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Mobile learning using extended UTAUT model during COVID-19: evidence from developed countries

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ABSTRACT

This research evaluates the extended unified theory of acceptance and use of technology (UTAUT) model from the context of mobile-based learning using smartphones amid COVID-19. It specifically examines the impact of exogenous variables such as social isolation besides standard dimensions and mediating variables such as perceived compatibility, perceived anxiety, and perceived value on mobile learning technology. The research also explores the impact of service quality and technological innovation as moderating variables on the modified and extended UTAUT model. The data for this research was gathered from 898 students in technologically advanced countries, for instance, Canada, the United Kingdom, Spain, France, the United States, Australia, and Germany. The outcomes of this research show that the exogenous dimensions of the UTAUT model, such as social isolation, have an affirmative and significant association with the behavioral intent to adopt mobile-based learning in an online education environment. The study's findings further exhibited that the mediating dimensions, such as perceived anxiety, perceived compatibility, and perceived value, have a robust and affirmative association between exogenous and endogenous factors. Moreover, the results demonstrated a strong influence of technological innovation and service quality on the association between independent and dependent factors. Overall, the research findings have significant implications for both industry and academia regarding management and theory.

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1. Introduction

Coronavirus erupted from the Chinese province of Wuhan in November 2019 and quickly spread to other countries such as Iran and Italy (Lu et al., 2020). According to Raza et al. (2021) and Ahmed et al. (2020), the World Health Organization announced a pandemic due to its speedy spread, significantly increasing mortality. Consequently, people worldwide were frightened, and governments of different countries declared an emergency and implemented lockdowns to slow the spread of the coronavirus (Ahmed et al., 2020). As a part of this response, many governments closed down educational institutions to safeguard the health of students and staff. As the pandemic continued, many governments issued directives promoting online education as an alternative, leading to a widespread shift toward online learning (Faqih, 2022a). The pandemic has led to the extensive acceptance of virtual learning, with students shifting from on-campus to online classrooms through various digital platforms, for instance, Google Classroom, MS Team, Zoom, Moodle, Blackboard, and others (Ismail et al., 2016). The panic over COVID-19 significantly affected the global education system, increasing mobile learning accessible through smartphones and other mobile devices (Faqih, 2022b). In online education, mobile-based learning is seen as an affordable and convenient way to access online education during the pandemic, as it permits students to access online education from everywhere through various software and learning management systems (LMS) (Faqih, 2022a; Raza et al., 2021).

The current literature has demonstrated several definitions for mobile-based learning, in which Crompton (2013) has exhibited the most accepted, such as 'learning in multiple contexts, through social interactions'. In this definition, the multiple contexts defined mobile learning because m-learning offers multiple options of online learning opportunities, for instance, flexibility in mobility, hustle-free transportation, and access to mobile applications of different learning software (Ahmed et al., 2022; Bannan et al., 2016). Mobile-based learning (m-learning) has increased in popularity during the COVID-19 pandemic due to its flexibility and accessibility (Faqih & Jaradat, 2015). The main concern for practitioners and researchers is cultivating a positive and innovative vision for implementing a mobile-based online education system (Faqih, 2022a). Despite the availability of several conceptual frameworks for mobile learning, these concepts still need to be fully developed, and there is a need for comprehensive validation of previous understandings (Bannan et al., 2016; Crompton, 2013). Previous studies have been conducted on learning management systems (LMS) during COVID-19. However, there is a need to further discover the effectiveness of mobile-based learning in an online education environment, particularly amid the COVID-19 pandemic, with additional dimensions (Raza et al., 2021; Faqih & Jaradat, 2015). According to previous literature, for instance, Ismail et al. (2016) and Bannan et al. (2016), mobile-based learning needs to be revised, and the results need to be reevaluated in the background of mobile-based learning in an online education environment. Earlier literature has shown that mobile-based education combines mobile technology (such as smartphones) and learning, creating an interface between learning and technology (Chen, 2018; Demir & Akpınar, 2018). However, it is essential to establish a flexible learning environment through mobile technology that provides a robust online educational environment for mobile learning rather than relying on a physical classroom (Ahmed et al., 2022; Khan et al., 2015). It allows for a greater emphasis on behavioral and social simulations, which can benefit the teaching and learning process.

The current study aims to examine the extended UTAUT model with new dimensions, such as social isolation, as independent variables during COVID-19. The research develops a novel modified conceptual framework of the extended UTAUT model. It examines the impact of m-learning in an online environment during COVID-19 with the help of additional independent, mediating, and moderating variables. However, other online learning gadgets, such as laptops, desktops, and iPads, are also used. However, this research aims to analyze the effectiveness of smartphone usage for online learning. Therefore, this study only caters to smartphone devices for m-learning during and after COVID-19. This novel study employs an extended UTAUT model with social isolation as an independent construct. In addition, this research includes perceived anxiety, perceived value, and perceived compatibility as mediating constructs in the novel extended UTAUT model. Finally, it incorporates two moderating variables, service quality and technological innovation, in the extended UTAUT model. This comprehensive study addresses the multidimensional extended UTAUT model to examine the impact of mobile-based learning on students' behavioral intention in an online environment during COVID-19. The significance and novelty of this article are multidimensional, such as the development of a novel conceptual framework with the extended UTAUT theory. The undertaken study offers a comprehensive and novel standpoint on the impact of mobile-based education amid the COVID-19 pandemic. In conclusion, this research examines mobile-based learning using a multifaceted and novel conceptual framework with the extended UTAUT theory (Venkatesh et al., 2012). While previous literature has used the UTAUT model, this research expands on those studies by incorporating additional dimensions (Faqih, 2022a; Raza et al., 2021; Demir & Akpınar, 2018). The study outcomes demonstrated a significant managerial and theoretical contribution important for industry practitioners and future researchers (Camilleri & Camilleri, 2020; Khan et al., 2015).

