., Karahanna et al., 1999), and habit (e.g., Alalwan, 2020). Moreover, many other researchers have also extended and adopted the ECT, including several factors, e.g., perceived playfulness (Lin et al., 2005), habit (Limayem and Cheung, 2008), and resource quality (Joo and Choi, 2016). In addition, following ECT, some studies found that confirmation is positively associated with satisfaction and perceived usefulness of IS based applications, by which they also proved the causal relationship between ESAT and the intention to use a particular e-Learning platform (Cheng, 2020; Lee et al., 2009; Hayashi et al., 2020; Joo et al., 2017; Mohammadi, 2015). Furthermore, some other studies have considered other models. For example, Raza et al. (2020) determined the impact of social isolation on acceptance of LMS during the COVID-19 crisis using the Unified Theory of Acceptance and Use of Technology (UTAUT) model. Besides, few researchers also considered IS Success Model (ISSM) to examine the effects of COVID-19 students intention toward e-Learning (Gan and Balakrishnan, 2017; Shahzad et al., 2020) and different levels of success related to a broad range of success determinants of e-Learning (Al-Fraihat et al., 2020). However, the other researchers utilized the theory of planned behavior (TPB, Al Amin et al., 2021c; Lee et al., 2010) in IS-based applications.

However, further study is essential to identify the predictors that can impede or contribute to adopting the e-Learning platform during the COVID-19 pandemic. Moreover, the impact of contextual variables (i.e., social isolation), psychological variables (i.e., Cyberchondria and fear of academic year loss), and supports related determinants (i.e., the government support and institutional support) on students’ e-Learning continuance intention during pandemic outbreaks have not investigated yet. Thus, the current study expects to fulfill the gaps practically validating the proposed e-Learning continuance model (ELCM) based on TAM and ECM along with contextual variables (i.e., social isolation), psychological variables (i.e., Cyberchondria and fear of academic year loss) and supports related determinants (government supports and institutional supports). Figure 1 shows the research model of the present study.

**Perceived ease of use**

Davis et al. (1989) defined Perceived ease of use as “the degree to which a person believes that using a particular system would be free from effort.” In the context of e-Learning, the students prefer those platforms which are easy to use and match their behavior. Sukendro et al. (2020) argued that PEOU of e-learning is assumed to affect the students’ attitudes for students during COVID-19 positively. Some other studies showed a positive relationship between PEOU and attitudes (ATT) (e.g., Buabeng-Andoh et al., 2019; Muhaimin et al., 2019) in the context of e-Learning usage intention. Moreover, many researchers confirmed the influence of PEOU on behavioral intention related to different forms of IS-based applications (e.g., Al-Gahtani, 2016; Cheng and Yuen, 2018; Venkatesh and Davis, 2000) due to the ease of use and user-friendliness of that particular system. In addition, a few studies found a positive influence of PEOU on CI in the case of e-Learning continuance...
intention (e.g., Gan and Balakrishnan, 2017; Joo et al., 2018; Wang et al., 2019). However, further research is needed to adopt e-Learning systems during emergent situations (e.g., coronavirus outbreaks). Therefore, we deposited the following hypotheses.

**H1a:** Perceived ease of use positively influences attitude to use e-learning applications during the COVID-19 pandemic.

**H1b:** Perceived ease of use positively influences intention to use e-learning applications during the COVID-19 pandemic.

**H1c:** Perceived ease of use positively influences e-Learning continuance intention to use during the COVID-19 pandemic.

**Perceived Usefulness**

According to Davis et al. (1989), perceived usefulness (PU) is defined as “the degree to which a person believes that using a particular system would enhance his/her job performance”. PU is one of the significant determinants that impact consumer attitudes toward accepting innovative technology (Davis et al., 1989; Taylor and Todd 1995). Students develop positive attitudes toward e-Learning systems in the e-Learning context when they perceive that the applications are useful for their academic purposes. Moreover, if the students perceive that e-Learning is valuable, their attitudes will be more favorable towards ELCI (Muhaimin et al., 2019), heightening the extent to which an app is viewed as trustworthy. The existing studies analogized the positive influence of PU on ATT relating to accepting new information (e.g., Vahdat et al., 2020; Nguyen et al., 2019). Moreover, PU simultaneously influences the willingness of students to execute a specific behavior (Kim and Woo, 2016). Several pieces of research confirmed the relationship between PU and IU (e.g., Al-Gahtani, 2016; Cheng, 2020; Cheng and Yuen, 2018; Sukendro et al., 2020; Lee, 2010; Umrani-Khan and Iyer, 2009) and the relationship between PU and continuance intention (e.g., Cheng, 2020; Gan and Balakrishnan, 2017; Wang et al., 2019) in the context of e-Learning. Drawn from ECM and TAM,
the relationship between PU and satisfaction (SAT) has been validated in many technology
continuance studies across contexts. By integrating ECM and TAM, the information system
continuance model states that PU is the antecedent of satisfaction and continuance intention
(Bhattacherjee, 2001). The relationship between PU and ESAT was also analogized in e-Learning
(Cheng, 2020; Lee et al., 2009), other forms of IS (Bhattacherjee, 2001; Lee, 2010; Lin, 2011).
However, they ignored the phenomenal cues (e.g., COVID-19). Thus, we deposit the following
hypothesis:

**H2a:** Perceived usefulness positively influences e-Learning attitudes during the COVID-19 pandemic.

**H2b:** The perceived usefulness positively influences intention to use e-Learning during the COVID-19 pandemic.

**H2c:** The perceived usefulness positively influences continuance intention to use e-Learning during the COVID-19 pandemic.

**H2d:** The perceived usefulness positively influences students’ satisfaction to use e-Learning during the COVID-19 pandemic.

---

**Attitudes to use e-Learning**

As per the theory of reasoned action (TRA), attitudes refer to the expression of an individual’s feelings regarding a particular behavior, and it acts as a critical determinant for behavioral intention (Ajzen and Fishbein, 1980; Fishbein and Ajzen, 1975). When an individual utilizes an innovative technology (e.g., an e-Learning system), attitudes determine the behavioral intention toward e-Learning continuance intention. The existing literature realized that attitudes build an effective response that influences the learners’ behavioral intention to use e-learning platforms (Buabeng-Andoh et al., 2019; Muhaimin et al., 2019; Sukendro et al., 2020). Besides, the students will have a stronger intention to continue e-learning systems when their behavioral beliefs and evaluations of behavioral beliefs match with e-learning systems. Moreover, as social distance is considered the key strategy to keep the COVID-19 pandemic under control for the last several months, the students are getting habituated to cope with this emergent situation to use e-Learning continuously. However, the relationship between users’ continuance intention and attitudes was analogized by few researchers (Hong et al., 2006; Hsu et al., 2006; Lee, 2010). Therefore, we deposited the following hypotheses.

**H3a:** The attitudes positively influence intention to use of e-learning during the COVID-19 pandemic.

**H3b:** The attitudes positively influence e-learning continuance intention to use during the COVID-19 pandemic.

---

**Students’ expectation’s confirmation**

Confirmation (CON) refers to the users’ perception of the expected benefits of E-learning platform use and its actual performance (Bhattacherjee, 2001). Bhattacherjee (2001) claimed that confirmation positively affects perceived satisfaction, implying the expected benefits of information system use. Bhattacherjee (2001) suggested that confirmation positively affects perceived satisfaction and services in using new technology, indicating the anticipated value of information system utilization. Many other researchers also found confirmation is positively associated with satisfaction and perceived quality of IT products/services for intention to use (e.g., Hayashi et al., 2020; Hsu et al., 2015; Lee, 2010; Lin, 2011). Thus, we have developed the following two hypotheses:
**H4a:** Students’ confirmation positively influences perceived usefulness to use e-Learning systems during the COVID-19 pandemic.

**H4b:** Students’ confirmation positively influences satisfaction to use e-Learning systems during the COVID-19 pandemic.

**Students’ e-satisfaction**

Anderson and Srinivasan (2003), defined e-satisfaction as the contentment of the customers concerning their prior purchasing experience with a given electronic commerce firm, while Continuance intention means "to repurchase a product or continue service use" (Bhattacharjee, 2001: p.353). If the e-Learning platform confirms students’ expectations, they are more likely to be delighted about their experiences and repeatedly use e-Learning for their virtual classes. The existing researchers found a causal relationship between ESAT and intention to consistently use a particular e-Learning platform (Chow and Shi, 2014; Hayashi et al., 2020; Joo et al., 2017; Mohammadi, 2015; Mtebe and Raphael, 2018). However, the extent of researches ignored the influence of pandemic outbreaks. Thus, we proposed the following hypothesis:

**H5:** Students’ e-satisfaction has a positive impact on continuance intention to use e-Learning systems.

**Social isolation**

Social isolation, also known in this study as social distance or physical distancing (PD) is defined as the objective physical separation of a human being from others or to live alone geographically and temporally or a condition for which a human being maintains a complete or near-complete lack of communication due to emergencies happened in any places (Eccles, 1987). The emergencies might include the COVID-19 pandemic, government emergency, and self-confinement, etc. In the context of e-Learning, Daugherty and Funke (1998) also emphasize that web-based learning is denied when going through a feeling of isolation. Moreover, Chiu and Wang (2008) found social isolation might be associated with behavioral intention. Furthermore, several studies suggested that students’ behavioral intention might be influenced by situational factors (Ghani et al., 2013). Raza et al. (2020) found social isolation might be related positively to the behavioral intention to accept LMS during COVID-19 outbreaks. In addition, when students are socially isolated due to the contextual cues (e.g., COVID-19), they repeatedly perform health-related online searches that fuel anxiety, distress, and fear regarding academic year loss, which lead to being cyberchondriacs. Thus, we deposited the following hypotheses.

**H6a:** Social isolation positively influences Cyberchondria to use e-Learning platforms COVID-19 Pandemic.

**H6b:** Social isolation positively influences intention to use e-Learning platforms during the COVID-19 pandemic.

**Cyberchondria**

The researchers have recently become conscious about Cyberchondria linked with a health concern, obsessive-compulsive disorder, etc. (Vismara et al., 2020). During a pandemic, a severe health threat is Cyberchondria (Laato et al., 2020). Cyberchondria refers to a situation when an individual is overly stressed or anxious about their health due to excessive online search to receive more
information regarding pandemic outbreaks, which increases a person’s anxiety, distress, and fear (Jokić-Begić et al., 2019). Laato et al. (2020) mentioned: "through excessive online searching cyberchondriacs equated to others discovery more information regarding the pandemic outbreaks which increases the cognitive load in the short run." As of June 2021, the outbreaks of COVID-19 are still not in the leveraging phase, and the nature of the Coronavirus is yet to discover and obscure. Government officials and health workers also emphasize voluntary self-isolation as an effective countermeasure to curb the pandemic (Farooq et al., 2020). Moreover, we argue that excessive online searches regarding COVID-19 anxiety lead the students (especially final year students) to worry about their academic year gap and continually influence students to use e-Learning systems. Therefore, we posited the following hypothesis:

**H7a:** The Cyberchondria positively influences fear of academic year loss during the COVID-19 pandemic.

**H7b:** The Cyberchondria positively influences e-Learning intention during the COVID-19 pandemic.

**Fear of academic year loss**

Fear of academic year loss (FAYL), also known as fear of academic irregularity, is defined as the students’ fear, stress, or distress regarding academic preparation, academic year gap, or session jam at the educational institutes. According to Hasan and Bao (2020) mentioned that due to this stress, "some students reported about their sleeping disorder, mental stress due to fear of uncertain future admission." Although the government of Bangladesh and the policymaker are applying many initiatives, including a reduction in the syllabus, online classes, virtual classes through the satellite television channel, etc., they have not been able to decide yet what the suitable solution is for university students, especially final year students (i.e., prospective undergraduate students). In contrast, a recent survey conducted by the Bangladesh Bureau of Statistics (BBS, 2019) indicates that 50% of households in Bangladesh do not have access to satellite television. Besides, the midterm and final examinations of school-going students are abandoned. More importantly, the HSC (Higher Secondary Certificate) examination, a public examination attended by more than 1.5 million students, was canceled along with 1.80 million awaited examinees of Secondary School Certificate (SSC) test without any clear direction from authorities. Thus, fear of academic year loss has been the most crucial concern that enhances students’ psychological anxiety during the COVID-19 pandemic. Hence, FAYL is thought to influence students’ continuance intention to use e-Learning or online classes. Accordingly, we posited the following hypothesis:

**H8:** The fear of academic year loss positively influences intention to use e-Learning platforms during the COVID-19 pandemic.

**Government support.** The educational institutions face a tremendous crisis during the COVID-19 period, and the on-campus classes are strictly prohibited from saving students from Coronavirus. Hence, most educational institutions accept different e-learning platforms worldwide, including Bangladesh (Yen, 2020; Zhou et al., 2020). However, due to the wide acceptance of online platforms, learning discrimination against better family facilities increases the digital disparities during COVID-19 outbreaks (Jæger and Blaabæk, 2020). Thus, in the context of e-Learning uneven opportunities, the government supports (e.g., devices support, tax rebate, interest-free student loan, security to attend online classes, technological supports, etc.) can play an essential role to solve the students’ digital disparities that may influence their behavioral intention to use e-learning systems (Rambocas and
Arjoon, 2012). Moreover, Ali et al. (2015) and Reni and Ahmad (2016) have proved the same relationship in Islamic banking and financing, and mobile commerce and government services were found by (Dawi, 2019; Mandari et al., 2017). Hence, we have posited the following hypothesis:

**H9**: Government support positively affects intention to use e-Learning during the COVID-19.

**Institutional Supports**

The institutional supports (InS) refer to the facilities (e.g., quality internet facilities, mental supports, reduced rate of tuition fees, online learning system, etc.) provided by the particular institution to their students (Al Amin et al., 2022a; Khan et al., 2017). Sintema (2020) described that the percentage of passing students would be lower in 2020 because of digital discrimination due to family’s financial condition and the longtime closure of educational institutions during the COVID-19. Therefore, in line with GS, InS can decrease the digital inequalities and ensure online class participation from all levels of students, especially from lower-income families, to escalate this year’s pass rate. Thus, we posited the following hypothesis:

**H10**: Institutional support positively affects intention to use MBSAs during COVID-19.

**Behavioral intention to use (IU) and continuance intention to use (CI).** Behavioral intention to use (IU) refers to the behavior intention approach that involves the action motivation and ideological tendency and “the strength of one’s intention to perform a specified behavior” (Ajzen, 1991). On the other hand, students’ intention refers ‘to repurchase a product or continue service use’ (Bhattacherjee, 2001; Bhattacherjee et al., 2008; Kang and Namkung, 2019). e-Learning usage intention is more likely to be continued when students enjoy the benefits of those platforms. Rodriguez-Ardura and Meseguer-Artola (2016) identified that users’ IU motivates CI to use E-learning technology. The existing research also identified that users’ IU motivates actual usage behavior (also known as continuance intention) of e-Learning (e.g., Lin, 2007; Zhou et al., 2020). Since students have limited options remaining to take classes in the pandemic period, considering this situation, they are more likely to continue using the e-Learning systems. Thus, we propose the following hypothesis:

**H11**: The behavioral intention to use positively influences continuance intention to use e-Learning during the COVID-19 pandemic.

**Intention to use as a mediator**

Behavioral intention to use (BIU) refers to the behavior intention approach involving action motivation and ideological tendency. Ajzen (1991) defined BIU as “the strength of one’s intention to perform a specified behavior”. Therefore, understanding the indirect influence of intention to use as an important mediator in the context of IS-based studies has been indispensable. For example, Mafabi (2017) analyzed the role of intention to use as a mediator between knowledge sharing and attitude, behavioral control, subjective norms in knowledge sharing behavior. Moreover, Al Amin et al. (2021b) understood intention to use as a mediator in the food delivery application context as consumer attitudes, norms, or behavioral control, which might impact continuance behavior during the COVID-19 pandemic. In this study, we claimed the crucial determinants, which guide the students’ intention to use different e-Learning platforms, might primarily shape students’ behavior to use those platforms repeatedly. Hence, we have posited the following hypotheses:
H12: The intention to use mediates the impact of a) perceived ease of use, b) perceived attitudes, c) perceived usefulness, d) social isolation, e) cyberchondria, and f) fear of academic year loss, g) government supports and h) institutional supports on e-Learning continuance intention during COVID-19 pandemic.

Research methodology

Research design

Moreover, since the population and sampling frame were not entirely known, this study chose the non-probability sampling method. The researchers could select the respondents by their subjective judgment (Saunders et al., 2019). Therefore, we decided to choose the purposive sampling method (i.e., judgmental, subjective, or selective sampling techniques), which is one of type of non-probability techniques by which we depend on our own decision while selecting the target audience for their surveys (Saunders et al., 2019) to lessen the convenient sampling technique problems (e.g., generalization of study findings). Besides, this technique enables a researcher to ease data collection with significantly less cost and greater consistency (Hair et al., 2017). Moreover, we focused on a more considerable variation of target respondents, representing the population more. At first, we developed the questionnaire into two sections (demographic information and measurement items). The questionnaire items were then translated into Bangla, the official language of Bangladesh, to better understand our respondents following the back-translation method (Brislin, 1976).

Research participants, and demographics

The study is about the eight-month-long research as part of the researchers’ academic research on e-Learning. The targeted respondents were students whose access was more natural to us from various public and private university students, Bangladesh, regardless of age, gender, and year of study. We have considered those students as respondents who have been intentionally confined during the COVID-19 pandemic and attended at least 10 online classes using any e-Learning platform (e.g., Online class, Zoom, Google meet, LMS, etc.). Most importantly, these students were familiar with coping with the educational expertise to represent basic knowledge of adopting e-Learning in their studies. The demographic profile of the respondents is sown in Table 1.

Data collection and research ethics

We have pretested (pilot study) our questionnaire to the same group of respondents before the actual data collection to ensure and confirm whether the survey questionnaire is understandably appropriate for the research. We have followed the suggestions provided by Dillman (2020) to send emails to respondents in July 2020. We allowed participation from 10 July 2020 to 30 July 2020. At first, we distributed 1050 questionnaires by email to the participants, and 410 responded positively at the first phase. After 2 weeks, we have sent another reminder email and received another 97 responses. A total of 507 responses were received, having a response rate of 48.28%. However, after careful examination of the filled-up questionnaire, we disregarded 67 questionnaires and recorded 440 responses.

Moreover, to confirm ethical issues, we have taken consent from all respondents in consent forms and information sheets, which explained the study’s true purpose. To avoid the overclaim usage of the respondents, they were given flexible time to fill in the questionnaire. The respondents were also
made aware of their rights to withdraw participation at any time during the study period. Confidentiality and anonymity were ensured in this study.

**Research measures**

We have used five Likert scales ranging from 1 (=Strongly Disagree) to 5 (=Strongly Agree). We built the main question items based on our conceptual framework. We have extracted the measurement item from existing research. The adopted measurement items and their sources are summarized in Appendix-A.