2. Review of previous literature

2.1. Mobile-based learning technology

The mobile-based learning platform has completely transformed the way of acquiring knowledge and education, taking advantage of the modernization of mobile technology and information communication technology (ICT). According to Raza et al. (2021), COVID-19 has potently influenced the higher education system, leading to widespread closures of universities and a shift towards home-based learning. The development of mobile learning technologies is driven by their immense potential for providing knowledge and learning without limitations of time and space. Mobile-based learning environments differ from other learning devices because they allow for a more precise, mobile, creative, inventive, collaborative, and easy way to access and deliver educational content (Camilleri & Camilleri, 2020; Miller & Cuevas, 2017).

These positive attributes have led to qualitative and transformative changes in the learning context (Faqih, 2022a; Khan et al., 2015). The mobile-based learning environment encourages customization and personalization, and mobile learning technology uses dynamic content modification to enhance learning materials. Previous literature has shown customized learning can increase motivation and engagement in acquiring desired knowledge and skills (Aliaño et al., 2019). The mobile-based learning system offers a unique solution to overcome the limitations of the online education environment (Bernacki et al., 2020; Almisad & Alsalim, 2020).

2.2. The UTAUT model

The technology acceptance model (TAM) is a widely used theoretical model that describes how individuals adopt and accept new technology (Davis, 1989). However, the TAM model has some limitations when applied to more complex backgrounds, and a more comprehensive technology model is needed to address these complexities (Chung et al., 2019; Davis et al., 1989). The extended unified theory of acceptance and use of technology (UTAUT) model is a suggested technology model that aims to address the limitations of previous models by being more robust. The UTAUT model was offered by Venkatesh et al. (2003). The UTAUT model is reliable, statistically significant, robust, and effective and has been widely used in several (IT) fields to solve complex problems and functions (Venkatesh et al., 2012). The potency of the UTAUT model lies in its integrative context, which includes eight prominent technology acceptance dimensions. The UTAUT model is suitable for more complex IT issues and has been found to provide 20-30% more robust results than the TAM model (Faqih, 2022a). The UTAUT model is a theoretical framework that explains why and how individuals embrace and use technology. Due to its comprehensive theoretical basis, it has been widely used and accepted in several fields, for instance, education, information systems, and healthcare. It has also been tested and cited globally in numerous studies and research articles (Venkatesh et al., 2003; Chen & Hwang, 2019).

2.3. Extended UTAUT model

Previous literature demonstrated that several new dimensions had been identified and successfully assimilated into the traditional UTAUT model, which exhibited that the UTAUT model has enormous flexibility to extend according to the technical issue and examine the problem without removing its dimensions (Aliaño et al., 2019; Thomas et al., 2020; Alshurideh et al., 2020). Previous studies have shown that the traditional UTAUT model has been adapted, integrated, and extended to meet a study's specific objectives and acceptance criteria for a particular technological problem (Kohnke et al., 2019). Several researchers, for instance, Thomas et al. (2020) and Kohnke et al. (2019), have identified and successfully incorporated new dimensions into the original UTAUT model, demonstrating its flexibility to be extended according to the technical issue and examine the problem without removing its dimensions. The current study follows the same tradition of extending the UTAUT model to better context-learning during the COVID-19 pandemic (Ahmed et al., 2022). Therefore, several researchers have conducted studies using the extended UTAUT model to understand better the reception process in different information technology (IT) fields (Rahi et al., 2018). Similarly, the current study has extended the UTAUT model by incorporating one exogenous variable (social isolation), three mediating variables (perceived compatibility, perceived anxiety, and perceived value), and two moderating variables (service quality and technological innovation) to evaluate the impact of mobile-learning and its impact on students' behavioral intention (Thomas et al., 2020; Raza et al., 2021).

2.4. Hypotheses development

2.4.1. Effort expectancy (EE)

According to Venkatesh et al. (2003), in the UTAUT model, effort expectancy (EE) is one of the critical determinants of an individual's behavioral intent to adopt mobile-based learning in an online education environment. The basic idea behind this concept is that personal motivation is necessary for accepting a technological innovation. The model suggests that people are more likely to embrace and use technology if they perceive it as requiring low effort. Venkatesh et al. (2012) state that effort expectancy is the degree of ease associated with using a particular system. They argue that effort expectancy is one of the essential elements of an individual's behavioral intent to adopt mobile-based learning in an online education environment. Mobile technology has some complexities that could be a barrier to its acceptance due to negative attitudes and anxiety levels, which may decrease the motivation to accept the behavioral intention (Venkatesh et al., 2003; Alshurideh et al., 2020). Greater effort expectancy leads to higher acceptance of mobile-based learning. Previous literature results have shown that effort expectancy (EE) has an affirmative impact on behavioral intentions to adopt mobile-based technological innovations for learning (Alawani & Singh, 2017; Nassuora, 2013). Hence, the researchers have articulated the hypothesis as follows:

> **Hypothesis H1:** The effort expectancy has a positive and significant relationship with behavioral intention to adopt mobile learning.