**Data analysis**

Structural Equation and Modeling (SEM) is used in this research to analyze causal models or equations comprehensively and simultaneously. SEM analyzes a complex model with a series of dependent variables (Cohen et al., 2018). However, there are two categories of SEM, namely CB-SEM and PLS-SEM. CB-SEM (covariance-based SEM) analyses the fit among the observed

| Table 1. Demographic profile of the respondents. |
|------------------------------------------------|
| **Variables** | **Number** | **Percentage, %** |
| Gender       |            |                  |
| Male         | 246        | 56               |
| Female       | 194        | 44               |
| Age          |            |                  |
| Below 20     | 210        | 47.7             |
| 21–24        | 130        | 29.5             |
| 25–30        | 100        | 22.72            |
| Universities|            |                  |
| DIU          | 65         | 14.77            |
| BUFT         | 65         | 14.77            |
| EWU          | 50         | 11.36            |
| BSMRSTU      | 150        | 34.1             |
| DU           | 110        | 25               |
| Levels       |            |                  |
| 1st year     | 40         | 09.1             |
| 2nd Year     | 35         | 0.08             |
| 3rd year     | 95         | 21.6             |
| 4th year     | 140        | 31.81            |
| Masters      | 120        | 27.27            |
| Internet users|          |                  |
| Mobile broadband | 165 | 37.5 |
| Wi-fi        | 275        | 62.5             |
| Devices      |            |                  |
| SMART phone  | 260        | 59               |
| Computer     | 110        | 25               |
| Tab          | 60         | 13.63            |
| Others       | 10         | 2.27             |
variables grounding in the covariance matrix, and PLS-SEM (Partial Least Square SEM) examines
the dependent and independent variables to maximize the explained variances based on the forecast
and estimation (Hair et al., 2017). Moreover, PLS-SEM also forecasts the degree of changes in
endogenous constructs due to a set of exogenous constructs (Wang et al., 2019). The structured
relationships and the confirmatory factor analysis (CFA) are measured in this study using SMART
PLS3 software (Hair et al., 2017).

Common method bias

We have performed Lindell and Whitney (2001) to undertake a theoretical-unrelated factor as a
marker variable to check the probability of common method bias (CMB). We have also taken
another survey variable not utilized in this study as a marker (workplace incivility). The $R^2$
(coefficient of correlation) and the marker variable showed low correlation (Maximum $R^2 = \text{0.00471}$). It shows that our study data does not comprise the CMB problem.

Research validation and discussion

Validating Measurement Model

The research model was validated by testing the outer measurement model following the suggestion
given by (Hair et al., 2017). We have tested the model’s construct reliability by examining roh_A,
CR, and Cronbach Alpha; the convergent validity was approved by AVE and factor loadings, and
the discriminant validity was tested by Fornell and Lacker criteria and HTMT ratio.

Construct reliability and convergent validity

We have ensured the construct reliability by recommendations of (Hair et al. (2017)). They
suggested that composite reliability (CR) be more than 0.7, explaining 70% of the measurement
model’s variation. Our analysis also validated the measurement model by the reference range given
Hair et al. (2017) for Cronbach’s alpha and roh_A, ranging from 0 to 1. The closer value near to
01 explains greater consistency. They mentioned the cut-off value is 0.7 (α: >0.7; rhoA: >0.7).
Moreover, we have confirmed convergent validity by AVE (average variance extracted) and cross-
loadings. According to Hair et al. (2017), the cut-off value for AVE for each construct was greater
than 0.5, representing 50% of the variance in the research model. The required criteria for roh_A,
CR, Cronbach Alpha, AVE, and factor loadings were met for each construct given in Table 2.

The discriminant validity by the Fornell and Lacker criteria and HTMT Ratio. To test the measurement
model’s discriminant validity, we examined the Fornell and Lacker criteria (see Table 3) and
heterotrait-monotrait ratio of correlations (HTMT) in Table 4. Fornell and Lacker criteria show that
the diagonal value resembles AVE’s squared root while the other cell represents the correlation. Hair
et al. (2017) suggested having greater diagonal values than off-diagonal values. Table 4 represents
the heterotrait-monotrait ratio of correlations (HTMT), which must be less than 0.85 (HTMT<0.85)
for ensuring validity (Henseler et al., 2015). The above mentioned are met for Discriminant Validity
our research model.
| Constructs                  | Items  | Loadings | CR>0.7 | Cronach’s alpha> 0.7 | rhoA> 0.7 | AVE> 0.5 |
|-----------------------------|--------|----------|--------|----------------------|-----------|----------|
| Continuance intention       | CI1    | 0.887    | 0.812  | 0.845                | 0.883     | 0.657    |
|                             | CI1    | 0.759    |        |                      |           |          |
|                             | CI3    | 0.875    |        |                      |           |          |
|                             | CI4    | 0.705    |        |                      |           |          |
| Intention to use            | IU1    | 0.885    | 0.875  | 0.756                | 0.825     | 0.613    |
|                             | IU1    | 0.713    |        |                      |           |          |
|                             | IU3    | 0.740    |        |                      |           |          |
| Attitudes                   | ATT1   | 0.743    | 0.803  | 0.819                | 0.887     | 0.662    |
|                             | ATT2   | 0.873    |        |                      |           |          |
|                             | ATT3   | 0.810    |        |                      |           |          |
|                             | ATT4   | 0.824    |        |                      |           |          |
| Perceived ease of use       | PEOU1  | 0.801    | 0.764  | 0.784                | 0.880     | 0.710    |
|                             | PEOU2  | 0.883    |        |                      |           |          |
|                             | PEOU3  | 0.841    |        |                      |           |          |
| Perceived usefulness        | PU1    | 0.823    | 0.840  | 0.881                | 0.831     | 0.622    |
|                             | PU2    | 0.746    |        |                      |           |          |
|                             | PU3    | 0.795    |        |                      |           |          |
| Confirmation                | CON1   | 0.813    | 0.851  | 0.780                | 0.871     | 0.629    |
|                             | CON2   | 0.765    |        |                      |           |          |
|                             | CON3   | 0.845    |        |                      |           |          |
|                             | CON4   | 0.745    |        |                      |           |          |
| E-satisfaction              | ESAT1  | 0.913    | 0.756  | 0.764                | 0.895     | 0.683    |
|                             | ESAT2  | 0.745    |        |                      |           |          |
|                             | ESAT3  | 0.870    |        |                      |           |          |
|                             | ESAT4  | 0.765    |        |                      |           |          |
| Social isolation            | SI1    | 0.793    | 0.834  | 0.856                | 0.862     | 0.610    |
|                             | SI2    | 0.746    |        |                      |           |          |
|                             | SI3    | 0.823    |        |                      |           |          |
|                             | SI4    | 0.759    |        |                      |           |          |
| Cyberchondria               | CRD1   | 0.854    | 0.824  | 0.823                | 0.868     | 0.688    |
|                             | CRD2   | 0.887    |        |                      |           |          |
|                             | CRD3   | 0.741    |        |                      |           |          |
| Fear of academic year loss  | FAYL1  | 0.871    | 0.706  | 0.754                | 0.864     | 0.681    |
|                             | FAYL2  | 0.735    |        |                      |           |          |
|                             | FAYL3  | 0.862    |        |                      |           |          |
|                             | FAYL4  | 0.845    |        |                      |           |          |
| Government support          | GS1    | 0.923    | 0.791  | 0.803                | 0.902     | 0.756    |
|                             | GS2    | 0.754    |        |                      |           |          |
|                             | GS3    | 0.921    |        |                      |           |          |
|                             | GS4    | 0.903    |        |                      |           |          |
| Institutional support       | InS1   | 0.745    | 0.841  | 0.839                | 0.936     | 0.712    |
|                             | InS2   | 0.884    |        |                      |           |          |
|                             | InS3   | 0.709    |        |                      |           |          |
|                             | InS4   | 0.795    |        |                      |           |          |
|                             | InS5   | 0.984    |        |                      |           |          |
|                             | InS6   | 0.913    |        |                      |           |          |
Validating Structural model

We have agreed with Henseler et al. (2015) to validate our structural model by squared multiple correlations ($R^2$). We have assessed the t-test value by the routine bootstrapping of 5000 resamples to determine the path coefficient for validating our proposed model using SMART PLS3 software.

Result of the proposed hypotheses, multicollinearity, and model fit. The research model was tested using the bootstrap routine with 5000 resamples for finding out the path coefficient in support of validating the research model using SmartPLS3 software. Result of Path coefficient and hypotheses has been given in Table 5. Table 5 shows that H1a and H1b was supported and the impact of PEOU on IU ($\beta = 0.340$, t statistics = 5.480, $p < 0.001$) and ELCI ($\beta = 0.281$, t statistics = 4.190, $p < 0.001$) was significant. In context of H2a, and H2b, we found that ATT had a significant positive influence on ATT ($\beta = 0.178$, t statistics = 3.79, $p < 0.001$) and CI ($\beta = 0.320$, t statistics = 13.910, $p < 0.001$) in supporting H2a and H2b. Moreover, in H3a, H3b, H3c, H3d, ATT ($\beta = 0.314$, t statistics = 7.30,
Before validating the structural model, the variance inflation factor (VIF) was utilized to assess the lateral collinearity effect. We follow the suggested parameter of Hair et al. (2017) who mentioned that the VIF value of more than 5.00 indicates a multicollinearity issue, and the perfect VIF should be less than 3.00. We confirmed that all of our lateral VIF values ranging between 0.895 to 2.567 are within the referenced value.

The study has also examined the model fit criteria of the structural model, such as standardized root mean square residual (SRMR), RMS_theta, and Normative Fit Index (NFI). The referenced value of SRMR is less than 0.08, and RMS_theta is less than 0.1 (Hair et al., 2019), whereas the
referenced value of NFI must be greater than 0.95 (Hu & Bentler, 1999). Our model confirmed the required criteria (SRMR = 0.048, RMS_theta of 0.086 and NFI = 0.958).

Mediation analysis. The current study has bootstrapped 5000 times to analyze the indirect effect and Sobel test (Sobel, 1982), which checks IU’s mediation effect on CI. Besides, we have also followed the recommended procedure of Baron and Kenny (1986) to estimate the asymmetric confidence intervals (CI). We have employed eight equations for determining indirect effect to assess the mediation effects (shown in Table 7) of IU between CI and PEOU, ATT, PU, SI, CRD, FAYL, GS, InS. In Table 6, we have shown the results that the mediation effect for eight hypotheses was significant with a p value less than 0.05 (p < 0.05) by Sobel test statistics (z value) greater than 1.96 (z > 1.96). According to Hair et al. (2017), the results suggested IU’s partial (complementary) mediation effect among all equations.

Coefficient of determination (R²) and strength of effect. The Table 6, the Coefficient of determination (R²) value for IU and ELCI was 0.786 and 0.812, respectively, which explains 78.6% and 81.2% variation in intention use (IU) and ELCI (e-Learning Continuance Intention (ELCI) are caused by independent variables. In addition, the R² value for ATT = 0.750, PU = 0.734, ESAT = 0.824, CRD = 0.648, FAYL = 0.607.
CRD = 0.731 and FAYL = 0.681 which are accounts for 75%, 73.4%, 82.4%, 73.1% and 68.1% variation in the attitudes, E-Satisfaction, Cyberchondria, and fear of academic year loss consecutively due to the independent variables in the model. Chin (1998) categorized effect sizes ($f^2$) of independent variables into small, medium, and large, with a value of 0.02, 0.15, and 0.35, respectively. From Table 6, we found that the effect size for our model ranges from 0.097 to 2.135.

Blindfolding-based cross-validated redundancy ($Q^2$) was utilized to examine provided parameters’ predictive ability. That the value of $Q^2$ value should be more than zero (0) for a particular endogenous construct for the overall path model’s predictive relevance is suggested by Hair et al. (2017). Our analysis picturized that $Q^2$ satisfied the minimum required criterion (given in Table 6).

**Discussion of study**

The research focused on incorporating TAM and ECM determinants, along with contextual variables (e.g., SI, FAYR, CRD, GS, and InS), to explore Bangladeshi university students’ behavioral intention to use (IU) e-learning platforms during the COVID-19 pandemic continuously as e-Learning platform is the only operational alternative maintaining a physical distance. The results of the path coefficient analysis showed that all of the hypotheses were supported. In hypotheses 1a and 1b, PEOU positively influences ATT and IU for e-learning systems. Our prediction found that ATT and IU’s key determinants for students’ e-learning systems’ continued behavior are PEOU during the outbreaks COVID-19. The previous study also found a similar finding between ATT and PEOU (e.g., Buabeng-Andoh et al., 2019; Muhaimin et al., 2019; Sukendro et al., 2020). A learner’s intention to use the e-Learning system depends on the e-learning system’s complexity concerning the interface system’s ease of use and friendliness. Moreover, previous studies also analogized the positive relationship between PEOU and IU (e.g., Al-Gahtani, 2016; Cheng and Yuen, 2018). This is due to students’ behavioral changes to search for a better alternative which lessens the possibility of COVID-19 infection without hampering educational progress.

In hypotheses 2a, 2b, 2c, and 2d, we hypothesized and found PU positively impacted ATT, IU, ELCI, and ESAT. Sukendro et al. (2020) argued that PU has been the most influential determinant to share the student’s attitudes and IU learning platforms during coronavirus outbreaks. Previous studies also reported the relationship between PU and ATT (e.g., Buabeng-Andoh et al., 2019; Muhaimin et al., 2019). PU was found as an antecedent of intention to use (Al-Gahtani, 2016; Cheng and Yuen, 2018; Lee; 2010; Sukendro et al., 2020) and as an antecedent of ELCI (Al-Gahtani, 2016; Chang et al., 2020; Gan and Balakrishnan, 2017; Wang et al., 2019). The advantageous features of e-learning platforms motivate students to continuously show a positive attitude and intentions to

| Hypotheses | Relationship | b     | Standard error | t-statistics | Sobel test | CI (95%)  | p value |
|------------|--------------|-------|----------------|--------------|------------|-----------|---------|
| H12a       | PEOU->IU->ELCI | 0.087 | 0.010          | 8.698        | z = 2.345  | (0.011, 0.435) | 0.018   |
| H12b       | ATT->IU->ELCI | 0.055 | 0.011          | 4.794        | z = 2.269  | (0.045, 0.194) | 0.021   |
| H12c       | PU->IU->ELCI  | 0.102 | 0.005          | 21.322       | z = 2.733  | (0.026, 0.327) | 0.006   |
| H12d       | SI->IU->ELCI  | 0.104 | 0.006          | 17.046       | z = 2.818  | (0.025, 0.238) | 0.005   |
| H12e       | CRD->IU->ELCI | 0.099 | 0.005          | 21.474       | z = 2.734  | (0.063, 0.532) | 0.006   |
| H12f       | FAYL->IU->ELCI| 0.085 | 0.005          | 17.887       | z = 2.693  | (-0.009, -0.248) | 0.007   |
| H12g       | GS->IU->ELCI  | 0.099 | 0.011          | 9.318        | z = 2.397  | (0.032, 0.438) | 0.016   |
| H12h       | InS->IU->ELCI | 0.097 | 0.008          | 12.809       | z = 2.576  | (0.016, 0.549) | 0.010   |
attend online classes during the COVID-19 pandemic constantly. We forecasted H3a, and H3b and found that ATT positively influences both IU and ELCI. The positive relations between ATT and IU are similar to existing research (e.g., Buabeng-Andoh et al., 2019; Mohammadi, 2015; Muhaimin et al., 2019; Sukendro et al., 2020). Several research pieces (Hong et al., 2006; Hsu et al., 2006; Lee, 2010) found the same relationship between ATT and CI. However, these researchers ignored the situational cues (e.g., pandemic outbreaks) for a developing economy.

In hypotheses 4a and 4b, we showed that CON positively influences PU and ESAT. Bhattacherjee (2001) provides the debates on varying and conflicting conceptualizations of the satisfaction construct in the ECT model. Finally, the relationship was also confirmed by Hsu et al. (2015) in the quality of IT products. Confirmation of expectations leads to higher levels of intimacy and familiarity, which further increases users’ involvement level. CON is positively correlated with PU and ESAT in different forms of IS usage intention (Hayashi et al., 2020; Lee, 2010). The present study also found the same causal relationship as e-learning was able to confirm the students’ long-desired academic progress through online classes during the closure of all educational institutions during pandemic outbreaks.

In hypothesis 5, we predicted that ESAT positively influences ELCI. When students are pleased with the service provided by online classes, the students are intended to have a continued intention to use different e-learning platforms, which can change the students’ anxiety into satisfaction to continue lessons using e-Learning platforms, consistent with the results of (Al-Fraihat et al., 2020; Bhattacherjee, 2001; Hayashi et al., 2020; Joo et al., 2017; Mohammadi, 2015). We argue that as students were being satisfied by services (e.g., online classes, communicating with friends virtually, online exam or quizzes, etc.) provided by e-Learning platforms during COVID-19.

We have hypothesized the influence of SI on IU and CRD in H6a and H6b to continuously use different e-learning platforms during the COVID-19 pandemic. The effect of SI on IU was also analogized (Chiu and Wang, 2008; Raza et al., 2020). In this context, Wilder-Smith and Freedman (2020) pointed out that due to the closure of physical gatherings, including physical classrooms for a long time, social distancing reduces the close contact among the people in a society leading to social isolation around the globe. Attending online classes through e-Learning platforms lessens the possibility of COVID-19 transmission which decreases COVID-19 anxiety among students. Moreover, e-Learning is considered the suitable alternative to the on-campus class maintaining a physical distance. Moreover, previous literature did not analyze the relationship between SI and CRD as the world did face such pandemic before, as per our knowledge. Instead, we argue that during outbreaks students are very concerned about their health. Hence, they search online excessively to receive more information regarding the pandemic outbreaks known as Cyberchondria which fuels them to be anxious, fearful, and distressed related to their education.

Besides, in hypotheses 7a and 7b, we posited that CRD positively influences IU and FAYL e-learning platforms during coronavirus outbreaks. As the epidemics of COVID-19 are still not in the leveraging phase and the Coronavirus’s nature is yet to discover obscure, the students are allowed to continue classes through e-learning platforms only. Some researchers (e.g., Laato et al., 2020) analogized the positive relationship between CRD and intention to make a usual online purchase during COVID-19. However, the existing research lacks the influence of CRD on intention and fear of academic year loss to use e-learning during COVID-19. Accordingly, the intention to use e-learning platforms and FAYL can strongly be predicted by the extent to which a learner intends to regularly searches online content.

Moreover, the hypothesis 8, 9 and 10 showed that FAYL, GS, and InS positively influence IU. Hasan and Bao (2020) found that FAYL has an impact on students’ mental health. However, the extent of literature did not correctly analyze the factors influencing the intention to use e-learning to
remove the barriers of digital disparity continuously. Students have sleeping disorders, mental stress as a result of uncertainty about academic year completion. Although some researchers found that InS and GS positively influence IU (e.g., Ali et al., 2015; Dawi, 2019; Mandari et al., 2017; Reni and Ahmad, 2016) in case of other types of IS based studies, none of these studies were conducted in the context of e-learning platforms during coronavirus outbreaks. However, we have reported this relation as crucial as the learning opportunity discrimination due to families’ financial situations can be solved by GS and InS during COVID-19. In addition, we argue that government and institutions’ support will encourage students to take final examinations and continue classes through e-learning platforms, which might improve the students’ mental conditions related to academic irregularities. Finally, in supporting hypothesis 11, we found that IU influenced continuance behavior to use e-learning platforms. This study result is matched with findings in the case of e-learning continuance behavior (e.g., Rodriguez-Ardura and Meseguer-Artola’s, 2016; Zhou et al., 2020).