2.4.2. Performance expectancy (PE)

The concept of performance expectancy (PE) is one of the most potent factors among the original dimensions of the UTAUT theory. Several studies have evidently and empirically evaluated PE as a significant dimension of accepting technological modernization (Thomas et al., 2020; Faqih & Jaradat, 2015). The findings of almost all studies have confirmed that performance expectancy correlates significantly with the acceptance of using novel technological platforms. In the UTAUT model, performance expectancy (PE) is described as 'the extent to which individuals trust for using a specific system that helps to enhance their work performance in a technological environment' (Venkatesh et al., 2003). Performance expectancy (PE) could also be defined from the mobile-based online education perspective as 'the individual believes and motivates to achieve the online learning objectives through mobile-based learning

(Almisad & Alsalim, 2020)'. Numerous research studies have established that performance expectancy (PE) has a cogent and affirmative association with behavioral intention to adopt mobile-based learning in an online education environment (Ahmed et al., 2022; Bernacki et al., 2020). Hence, the researchers have articulated the hypothesis as follows:

Hypothesis H2: Performance expectancy has a positive and significant relationship with behavioral intention to adopt mobile learning.

2.4.3. Social influence (SI)

Social influence is also one of the critical determinants of an individual's behavioral intention to adopt and use technology (Alsswey et al., 2020; Venkatesh et al., 2003). The theory of planned behavior (TPB) is a theoretical framework that clarifies how and why individuals engage in certain behaviors. It also introduced the concept of social influence, widely accepted in technology (Fishbein & Ajzen, 1975). Previous literature has shown that social influence strongly correlates with the behavioral intent to adopt mobile-based learning in an online education environment (Yang, 2013; Kang et al., 2015; Raza et al., 2021). Previous literature has also established that the stimulus of others, in the form of both subjective norms and perceived behavioral control, shows a significant function in the acceptance and use of mobile-based learning technology in online education (Wan Hamzah et al., 2020; Hao et al., 2017; Thomas et al., 2020). It is imperative to explore the role of social influence and how it influences the reception and adoption of mobile-based learning in different backgrounds. Hence, the researchers have articulated the hypothesis as follows:

Hypothesis H3: The social influence has a positive and significant relationship with behavioral intention to adopt mobile learning.

2.4.4. Facilitating conditions

In the UTAUT model, technical support is considered a facilitating condition, which refers to the resources and assistance an organization provides to enable the use and adoption of technology. According to Venkatesh et al. (2003), facilitating conditions is crucial, especially from the perspective of innovation acceptance. (Kang et al., 2015). According to Thomas et al. (2020), Raza et al. (2021), and Ahmed et al. (2022), the facilitating condition was used as a set of psychological methods to assess the influence of FC on mobile-based education in the online environment. Preceding literature has demonstrated an affirmative and robust association between facilitating conditions and behavioral intent to adopt mobile-based learning (Aliaño et al., 2019; Alshurideh et al., 2020; Thomas et al., 2020). Studies have found that the availability of technical help and other facilitating conditions, such as training and documentation, positively impact individuals' intention to embrace and use mobile-based learning technology (Faqih, 2022a; Rahi et al., 2018). According to Alsswey et al. (2020) and Al-Adwan et al. (2018), individuals are more likely to embrace and use mobile-based learning technology when these conditions are present. Hence, the researchers have articulated the hypothesis as follows:

Hypothesis H4: The facilitating conditions have a positive and significant relationship with behavioral intention to adopt mobile learning.

2.4.5. Social isolation

The COVID-19 pandemic has considerably influenced the overall education system globally, with many institutions shifting to virtual education to resume learning and teaching. According to Ahmed et al. (2020), this change has led to the enhancement or adoption of mobile devices and m-learning. The COVID-19 pandemic has led to widespread social isolation as people must stay home to avoid spreading the virus. It has resulted in many physical and mental health issues and a shift in educational practices towards online modes of learning (Garrett, 2020; Rahi et al., 2018). Therefore, this research has incorporated social isolation as an extended dimension of UTAUT to examine its influence on behavioral intention toward mobile-based learning during COVID-19. Mobile devices have become increasingly prevalent due to the COVID-19 pandemic, as people have been forced to stay home and adapt to remote working and learning (Faqih, 2022a; Raza et al., 2021). It has also changed how businesses and educational institutions provide services and resources, with many shifting to mobile-friendly and mobile-optimized solutions (Kang et al., 2015; Hao et al., 2017). Hence, the researchers have articulated the hypothesis as follows:

Hypothesis H5: Social isolation has a positive and significant relationship with behavioral intention to adopt mobile learning.