Moreover, this study found that intention to use mediated the influence of a) perceived ease of use, b) perceived attitudes, c) perceived usefulness, d) social isolation, e) cyberchondria, and f) fear of academic year loss, g) government supports and h) institutional supports on continuance intention to use different e-Learning platforms. The findings of this study are analogous with Mafabi (2017) who also found the mediating role of BIU in the context of knowledge sharing behavior and Al Amin et al., (2021b), who showed the indirect influence of perceived food safety, delivery hygiene, attitudes, and behavioral control on continuance behaviors through behavioral intention to use food delivery applications. We report this casual the indirect relationship between BIU and continuance intention associated e-learning platform because of students’ changes in attitudes, long time closure of educational institutions, malignance of social distance, and excessive online search of coronavirus diseases.

**Theoretical contribution**

This study provides several theoretical contributions. First, the present study developed and validated the proposed e-Learning Continuance Model (ELCM) by integrating Technology Acceptance Model (TAM) and Expectation-Confirmation Theory (ECT) along with five new variables (i.e., social isolation, Cyberchondria, fear of academic irregularity/fear of academic year loss, the government supports and institutional supports) which is unique in existing literature till to date. Earlier only a few theoretical frameworks were developed to examine the underlying success factors influencing students’ e-Learning continuance intention during COVID-19 outbreaks. Second, the present study has contributed to the extant literature emphasizing contextual variables (i.e., social isolation), psychological variables (i.e., Cyberchondria and fear of academic year loss), and supports related variables (i.e., the government support and institutional support) during the pandemic outbreaks as new dimensions by examining an innovative technology (smartphone), new technological services (e-Learning), conducting in a new outbreak (COVID-19 Pandemic) and a new context (Bangladesh). The new dimensions will impact the students’ critical aspects for establishing the future decision and intention to use e-Learning platforms continuously in any confined situations (e.g., COVID-19 period). Third, the findings of the study contribute to e-Learning literature to examine how policymakers may understand the impact of contextual variables (e.g., social isolation, psychological variables such as Cyberchondria, and various supports from a government and respective institution) on the students’ continuance intention to use e-Learning platforms during a pandemic.

Moreover, government and institutional supports are important to minimize students’ digital discrimination barriers. Existing literature ignored the impact of these supports on students’ e-Learning usage intention. The proposition regarding students’ negative perception of e-Learning
behavior analogized by Rohman et al. (2020) has already been obsolete as e-Learning is considered the only promising alternative to on-campus education with its timely advantages during COVID-19 outbreaks. Finally, the current study contributes methodologically and controls the problems caused by common method variance by using the PLS marker variable approach to estimate structure equations of a series of dependent partial least square (PLS) models. This enables common methods to bias to be strongly controlled by the partial least square (PLS) marker tool.

**Practical implications**

In addition to the theoretical implications, the present study consists of several implications. During the COVID-19 pandemic, the habitual behavior of students changed around the world within a short time, which affected the education sector massively. As the COVID-19 has created a long-term impact on the education sector, most of the educational institutions will offer online courses to students. If any country sees the wave of outbreaks, the only operational alternative to on-campus classes is e-Learning system. The educational institutions can come up with different supports (e.g., network infrastructure, policy packages, and digital security guarantees) confirming these students’ expectation of removing digital discrimination and psychological imbalance such as fear of academic year loss. Hence, it is essential to heighten the investment (i.e., government and institutional supports) for e-Learning in every level of education.

Moreover, the present findings considered empirical instances of the critical dimensions related to students’ psychological distress affecting the students’ intention toward e-Learning during pandemic (e.g., COVID-19) should be implemented by the developers and marketers of e-Learning applications in different contexts and settings. In the proposed research model, it has been depicted that the successful implementation of e-Learning systems and the decrease of fear of academic year loss and Cyberchondria are key to the mental health of students. There are several suggestions to overcome these psychological problems of the students. For example, the educational institutes and teachers can counsel students and provide attractive teaching material, sufficient e-course module, accessibility of e-Learning portal 24/7, error-free information, quality of information, content quality, user-friendly design of the portal, and time to time feedback which ultimately improve the mental health of the students. Various digital marketing techniques (e.g., affiliate marketing) or lucrative opportunities could be considered here to divert these students to e-Learning portals. This will also upsurge the durability and acceptability of the e-Learning portals.

Moreover, the current study also suggests that students should be interested in continuing academic progress to use e-Learning applications due to maintaining social distancing (i.e., SI), which will lessen the COVID-19 transmission. It would be easier to convince students to continue to classes virtually during a pandemic period from an educational institution’s perspective. During a pandemic, such as COVID-19, the authorities would be able to use travel restrictions or social distancing measures as reasons to convince students to continue to adopt e-Learning platforms so they don’t have to visit universities in person. Finally, the present study will help the educational policymakers, government authority, experts, students, teachers, and researchers to recognize the students’ physical and mental health and take quick appropriate measurements to lessen the pandemic outbreaks (e.g., COVID-19) within a short time.

**Concluding remarks**

The study has validated an integrated research model, namely the e-Learning continuance model (eLCM), to find out the determinants of students’ e-Learning continuance intention and to examine
the role of government supports (GS) and institutional support (InS) as the possible solution to learning opportunity-barriers due to e-learning platform emergence during COVID-19 pandemic. Moreover, this study’s findings replaced the proposition regarding students’ negative perception of e-Learning behavior. The e-Learning platform is considered the most promising operational alternative to the traditional learning method (i.e., classroom-based education). While conducting the research, we have faced several limitations. First, this study’s nature is a cross-sectional study that is prone to be methodological biases. Thus, the causality among the study variables can be ensured cautiously. Future studies may undertake a longitudinal study to investigate the study variables’ relationships over time and confirm the variables’ causality. Second, the data were collected during the COVID-19 pandemic, limiting the generalization of the research results compared to a regular period. Social isolation might be varied to different extents depending on the level of the outbreak of COVID-19 in various countries. This study was conducted during the COVID-19 pandemic period in Bangladesh. The severity of the pandemic might affect the adoption of social isolation. Future studies may concentrate on multiple countries to generalize the results across wider geographical regions. Third, since the data were collected from a single source (e.g., the students), the common method variance (CMB) might impact the study. However, the results of the survey confirmed that CMB was not an issue in the present study.

**Author Contributions**

The present study developed and validated the proposed e-Learning Continuance Model (eLCM) by integrating Technology Acceptance Model (TAM) and Expectation-Confirmation Theory (ECT) along with five new variables which are contextual (i.e., social isolation), psychological (academic year loss and cyberchondria), and student support-related determinants (government and institutional supports) being unique in existing literature up to date. No such theoretical framework was developed before to examine the underlying success factors influencing students’ e-Learning continuance intention during COVID-19 outbreaks. Moreover, the present study has contributed to the extent of literature emphasizing contextual, psychological, and student support-related variables during the pandemic outbreaks as new dimensions. Finally, the study has made the proposition regarding students’ negative perception of e-Learning behavior analogized by Rohman et al. (2020) obsolete as e-Learning is considered the only promising operational alternative to on-campus education with its timely advantages during COVID-19 outbreaks in Bangladesh.

**Declaration of conflicting interests**

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

**Funding**

The author(s) received no financial support for the research, authorship, and/or publication of this article.

**ORCID iDs**

Al Amin MD https://orcid.org/0000-0003-2303-082X
Razib Alam MD https://orcid.org/0000-0003-0054-1272

**References**

Adam T, Kaye T and Haßler B (2020) The Maldives and Sri Lanka: Question & Answer Session. 18, June. EdTech Hub. DOI: 10.53832/edtechhub.0018
Ajzen I (1991) The theory of planned behavior. _Organizational Behavior and Human Decision Processes_ 50(2): 179–211. DOI: 10.1016/0749-5978(91)90020-t

Ajzen I and Fishbein M (1980) _Understanding Attitudes and Predicting Social Behavior_. Englewood Cliffs, NJ: Prentice-Hall. Available at: https://nla.gov.au/nla.cat-vn3068475 (accessed 20 October 2021).

Al Amin M, Arefin M, Hossain I, et al. (2021c) Evaluating the Determinants of Customers’ Mobile Grocery Shopping Application (MGSA) Adoption during COVID-19 Pandemic. _Journal of Global Marketing_. DOI: 10.1080/08911762.2021.1980640

Al Amin M, Arefin MS, Alam MR, et al. (2021b) Using Mobile Food Delivery Applications during COVID-19 Pandemic: An Extended Model of Planned Behavior. _Journal of Food Products Marketing_ 27(2): 105–126. DOI: 10.1080/10454446.2021.1906817

Al Amin M, Arefin MS, Sultana N, et al. (2021a) Evaluating the customers’ dining attitudes, e-satisfaction and continuance intention toward mobile food ordering apps (MFOAs): evidence from Bangladesh. _European Journal of Management and Business Economics_ 30(2): 211–229. DOI: 10.1108/EJMBE-04-2020-0066

Al Amin M (2022a) The Influence of Psychological, Situational and the Interactive Technological Feedback-Related Variables on Customers’ Technology Adoption Behavior to Use Online Shopping Applications. _Journal of Global Marketing_. DOI: 10.1080/08911762.2022.2051157

Al Amin M, Arefin MS, Rasul TF and Alam MS (2022b) Understanding the Determinants of Mobile Banking Services Continuance Intention in Rural Bangladesh during the COVID-19 Pandemic. _Journal of Global Marketing_. DOI: 10.1080/08911762.2021.2018750

Alalwan AA (2020) Mobile food ordering apps: An empirical study of the factors affecting customer e-satisfaction and continued intention to reuse. _International Journal of Information Management_ 50: 28–44. DOI: 10.1016/j.ijinfomgt.2019.04.008

Alam A (2020) Challenges and possibilities of online education during covid-19. _Preprints_ 2020: 2020060013. DOI: 10.20944/preprints202006.0013.v1

Al-Fraihat D, Joy M, Masa’deh R, et al. (2020) Evaluating E-learning systems success: An empirical study. _Computers in Human Behavior_ 102: 67–86. DOI: 10.1016/j.chb.2019.08.004

Al-Gahtani SS (2016) Empirical investigation of e-learning acceptance and assimilation: A structural equation model. _Applied Computing and Informatics_ 12(1): 27–50. DOI: 10.1016/j.aci.2014.09.001

Ali M, Syed ali R and Chin-Hong P (2015) Factors affecting intention to use islamic personal financing in pakistan: evidence from the modified. _TRA model_. Available at: https://mpra.ub.uni-muenchen.de/66023/ (accessed 20 October 2021).