2.5. Extended UTAUT model with mediating constructs

2.5.1. Perceived anxiety

Perceived anxiety is a cognitive feeling of danger and threat posed by stressors and an individual ability to cope with these dangers and threats. Information technology (IT) products and services are not easy for the general population, which can create a certain level of fear, anxiety, and stress. This fear, stress, and anxiety caused by using IT products and services are known as technophobia, also called the fear of technological innovation (Nagar, 2016). Similarly, people may be unfamiliar with smartphones or Android mobile devices, referred to as mobile anxiety (Faqih, 2022b; Faqih & Jaradat, 2015). Many studies have been conducted on technology-related anxiety, negatively influencing technology acceptance. They also looked at the adverse influence of anxiety to adopt the technology and its benefits (Faqih, 2020; Imran et al., 2016). This construct is considered a mediating variable in this research, and it examines the influence of fear of smartphone technology in an online learning environment (Tout et al., 2019; Moore & Benbasat, 1991). However, perceived anxiety has not been extensively studied from the perspective of mobile-based schooling, especially in an online education environment during COVID-19 (Raza et al., 2021; Rusli et al., 2008). As a result, we have outlined the following hypothesis:

Hypothesis H6: Perceived anxiety significantly and negatively mediates between effort expectancy, performance expectancy, social influence, facilitating conditions, social isolation, and behavioral intention to adopt mobile learning.

2.5.2. Perceived value

Perceived value is a crucial determinant of users' perceptions regarding the acceptance and usage of Internet services and technologies in various areas of life, significantly affecting satisfaction and social status (Wan Hamzah et al., 2020; Kang et al., 2015). It is essential to contemplate the influence of perceived value on m-learning acceptance behavior to develop successful and effective mobile-based learning experiences (Raza et al., 2021; Imran et al., 2016). Perceived value denotes how individuals perceive the practice of technology to enhance their social status within society and culture. This perception can be influenced by factors such as the availability and accessibility of technology and how it is marketed and perceived by others in the community (Tout et al., 2019; Ahmed et al., 2022). The current study has used an extended UTAUT theory to evaluate the mediation of perceived value in adopting mobile-based learning. Several studies have confirmed that perceived value significantly mediates the extended UTAUT theory and behavioral intention to adopt m-learning technologies (Faqih, 2022b; Jaradat et al., 2020; Moore & Benbasat, 1991). Hence, the researchers have formulated the subsequent hypothesis:

> **Hypothesis H7:** Perceived value significantly and positively mediates between effort expectancy, performance expectancy, social influence, facilitating conditions, social isolation, and behavioral intention to adopt mobile learning.

2.5.3. Perceived compatibility

The diffusion theory and innovation acceptance have proposed and theorized the concept of perceived compatibility (Faqih, 2022b; Jaradat et al., 2020). Perceived compatibility is now widely used as a mediator to examine the acceptance of various digital platforms and technologies (Nguyen et al., 2020; Hsu & Lin, 2016). This research has integrated perceived compatibility as a mediating variable between the extended UTAUT model and behavioral intention to use m-learning (Faqih, 2022b; Miller & Cuevas, 2017; Alshurideh et al., 2020). Perceived compatibility provides a user-friendly and conducive technological platform for mobile-based learning. Several studies have included perceived compatibility in the UTAUT and TAM model and have found that Perceived compatibility has an affirmative and cogent influence between extended UTAUT model and behavioral intention towards m-learning technology for online learning (Kang et al., 2015; Raza et al., 2021; Ahmed et al., 2022). Hence, the researchers have formulated the subsequent hypothesis:

> **Hypothesis H8:** Perceived compatibility significantly and positively mediates between effort expectancy, performance expectancy, social influence, facilitating conditions, social isolation, and behavioral intention to adopt mobile learning.

2.6. Extended UTAUT model with moderating constructs

2.6.1. Service quality

Service quality is crucial in internet-related technologies, including e-banking, e-shopping, e-service centers, online education, and other mobile-based services (Alsswey et al., 2020; Chen & Hwang, 2019). According to Raza et al. (2021), service quality also plays a vital role in an online education environment through mobile-based learning technology. Earlier studies have shown that service or e-service quality improves the quality of work, user-friendliness, and productivity (Baccari & Neji, 2016). It highlights the importance of considering service quality as a vital element in understanding the use of mobile-based learning during COVID-19. The study includes service quality as a moderating variable on the association between the extended UTAUT theory and behavioral intention towards mobile-based learning during COVID-19 (Ahmed et al., 2022). Numerous studies have examined the influence of service quality as a moderator on the acceptance of m-learning in an online environment and have established a potent and affirmative impact on behavioral intention (Almaiah & Alismaiel, 2019; Al-Nassar, 2020; Akter et al., 2013). Hence, the researchers have formulated the subsequent hypothesis:

Hypothesis H9: Service quality significantly moderates between effort expectancy, performance expectancy, social influence, facilitating conditions, social isolation, and behavioral intention to adopt mobile learning.

2.6.2. Technological innovation

The factors influencing people's adoption of technological innovation include functional aspects, social prospects, psychological aspects, imperative and economic needs, and situational and environmental reasons (Almaiah & Alismaiel 2019). Huang et al. (2020) have introduced the new concept of technological innovation as a perceived innovation in IT acceptance behavior. They argue that innovation should be incorporated into technology adoption models, as technology-savvy consumers are more likely to take risks with innovations and technologies and more willing to try new experiments. It highlights the importance of considering technological innovation as a crucial element in understanding the adoption of m-learning during COVID-19 (Raza et al., 2021; Faqih, 2022a). Preceding studies have also demonstrated that technology or technological innovation is a significant moderator in mobile-based learning in an online education environment (Al-Nassar, 2020; Huang et al., 2020; Makki et al., 2016). Hence, the researchers have formulated the subsequent hypothesis:

Hypothesis H10: Technological innovation significantly moderates effort expectancy, performance expectancy, social influence, facilitating conditions and social isolation, and behavioral intention to adopt mobile learning.

3. Materials AND METHODS

3.1. Sampling strategy and research design

This research examines the impact of mobile learning technologies in higher education during COVID-19. However, other online learning gadgets, such as laptops, desktops, and iPads, are also used. However, this research aims to analyze the effectiveness of smartphone usage for online learning. Therefore, this study only caters to smartphone devices for m-learning during COVID-19. The quantitative research technique is employed to achieve the objective of the current study. The cross-sectional survey questionnaire is a commonly used and preferred method for dataset gathering and analysis in such studies. The researchers have gathered the responses from those students who have used mobile learning during COVID-19, for instance, from March 2020 to January 2022. After that period, students returned to traditional classroom learning in the most advanced countries. Thus, the longitudinal survey was not employed to carry out this research due to the study's objectivity; the primary objective was to examine the effectiveness of mobile learning technologies in online education during COVID-19. The current research used a modified five-point Likert scale to accumulate 898 responses from technologically advanced countries. The research employed a convenient sampling strategy to collect data, as the desired sampling frame was unknown because researchers need to know how many students have used smartphones for online learning during COVID-19. Secondly, the disadvantage of probability sampling is the recruitment of an undesirable or redundant sample, for instance, those respondents who did not use smartphones for online education; instead, they used laptops, desktops, and iPads. Therefore, to achieve the objective of this research, researchers used a non-probability sampling technique. Secondly, the sampling frame is unknown. Thus, this research employed a non-probability sampling technique (Sekaran & Bougie, 2016). The researchers have used convenient sampling; convenience sampling is a non-probabilistic technique in which the researcher chooses participants that are readily available or accessible to them and fulfill the study's objectivity.

3.2. Measurement scaling

The scales of a traditional UTAUT model and extended dimensions were taken from previous research studies. However, the items of the constructs were tailored and modified according to the objectives of this research study. The scales for the classic dimensions of the UTAUT model, such as social influence, effort expectancy, facilitating conditions, and performance expectancy, taken from earlier studies, for instance, Venkatesh et al. (2012), Thomas et al. (2020), and Venkatesh et al. (2003). Moreover, the scales of extended predictor social isolation and behavioral intention were extracted from previous literature, such as Kang et al. (2015), Yang (2013), Raza et al. (2021), Thomas et al. (2020), Ahmed et al. (2022), and Faqih (2022a). The measures or items for perceived value, perceived anxiety, and perceived compatibility were extracted from previous studies (Faqih, 2022b; Tout et al., 2019; Moore & Benbasat, 1991), (Faqih, 2022b; Nagar, 2016; Imran et al., 2016), and (Faqih, 2022b; Nguyen et al., 2020; Hsu & Lin, 2016) respectively. The scales for service quality were extracted from earlier literature (Baccari & Neji, 2016; Akter et al., 2013), and technological innovation items were taken from Al-Nassar (2020), Huang et al. (2020), and Almaiah and Alismaiel (2019). The current research has used a modified (altered according to the study's objective and demographic and cultural factors) and structured five-point Likert scale to accumulate responses; the detailed measurement scaling with citations is provided in Table A1 (Appendix 1).

3.3. Data collection method

The current research used a modified five-point Likert scale to accumulate responses. The dataset was collected both in-person and online using a convenient sampling technique. The participants were undergraduate, graduate, post-graduate, Ph.D., and post-doctoral students from different disciplines. The data was collected from September 2020 to January 2022; it took more than a year to collect the desired data during and after COVID-19. The data of 898 respondents was collected from students of technologically advanced countries, including Canada, the USA, Germany, the United Kingdom, Australia, Spain, and France. Since the data was collected from different countries with diverse ethnicity, education, and experience, it was essential to examine any biases. The data cleansing and biases were examined in sub-section 4.4 of the study, and it was found that there was an absence of biases. It allowed the researchers to proceed with the further analysis of the data without any concerns about the probable effect of biases on the outcomes. The data was collected online using social media, Google Docs, personal emails, LinkedIn, and University contacts. The research used a sample of 224 responses from the USA, 119 from the United Kingdom, 121 from Canada, and 113 from Australia. Additionally, 109 responses were collected from Germany, 107 from France, and 105 from Spain.