Al-Okaily M, Alqudah H, Matar A, et al. (2020) Dataset on the Acceptance of e-learning System among Universities Students’ under the COVID-19 Pandemic Conditions. _Data in Brief_ 32: 106176. DOI: 10.1016/j.dib.2020.106176

Amoroso D and Lim R (2017) The mediating effects of habit on continuance intention. _International Journal of Information Management_ 37(6): 693–702. DOI: 10.1016/j.ijinfomgt.2017.05.003

Amoroso DL and Ogawa M (2011) Japan’s Model of Mobile Ecosystem Success: The Case of NTT DoCoMo. _Journal of Emerging Knowledge on Emerging Markets_ 3(1). DOI: 10.7885/1946-651x.1064

Anderson RE and Srinivasan SS (2003) E-satisfaction and e-loyalty: A contingency framework. _Psychology and marketing_ 20(2): 123–138. DOI: 10.1002/mar.10063

Bao W (2020) COVID-19 and online teaching in higher education: A case study of Peking University. _Human Behavior and Emerging Technologies_ 2(2): 113–115. DOI: 10.1002/hbe2.191

Baron RM and Kenny DA (1986) The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. _Journal of Personality and Social Psychology_ 51(6): 1173–1182. https://psycnet.apa.org/buy/1987-13085-001

Bhattacherjee A (2001). Understanding Information Systems Continuance: An ExpectationConfirmation Model, _MIS Quarterly_, 25(3). 351–370. DOI: 10.2307/3250921.
Bhattacherjee A, Perols J and Sanford C (2008) Information technology continuance: a theoretic extension and empirical test. *Journal of Computer Information Systems* 49(1): 17–26. DOI: 10.1080/08874417.2008.11645302.

Brislin RW (1976) Comparative research methodology: cross-cultural studies. *International Journal of Psychology* 11(3): 215–229. DOI: 10.1080/00207597608247359.

Buabeng-Andoh C, Yaokumah W and Tarhini A (2019) Investigating students’ intentions to use ICT: A comparison of theoretical models. *Education and Information Technologies* 24(1): 643–660. DOI: 10.1007/s10639-018-9796-1.

Cakır R and Solak E (2015) Attitude of turkish EFL learners towards e-Learning through tam model. *Procedia - Social and Behavioral Sciences* 176: 596–601. DOI: 10.1016/j.sbspro.2015.01.515.

Chang C-C, Liang C and Chiu Y-C (2020) Direct or indirect effects from "perceived characteristic of innovation" to "intention to pay": mediation of continuance intention to use e-learning. *Journal of Computers in Education*. DOI: 10.1007/s40692-020-00165-6.

Cheng M and Yuen AHK (2018) Student continuance of learning management system use: A longitudinal exploration. *Computers & Education* 120: 241–253. DOI: 10.1016/j.compedu.2018.02.004.

Cheng Y-M (2020) Investigating medical professionals’ continuance intention of the cloud-based e-learning system: an extension of expectation–confirmation model with flow theory. *Journal of Enterprize Information Management*. ahead-of-print. DOI: 10.1108/jeim-12-2019-0401.

Chin WW (1998) Commentary: Issues and Opinion on Structural Equation Modeling. *MIS Quarterly* 22(1). 7–16. Available at: https://www.jstor.org/stable/249674.

Chiu C-M and Wang ETG (2008) Understanding Web-based learning continuance intention: The role of subjective task value. *Information & Management* 45(3): 194–201. DOI: 10.1016/j.im.2008.02.003.

Chow WS and Shi S (2014) Investigating Students’ Satisfaction and Continuance Intention toward E-learning: An Extension of the Expectation – Confirmation Model. *Procedia - Social and Behavioral Sciences* 141: 1145–1149. DOI: 10.1016/j.sbspro.2014.05.193.

Cohen L, Manion L and Morrison K (2018) *Research Methods in Education*. 8th ed. New York, NY: Routledge.

Dahlstrom E, Brooks D and Bichsel J (2014) The current ecosystem of learning management systems in higher education: Student, faculty, and IT perspectives. *Louisville: ECAR*. DOI: 10.13140/RG.2.1.3751.6005.

Daugherty M and Funke BL (1998) University Faculty and Student Perceptions of Web-Based Instruction. *The Journal of Distance Education/Revue de l’education Distance* 13(1): 21–39. Available at: https://www.learntechlib.org/p/86789/(accessed 20 October 2021).

Davis FD (1989) Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly* 13(3): 319–340. DOI: 10.2307/249008.

Davis FD, Bagozzi RP and Warshaw PR (1989) User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science* 35(8): 982–1003. DOI: 10.1287/mnsc.35.8.982.

Dawi NM (2019) Factors Influencing Consumers Intention to Use QR Code Mobile Payment – A Proposed Framework. *International Journal of Recent Technology and Engineering (IJRTE)* 8(2s).

Dhaka Tribune(2021) UGC, GP Sign MoU to Facilitate Online Classes of Public, Pvt Univs. Media LTD. https://www.dhakatribune.com/bangladesh/2020/11/12/ugc-gp-sign-mou-to-facilitate-online-classes-of-public-pvt-univs

Dhawan S (2020) Online Learning: A Panacea in the Time of COVID-19 Crisis. *Journal of Educational Technology Systems* 49(1): 5–22. DOI: 10.1177/0047239520934018

Dillman D. A. (2000) Mail and internet surveys: The tailored design method. John Wiley & Sons New York: Wiley.

Eccles JS (1987) Gender Roles and Women’s Achievement-Related Decisions. *Psychology of Women Quarterly* 11(2): 135–172. DOI: 10.1111/j.1471-6402.1987.tb00781.x
Eizenberger R, Huntington R, Hutchison S, et al. (1986) Perceived organisational support. *Journal of Applied Psychology* 71(3): 500–507. DOI: 10.1037/0021-9010.71.3.500

Farooq A, Laato S and Islam AKMN (2020) The Impact of Online Information on Self-isolation Intention during the COVID-19 Pandemic: A cross-sectional study (Preprint). *Journal of Medical Internet Research* 22(5). DOI: 10.2196/19128

Fishbein M and Ajzen I (1975) Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research. *Contemporary Sociology* 6(2): 244. DOI: 10.2307/2065853

Gan CL and Balakrishnan V (2017) Predicting acceptance of mobile technology for aiding student-lecturer interactions: An empirical study. *Australasian Journal of Educational Technology* 33: 143–158.

Ghani WAWAbK, Rusli IF, Biak DRA, et al. (2013) An application of the theory of planned behaviour to study the influencing factors of participation in source separation of food waste. *Waste Management* 33(5): 1276–1281. DOI: 10.1016/j.wasman.2012.09.019

Hair JF (2017) *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Los Angeles: Sage.

Hamid AAbd, Razak FZA, Baka AA, et al. (2016) The Effects of Perceived Usefulness and Perceived Ease of Use on Continuance Intention to Use E-Government. *Procedia Economics and Finance* 35: 644–649. DOI: 10.1016/s2212-5671(16)00079-4

Hasan N and Bao Y (2020) Impact of "e-Learning crack-up" perception on psychological distress among college students during COVID-19 pandemic: A mediating role of "fear of academic year loss. *Children and Youth Services Review* 118(105355): 105355. DOI: 10.1016/j.childyouth.2020.105355

Hayashi A, Chen C, Ryan T, et al. (2004) The Role of Social Presence and Moderating Role of Computer Self Efficacy in Predicting the Continuance Usage of E-Learning Systems. *Journal of Information Systems Education* 15(2): 139–154. Available at: https://aizel.aisnet.org/jise/vol15/iss2/5/(accessed 20 October 2021).