3.4. Estimation techniques

The study used SEM-based multivariate modeling, which requires validation of the hypothesized extended UTAUT model through the validation of measurement and structural models. This study employed various statistical techniques, for instance, multicollinearity diagnosis, to evaluate the multicollinearity among the predictors. To validate the measurement model, the researchers have employed exploratory factor analysis with a rotated component matrix, cross-loading, Fornell & Larcker criterion, Bartlett's Sphericity & KMO techniques, and total variance explained analysis. These techniques commonly establish convergent and discriminant validities, data suitability, and total variance explained among the constructs (Lu et al., 2020). The confirmatory factor analysis and fit indicators are used to measure and validate the structural and measurement models. The study presents fit indices to support the proposed hypothesized structural and measurement models. Lastly, the study employed the conditional process approach to evaluate and measure the constructs' direct and indirect (mediation and moderation) association (Hayes & Rockwood, 2020).

3.5. Demographic analysis

The study focuses on students who studied online during COVID-19 through m-learning. A structured questionnaire was sent to 1000 students from technologically advanced countries, and we received 898 complete responses. Therefore, it is established that the response rate was 89.80%. There were 505(56.2%) males, and 393(43.8%) females' respondents. The overall age group of respondents in age brackets from 18 to over 60 years. 388(43.2%) undergraduate students must complete their first university degree. Similarly, 286(31.8%) graduate students have completed their first Bachelor's degree. Of the Ph.D. scholars and post-doctoral researchers (8.9%), 144(16.0%) respondents belonged to the post-graduation education bracket, including a Master's degree or a post-graduation diploma in any field. Thus, fellows are technically students at different levels, from undergraduate to post-doctoral research. The experience bracket started from 1 year to 15 years, in which graduate, post-graduate, and Ph.D. scholars and post-doctoral research fellows have different years of experience. Finally, the income bracket of respondents belongs to 30K to 150K per annum as per their education and experience. The findings of Table A2 in Appendix 2 exhibited the details of demographic information regarding the respondents.

4. Findings and results

4.1. Descriptive statistics

To analyze the primary characters of the variables, descriptive analysis was used. The study showed descriptive statistics, demonstrating that the standard deviation and skewness readings are within the threshold range of ±1.5, and kurtosis values fall within the limit of ±3. It suggested that the considered dataset follows the normality pattern, a prerequisite for using the CB-SEM approach (Hair et al., 2020; Lu et al., 2020).

4.2. Exploratory factor analysis—EFA

This research used the EFA approach to confirm the reliabilities and validities of variables and items. Firstly, the study extracted the rotated component matrix. To determine the reliabilities, the study used factor loading (FL), Cronbach's alpha (CA), and composite reliabilities (CR) for indicators and variables. The study also used factor loading (FL) and average variance extracted (AVE) to examine the validities of factors and items. Table A3, presented in Appendix 3, shows that the FL for each indicator ranges from 0.880 to 0.950, and composite reliability readings are more significant than 0.70, confirming the convergent validity of factors and indicators (Lu et al., 2020). The study establishes the discriminant validities of the factors through the readings of AVE, as readings of each construct are more potent than 0.50; hence, the condition of discriminant validity was also achieved. Hence, the reliability and validity of each item and factor are endorsed. Therefore, the study concludes that further research on SEM-based multivariate modeling can be performed (Ahmed, 2023; Hair et al., 2020).

4.3. Cross-Loading statistics

The findings of Table A4 were presented in Appendix 4, describing and highlighting items of the constructs that have higher loadings than the corresponding cross-loadings of other items of different constructs, which again establishes the discriminant validities of each item. In factor analysis, items that measure the same construct will have high inter-item correlation and load on the same factor. On the other hand, items that measure different constructs will have low inter-item correlation and load on different factors (Hussain et al., 2019).

4.4. Multicollinearity and data biases analysis

The study showed the descriptive statistics in Table 1, demonstrating that the standard deviation and skewness readings are within the threshold range of ±1.5, and kurtosis values fall within the limit of ±3. It suggested that the considered dataset follows the normality pattern, a prerequisite for using the CB-SEM approach (Ahmed, 2023; Hair et al., 2020). The researchers also evaluated the potential biases through the variance inflation factor and found no multicollinearity among the independent variables. Table 1 demonstrated the variance inflation factor (VIF) values that showed each independent construct is less than the benchmark of 3.3 (Hussain et al., 2019). Hence, it is established that the absence of multicollinearity among the predictors also demonstrates the nonexistence of data biases.

4.5. Fornell & Larcker discriminant validity

Table 2 demonstrates the values of the Fornell & Larcker (1981) criterion, which established the discriminant validities of all constructs. Table 2 exhibited that the square root of AVE readings is more potent (as seen in the diagonal readings) than the correlation between constructs. Hence, it has been established that the factors are distinct and discriminant validities have been achieved.

4.6 KMO and Bartlett's Sphericity analysis

The acceptability of the dataset is validated through two imperative techniques, for instance, Kaiser-Meyer-Olkin (KMO) and Bartlett's Sphericity, in an SEM-based multivariate approach. A KMO value ranging from 0.70 to 0.79 is generally considered satisfactory, and a value of 0.720 falls within this range, demonstrating that the considered dataset is acceptable for the SEM-based multivariate technique. Similarly, the probability of Bartlett's Sphericity is less than 0.05, indicating the data's suitability for the SEM-based analysis (Hair et al., 2020).

4.7. Total variance extracted

The findings of total variance explained that the sample data is suitable for SEM-based analysis. The cumulative variance of seven variables is 85.88%, more significant than the cut-off reading of 50%. Additionally, the eigenvalues of the individual variables are more significant than 1, which is a sign of consistency and relevance of the accumulated data for structural equation modeling (Lu et al., 2020).

4.8. Confirmatory factor analysis—CFA

The CFA approach is used to authenticate a proposed measurement model using observed and latent variables (Ahmed, 2023; Hair et al., 2020). The hypothesized measurement extended UTAUT model includes five predictors. The effort expectancy has three indicators; performance expectancy has four items; social influence has four indicators; social isolation and facilitating conditions have three indicators each. The

Table 1. Multicollinearity and data biases analysis.

Multicollinearity Diagnosis[a]

Predictors	Collinearity Statistics	
	Tolerance	VIF
Performance Expectancy	0.322	3.105
Effort Expectancy	0.488	2.049
Social Influence	0.462	2.164
Facilitating Conditions	0.340	2.941
Social Isolation	0.310	3.225

[a]Dependent Variable: Behavioral Intention.
Source: Authors through their estimations.

Table 2. Fornell and Larcker Discriminant validity.

Factors	BI	PE	EE	SI	FC	SOI	PA	PC	PV	SQ	TI
Behavioral Intention	0.818										
Performance Expectancy	0.746	0.881									
Effort Expectancy	0.751	0.806	0.883								
Social Influence	0.436	0.465	0.487	0.786							
Facilitating Conditions	0.627	0.376	0.546	0.512	0.749						
Social Isolation	0.515	0.508	0.552	0.436	0.702	0.821					
Perceived Anxiety	0.637	0.679	0.731	0.449	0.607	0.673	0.866				
Perceived Compatibility	0.561	0.567	0.677	0.432	0.576	0.532	0.675	0.845			
Perceived Value	0.675	0.554	0.544	0.411	0.598	0.609	0.567	0.765	0.787		
Service Quality	0.566	0.378	0.621	0.395	0.612	0.599	0.633	0.623	0.609	0.799	
Technological Innovation	0.629	0.728	0.679	0.389	0.549	0.621	0.787	0.611	0.567	0.621	0.801

Source: Authors through their estimations.

model also includes one dependent construct, behavioral intention, with four items and three mediating variables: perceived anxiety, perceived compatibility, and perceived value, each with various indicators (Hair et al., 2020). The measurement model incorporates mediating variables such as perceived anxiety (with three indicators), perceived compatibility (with four indicators), and perceived value (with three indicators. Moreover, it also includes two moderating constructs: service quality and technological innovation, with three and four indicators, respectively. The model also includes one dependent variable, behavioral intention, with four indicators. Therefore, the study includes 11 factors, covering 38 indicators in the considered measurement model (Hair et al., 2020). The findings of Table 3 demonstrated that all fit-indices values are within the threshold limit for a good fit of the model (Ahmed, 2023; Hair et al., 2020). Hence, it is confirmed that the proposed measurement model is validated for behavioral intention to adopt m-learning during COVID-19.

4.9. Structural equation modeling—SEM

The SEM-based multivariate technique was also used to examine the proposed structural model using AMOS software (Hair et al., 2020). The hypothesized structural model includes 11 factors, covering 38 indicators described in the previous sub-section 4.9. The fit-statistic or indices values support the proposed hypothesized structural model, validated for behavioral intention. Table 3 exhibited that the fit indices readings fall within the threshold limit of fit indices (Ahmed, 2023; Hair et al., 2020). Therefore, the hypothesized structural model is validated for the behavioral intention to adopt the m-learning environment.

Table 3. Model Fit-indices for Measurement and Structural model.

A goodness of Fit Measures	Absolute Fit Indices			Relative Fit Indices			Non-centrality-based Indices			Parsimonious Fit Indices	
	$\chi2$/df	Probability	GFI	NFI	IFI	TLI	CFI	RMSEA	RNI	PCFI	PNFI
Measurement Model	3.39	0.0033	0.96	0.95	0.97	0.96	0.97	0.034	0.98	0.86	0.87
Structural Model	3.44	0.0047	0.97	0.94	0.98	0.97	0.96	0.031	0.99	0.85	0.86
Criterion (Threshold values)	<5.0	<0.05	>0.95	>0.90	>0.95	>0.95	>0.95	<0.05	>0.95	>0.75	>0.75

Note. TLI: Tucker-Lewis Index; $\chi2$/d: Relative Chi-square; GFI: Goodness of Fit Index; RMSEA: Root mean squared error of approximation; CFI: Comparative fit index; NFI: Normed fixed index; IFI: Incremental fixed index; RNI: Relative Non-Centrality Index; PNFI: Parsimony-adjusted normed fit index; PCFI: Parsimonious-adjusted fit index. Source: Authors' estimation. Source: Authors through their estimations.

4.10. Hypothesized direct association

Table 4 in the study shows the proposed direct relationship between independent constructs; for instance, social influence, performance expectancy, facilitating conditions, effort expectancy, and social isolation demonstrated an affirmative and cogent relationship with behavioral intention. The individual effect of each independent variable demonstrated the most substantial influence of effort expectancy with a coefficient of 0.6180 on the outcome variable. The outcomes of Table 4 demonstrated that performance expectancy has the second highest impact, with a coefficient of 0.2115 on behavioral intention, followed by social isolation with a coefficient of 0.1431 and facilitating conditions with a coefficient of 0.1128. Social isolation has the most negligible impact, with a coefficient of 0.1074 on behavioral intention. Therefore, the study established that all the independent constructs significantly and positively influence behavioral intention. Thus, it is finally confirmed that hypotheses H1 to H5 are validated.