Hayashi R, Garcia M, Maddawin TF, et al. (2022b) Understanding the Determinants of Mobile Banking Services Continuance Intention in Rural Bangladesh during the COVID-19 Pandemic. *Journal of Global Marketing*. Vol. ahead-of-print No. ahead-of-print, Vol. ahead-of-print No. ahead-of-print. DOI: 10.1080/08911762.2021.2018750

Hayashi R, Garcia M, Maddawin A, et al. (2020). *Online Learning in Sri Lankas Higher Education Institutions during the Covid-19 Pandemic*. DOI: 10.22617/BRF200260-2

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

Hong S, Thong JYL and Tam KY (2006) Understanding continued information technology usage behavior: A comparison of three models in the context of mobile internet. *Decision Support Systems* 42(3): 1819–1834. DOI: 10.1016/j.dss.2006.03.009

Hsu M-H, Yen C-H, Chiu C-M, et al. (2006) A longitudinal investigation of continued online shopping behavior: An extension of the theory of planned behavior. *International Journal of Human-Computer Studies* 64(9): 889–904. DOI: 10.1016/j.ijhcs.2006.04.004

Hsu M-H, Chang C-M and Chuang L-W (2015) Understanding the determinants of online repeat purchase intention and moderating role of habit: The case of online group-buying in Taiwan. *International Journal of Information Management* 35(1): 45–56. DOI: 10.1016/j.ijinfomgt.2014.09.002

Jæger MM and Blaabæk EH (2020) Inequality in Learning Opportunities during Covid-19: Evidence from Library Takeout. *Research in Social Stratification and Mobility* 68: 100524. DOI: 10.1016/j.rssm.2020.100524

Jena PK (2020) Impact of Covid-19 on higher education in India. *International Journal of Advanced Education and Research* 5(3): 77–81.
Jokić-Begić N, Mikac U, Ćuržik D, et al. (2019) The Development and Validation of the Short Cyberchondria Scale (SCS). *Journal of Psychopathology and Behavioral Assessment* 41(4): 662–676. DOI: 10.1007/s10862-019-09744-z

Joo S and Choi N (2016) Understanding users’ continuance intention to use online library resources based on an extended expectation-confirmation model. *The Electronic Library* 34(4): 554–571. DOI: 10.1108/el-02-2015-0033

Joo YJ, So H-J and Kim NH (2018) Examination of relationships among students’ self-determination, technology acceptance, satisfaction, and continuance intention to use K-MOOCs. *Computers & Education* 122: 260–272. DOI: 10.1016/j.compedu.2018.01.003

Jou M and Wang J (2013) Observations of achievement and motivation in using cloud computing driven CAD: Comparison of college students with high school and vocational high school backgrounds. *Computers in Human Behavior* 29: 364–369. DOI: 10.1016/j.chb.2012.08.001

Kang J-W and Namkung Y (2019) The role of personalisation on continuance intention in food service mobile apps. *International Journal of Contemporary Hospitality Management* 31(2): 734–752. DOI: 10.1108/ijchm-12-2017-0783

Karahanna E, Straub DW and Chervany NL (1999) Information Technology Adoption Across Time: A Cross-Sectional Comparison of Pre-Adoption and Post-Adoption Beliefs. *MIS Quarterly* 23(2): 183. DOI: 10.2307/249751

Khan A, Egbue O, Palkie B, et al. (2017) Active learning: Engaging students to maximize learning in an online course. *Electronic Journal of e-Learning* 15(2): 107–115.

Kim YG and Woo E (2016) Consumer acceptance of a quick response (QR) code for the food traceability system: Application of an extended technology acceptance model (TAM). *Food Research International* 85: 266–272. DOI: 10.1016/j.foodres.2016.05.002

Laato S, Islam AKMN, Farooq A, et al. (2020) Unusual purchasing behavior during the early stages of the COVID-19 pandemic: The stimulus-organism-response approach. *Journal of Retailing and Consumer Services* 57: 102224. DOI: 10.1016/j.jretconser.2020.102224

Lee M-C (2010) Explaining and predicting users’ continuance intention toward e-learning: An extension of the expectation–confirmation model. *Computers & Education* 54(2): 506–516. DOI: 10.1016/j.compedu.2009.09.002

Lee B-C, Yoon J-O and Lee I (2009). Learners’ Acceptance of E-Learning in South Korea. *Theories and Results. Computers & Education* 53(4): 1320–1329. DOI: 10.1016/j.compedu.2009.06.014

Limayem M and Cheung CMK (2008) Understanding information systems continuance: The case of Internet-based learning technologies. *Information & Management* 45(4): 227–232. DOI: 10.1016/j.im.2008.02.005

Lin CS, Wu S and Tsai RJ (2005) Integrating perceived playfulness into expectation-confirmation model for web portal context. *Information & Management* 42(5): 683–693. DOI: 10.1016/j.im.2004.04.003

Lin H-F (2007) Predicting consumer intentions to shop online: An empirical test of competing theories. *Electronic Commerce Research and Applications* 6(4): 433–442. DOI: 10.1016/j.elerap.2007.02.002

Lin K-M (2011) e-Learning continuance intention: Moderating effects of user e-learning experience. *Computers & Education* 56(2): 515–526. DOI: 10.1016/j.compedu.2010.09.017

Lin Y-T, Wen M-L, Jou M, et al. (2014) A cloud-based learning environment for developing student reflection abilities. *Computers in Human Behavior* 32(March): 244–252. DOI: 10.1016/j.chb.2013.12.014

Lindell MK and Whitney DJ (2001) Accounting for common method variance in cross-sectional research designs. *Journal of Applied Psychology* 86(1): 114–121. DOI: 10.1037/0021-9010.86.1.114

Mafabi S, Nasiima S, Muhimbize EM, et al. (2017) The mediation role of intention in knowledge sharing behaviour. *VINE Journal of Information and Knowledge Management Systems* 47(2): 172–193. DOI: 10.1108/vjikms-02-2016-0008
Mandari HE, Chong Y-L and Wye C-K (2017) The influence of government support and awareness on rural farmers’ intention to adopt mobile government services in Tanzania. *Journal of Systems and Information Technology* 19(1/2): 42–64. DOI: 10.1108/jsit-01-2017-0005

Martinez J (2020) Take this pandemic moment to improve education. Available at: https://edsource.org/2020/take-this-pandemic-moment-to-improve-education/633500 (accessed 20 October 2021).

McGill TJ and Klobas JE (2009) A task–technology fit view of learning management system impact. *Computers & Education* 52(2): 496–508. DOI: 10.1016/j.compedu.2008.10.002

Mohammadi H (2015) Investigating users’ perspectives on e-learning: An integration of TAM and IS success model. *Computers in Human Behavior* 45: 359–374. DOI: 10.1016/j.chb.2014.07.044

Mtebe JS and Raphael C (2018) Key factors in learners’ satisfaction with the e-learning system at the University of Dar es Salaam, Tanzania. *Australasian Journal of Educational Technology* 34(4). DOI: 10.14742/ajet.2993

Muhamin HA and Mukminin A (2019) Predicting factors affecting intention to use Web 2.0 in learning: evidence from science education. *Journal of Baltic Science Education* 18(4). DOI: 10.33225/jbse/19.18.595

Nguyen TTH, Nguyen N, Nguyen TBL, et al. (2019) Investigating Consumer Attitude and Intention towards Online Food Purchasing in an Emerging Economy: An Extended TAM Approach. *Foods* 8(11): 576. DOI: 10.3390/foods8110576

Qazi A, Tamjidymacholo A, Raj RG, et al. (2017) Assessing consumers’ satisfaction and expectations through online opinions: Expectation and disconfirmation approach. *Computers in Human Behavior* 75: 450–460. DOI: 10.1016/j.chb.2017.05.025

Rambocas M and Arjoon S (2012) Using Diffusion of Innovation Theory to Model Customer Loyalty for Internet Banking: A TT Millennial Perspective. *International Journal of Business and Commerce* 1(8): 1–14.

Ray A, Dhir A, Bala PK, et al. (2019) Why do people use food delivery apps (FDA)? A uses and gratification theory perspective. *Journal of Retailing and Consumer Services* 51: 221–230. DOI: 10.1016/j.jretconser.2019.05.025

Raza SA, Qazi W, Khan KA, et al. (2020) Social Isolation and Acceptance of the Learning Management System (LMS) in the time of COVID-19 Pandemic: An Expansion of the UTAUT Model. *Journal of Educational Computing Research*. DOI: 10.1177/0735633120960421

Reni A and Ahmad NH (2016) Application of theory reasoned action in intention to use islamic banking in Indonesia. *Al-Iqtishad: Journal of Islamic Economics* 8(1). DOI: 10.15408/aiq.v8i1.2513

Rodriguez-Ardura I and Meseguer-Artola A (2016) E-learning continuance: The impact of interactivity and the mediating role of imagery, presence and flow. *Information & Management* 53(4): 504–516. DOI: 10.1016/j.im.2015.11.005

Rohman M and Sudjimat DA (2020) Online Learning in Higher Education During Covid-19 Pandemic: Students’ Perceptions. *Journal of Talent Development and Excellence* 12(2s): 3644–3651. Available at: https://iratde.com/index.php/jtde/article/view/1272 (accessed 23 June 2021).

Saeed Al-Marooof R, Alhumaid K and Salloum S (2020) The Continuous Intention to Use E-Learning, from Two Different Perspectives. *Education Sciences* 11(1): 6. DOI: 10.3390/educsci11010006

Saunders M, Lewis P and Thornhill A (2019) *Research Methods for Business Students*. 8th ed. Harlow, United Kingdom; New York: Pearson.

Shahzad A, Hassan R, Aremu AY, et al. (2020) Effects of COVID-19 in E-learning on higher education institution students: the group comparison between male and female. *Quality & Quantity*. DOI: 10.1007/s11135-020-01028-z

Shankar A and Jebaraajakirthy C (2019) The influence of e-banking service quality on customer loyalty. *International Journal of Bank Marketing* 37(5): 1119–1142. DOI: 10.1108/ijbmr-03-2018-0063

Singh V and Thurman A (2019) How many ways can we define online learning? a systematic literature review of definitions of online learning (1988-2018). *American Journal of Distance Education* 33(4): 289–306. DOI: 10.1080/08923647.2019.1663082
Sintema EJ (2020) Effect of COVID-19 on the Performance of Grade 12 Students: Implications for STEM Education. *Eurasia Journal of Mathematics, Science and Technology Education* 16(7). DOI: 10.29333/ejmste/7893

Sobel ME (1982) Asymptotic Confidence Intervals for Indirect Effects in Structural Equation Models. *Sociological Methodology* 13: 290–312. DOI: 10.2307/270723

Sukendro S, Habibi A, Khaeruddin K, et al. (2020) Using an extended Technology Acceptance Model to understand students’ use of e-learning during Covid-19: Indonesian sport science education context. *Heliyon* 6(11): e05410. DOI: 10.1016/j.heliyon.2020.e05410

Taylor S and Todd P (1995) Assessing IT Usage: The Role of Prior Experience. *MIS Quarterly* 19(4): 561. DOI: 10.2307/249633

Teo T, Huang F and Hoi CKW (2017) Explicating the influences that explain intention to use technology among English teachers in China. *Interactive Learning Environments* 26(4): 460–475. DOI: 10.1080/10494820.2017.1341940

Umrani-Khan F and Iyer S (2009) ELAM: A Model for Acceptance and Use of Elearning by Teachers and Students. Reading: 4th International Conference on e-Learning. Canada: University of Toronto Academic Publishing.

Vahdat A, Alizadeh A, Quach S, et al. (2020) Would you like to shop via mobile app technology? The technology acceptance model, social factors and purchase intention. *Australasian Marketing Journal (AMJ)*. DOI: 10.1016/j.ausmij.2020.01.002

Venkatesh V and Bala H (2008) Technology Acceptance Model 3 and a Research Agenda on Interventions. *Decision Sciences* 39(2): 273–315. DOI: 10.1111/j.1540-5915.2008.00192.x

Venkatesh V and Davis FD (2000) A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science* 46(2): 186–204. DOI: 10.1287/mnsc.46.2.186.11926

Venkatesh V, Thong JYL and Xu X (2012) Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly* 36(1): 157. DOI: 10.2307/41410412

Vismara M, Caricasole V, Starcevic V, et al. (2020) Is cyberchondria a new transdiagnostic digital compulsive syndrome? A systematic review of the evidence. *Comprehensive Psychiatry* 99: 152167. DOI: 10.1016/j.comppsych.2020.152167

Wang L-Y-K, Lew S-L, Lau S-H, et al. (2019) Usability factors predicting continuance of intention to use cloud e-learning application. *Heliyon* 5(6): e01788. DOI: 10.1016/j.heliyon.2019.e01788

Wilders-Smith A and Freedman DO (2020) Isolation, quarantine, social distancing and community containment: pivotal role for old-style public health measures in the novel Coronavirus (2019-nCoV) outbreak. *Journal of Travel Medicine* 27(2). DOI: 10.1093/jtm/taaa020

Wolfinbarger M and Gilly MC (2003) eTailQ: dimensionalising, measuring and predicting etail quality. *Journal of Retailing* 79(3): 183–198. DOI: 10.1016/s0022-4359(03)00034-4.

Yen T-F (TF) (2020) The Performance of Online Teaching for Flipped Classroom Based on COVID-19 Aspect. *Asian Journal of Education and Social Studies*: 57–64. DOI: 10.9734/ajess/2020/v8i330229.

Yeo VCS, Goh S-K and Rezaei S (2017) Consumer experiences, attitude and behavioural intention toward online food delivery (OFD) services. *Journal of Retailing and Consumer Services* 35: 150–162. DOI: 10.1016/j.jretconser.2016.12.013.

Zhang S, Zhao J and Tan W (2008) Extending TAM for online learning systems: An intrinsic motivation perspective. *Tsinghua Science and Technology* 13(3): 312–317. DOI: 10.1016/S1007-0214(08)70050-6.

Zhou L, Wu S, Zhou M, et al. (2020) School’s out, but class“ On”, the largest online education in the world today: taking china’s practical exploration during The COVID-19 epidemic prevention and control as an example. *SSRN Electronic Journal*. DOI: 10.2139/ssrn.3555520.
## Appendix-A: measurement items

| Research constructs and source | Measurement items |
|-------------------------------|-------------------|
| **Perceived ease of use (PEOU)** <br> (Venkatesh et al., 2012) and Davis (1989) | PEOU1: My university’s e-learning system is easy to use  
PEOU2: My university’s e-learning system is clear and understandable  
PEOU3: My university’s e-learning system saves me a lot of time and energy |
| **Perceived usefulness (PU)** <br> Bhattacherjee, et al., (2008) and Yeo et al. (2017) | PU1: I will find My university’s e-learning system to be useful in my virtual class  
PU2: My university’s e-learning system would enable me to accomplish shopping more quickly than using a traditional classroom  
PU3: Using an e-learning system would enhance my effectiveness in attending classes or information seeking |
| **Attitudes (ATT)** <br> Amoroso and Lim, 2017 and Lin (2011) | ATT1: It is a good idea to use an e-learning system  
ATT2: I am strongly in favor of the e-learning system  
ATT3: I desire to use an e-learning system when I think of my academic life  
ATT4: My perception of the e-learning system is positive |
| **Confirmation (CON)** <br> Bhattacherjee, 2001  
Joo and Choi, 2016  
Kim, 2016 | EXP1: My experience with using an e-learning system was better than what I expected  
EXP2: The service level provided by the e-learning system was better than what I expected  
EXP3: Overall, most of my expectations from using the e-learning system were confirmed  
EXP4: The expectations that I have regarding the e-learning system were correct |
| **E-satisfaction (E-SAT)** <br> Alalwan, 2020; Anderson and Srinivasan, 2003 | E-SAT1: I am generally pleased with my university’s e-learning system  
E-SAT2: My choice to use my university’s e-learning system was a wise one  
E-SAT3: I am very satisfied with my university’s e-learning system  
E-SAT4: I am satisfied with the way that my university’s e-learning system has carried out virtual classes |
| **Social isolation (SI)** <br> Chiu and Wang (2008) | SI1: I get influenced by the e-learning system due to the lack of opportunities for face-to-face interactions during COVID-19  
SI2: I think the e-learning system increases opportunities due to having face-to-face interactions COVID-19  
SI3: e-learning system removes the barrier of social isolation COVID-19  
SI4: I think e-learning system increases may remove the fear of academic year loss even if I am confined in the covid-19 period |

(continued)
| Research constructs and source | Measurement items |
|-------------------------------|-------------------|
| Cyberchondria (CRD) (Jokić-Begić et al., 2019) | CRD1: I feel frightened after reading information about COVID-19 online  
CRD2: I feel frustrated after reading information about COVID-19 online  
CRD3: Once I start reading information about COVID-19 online, it is hard for me to stop |
| Fear of academic year loss (FAYL) Hasan and Bao (2020) | FYAL1: It is uncertain when the academic session will start  
FYAL2: I am afraid with assessment systems if public examination may not be held  
FYAL3: I become nervous concerning the academic year decision  
FYAL4: I am worried about my future higher studies because I probably would not admit myself |
| Government supports (GS) Shankar and Jebarajkirthy (2019) Wolfinbarger and Gilly (2003) | GS1: During the COVID-19 pandemic, the government encourages to attend online classes using an e-learning system  
GS2: During the COVID-19 pandemic, the government controls e-learning system platforms  
GS3: Government authorities provide extra services to the users of the e-learning system during COVID-19  
GS4: During the COVID-19 pandemic, the government provided e-learning system facilities (e.g., interest-free loans, security to attend online classes, devices support, etc.) are important to use online classes |
| Institutional support (InS) Eizenberger et al. (1986) | InS1: Help (e.g., quality internet facilities, mental supports, reduced rate of tuition fees) is available from the university when I have a problem using e-learning platforms  
InS 2: The university cares about my well-being  
InS 3: The university strongly considers my goals and values  
InS 4: The university would grant a reasonable request for a change in my academic schedule and assignment  
InS 5: The university takes pride in my accomplishments  
InS 6: The university disregards my best interests when it makes decisions that affect me |
| Behavioral intention to use (IU) Venkatesh et al. (2012) and Chiu and Wang (2008) | IU1: I intend to continue using learning system in the future  
IU2: I will always try to use an e-learning system in my daily life  
IU3: I plan to continue to use the e-learning system. Frequently |
Research constructs and source Measurement items

Continuance intention (CI) (Bhattacherjee et al., 2008); Amoroso and Ogawa (2011); Cho et al., 2019

| CI1: I intend to use an e-learning system for my university class |
| CI2: If I have an opportunity, I will attend classes through the e-learning system |
| CI3: I intend to keep using the e-learning system |
| CI4: I intend to continue using the e-learning system for unceasing academic progress during COVID-19 |

Author Biographies

**Mr. Md Al Amin** is an Assistant Professor of Marketing, Bangabandhu Sheikh Mujibur Rahman Science and Technology University (BSMRSTU), Gopaganj-8100, Bangladesh. He is currently pursuing his M.Phil degree from the Department of Marketing, University of Dhaka, Bangladesh. He is also an MBA (major in marketing) from the University of Dhaka, Bangladesh. Mr. Al Amins main research area is the consumer technology adoption behavior, service profit chain, social media marketing and tourism. He has published 15+ research works in different top tier national and intentional journals (e.g., Journal of Food Products Marketing, E-Learning and Digital Media, Journal of Global Marketing, European Journal of Management and Business Economics, Academy of Strategic Management Journal etc.).

**Dr. Md Razib Alam** is an Associate Professor at the Department of Marketing, University of Dhaka, Bangladesh. He pursued his Ph.D and MASc from the University of Waterloo, Canada. Dr. Alams main research area is in the innovation landscape, Technological Diversity, Invention Ownership, and University Intellectual Property Policies. His research works appeared in different reputed national and international journals.

**Dr. Mohammad Zahedul Alam** is an Associate Professor at the Department of Marketing, Bangladesh University of Professionals, Dhaka, Bangladesh. He pursued his Ph.D from Wuhan University of Technology, China. Dr. Alam’s research interest is Services Marketing, Technology Adoption in Services, Post-adoption behaviour of consumer, m-Health behaviour. His research works appeared in different reputed national and international journals (e.g., International Journal of Information Management, Journal on Innovation and Sustainability, Technology in Society, Journal of Marketing Communications).