4.11 Mediation analysis

Table 5 in the study showed a significant mediation of perceived anxiety, perceived compatibility, and perceived value between independent constructs: effort expectancy, social influence, facilitating conditions, performance expectancy, and social isolation and behavioral intention. Two methods were used to evaluate the mediation: 1) the Bootstrapping technique and 2) the Sobel or Normal theory method. Table 5 demonstrated that zero has not occurred between the Boot LLCI and Boot ULCI, indicating a perfect mediation (Hayes & Rockwood, 2020). Table 5 also showed the results of the Sobel technique or the Normal theory approach and demonstrated the same conclusion that perceived anxiety, perceived compatibility, and perceived value significantly influence the association between exogenous and endogenous factors. However, perceived anxiety has a significant but negative influence between independent and dependent factors. Therefore, it is finally concluded that the hypotheses H6, H7, and H8 are supported.

4.12. Proposed hypothesized moderation

Hayes and Rockwood (2020) have demonstrated that moderation is measured through conditioned process analysis. The findings of Table 6 exhibited that service

Table 4. Proposed direct association.

Hypotheses	Independent Variables	Dependent Variable	Regression Paths	Standardized Regression weights (β)	SE	T	P	Decision
H1:	Performance Expectancy	Behavioral Intention	PE → BI	0.2115	0.0348	6.25	0.0000	Supported
H2:	Effort Expectancy	Behavioral Intention	EE → BI	0.6180	0.0296	21.05	0.0000	Supported
H3:	Social Influence	Behavioral Intention	SI → BI	0.1431	0.0309	4.71	0.0000	Supported
H4:	Facilitating Conditions	Behavioral Intention	FC → BI	0.1128	0.0258	4.44	0.0000	Supported
H5:	Social Isolation	Behavioral Intention	SOI → BI	0.1074	0.0228	5.95	0.0000	Supported

Source: Authors through their estimations.

Table 5. Hypothesized mediating effect.

		Bootstrapping Method				Normal Theory Method				
Hypotheses	Mediation	Indirect Effect	Boot SE	Boot LLCI	Boot ULCI	Indirect Effect	SE.	Z*	Prob.**	Decision
H6	PE→PA→BI	−0.1028	0.0292	−0.7660	−0.8811	−0.1028	0.0204	−5.04	0.0000	Supported
	EE→PA→BI	−0.0711	0.0126	−0.0467	−0.0970	−0.0711	0.0126	−5.64	0.0000	Supported
	SI→PA→BI	−0.1315	0.0174	−0.0977	−0.1657	−0.1315	0.0176	−7.47	0.0000	Supported
	FC→PA→BI	−0.1698	0.0230	−0.1256	−0.2162	−0.1698	0.0234	−7.26	0.0000	Supported
	SOI→PA→BI	−0.0976	0.0207	−0.0585	−0.1385	−0.0976	0.0204	−4.78	0.0000	Supported
H7	PE→PC→BI	0.3262	0.0212	0.2866	0.3692	0.3262	0.0220	14.79	0.0000	Supported
	EE→PC→BII	0.2862	0.0236	0.2413	0.3331	0.2862	0.0237	12.08	0.0000	Supported
	SI→PC→BI	0.4069	0.0230	0.3628	0.4523	0.4069	0.0244	16.64	0.0000	Supported
	FC→PC→BI	0.3376	0.0215	0.3696	0.4555	0.3376	0.0214	15.77	0.0000	Supported
	SOI→PC→BI	0.3494	0.0229	0.3042	0.3939	0.3494	0.0237	14.71	0.0000	Supported
H8	PE→PV→BI	0.3907	0.0221	0.3506	0.4374	0.3907	0.0227	17.22	0.0000	Supported
	EE→PV→BI	0.3325	0.0237	0.2864	0.3799	0.3325	0.0247	13.46	0.0000	Supported
	SI→PV→BI	0.4419	0.0229	0.4010	0.4898	0.4419	0.0232	19.08	0.0000	Supported
	FC→PV→BI	0.4097	0.0218	0.3696	0.4555	0.4097	0.0221	18.57	0.0000	Supported
	SOI→PV→BI	0.3974	0.0228	0.3539	0.4437	0.3974	0.0229	17.39	0.0000	Supported

Note. Predictor: EE: Effort expectancy; SI: Social influence; FC: Facilitating conditions; Mediating variables: PA: Perceived anxiety; PC: Perceived compatibility; PV: Perceived value; Dependent variables: BI: Behavioral intention.
Source: Authors through their estimations.

quality and technological innovation significantly moderated social isolation, facilitating conditions, effort expectancy, performance expectancy, social isolation, and the outcome construct (Behavioral intention) of students from technologically advanced countries to adopt mobile learning during COVID-19. It is supported by Table 6, which shows that the $T > \pm 1.96$ and $p < 0.05$. Therefore, the current research has confirmed that propositions H9 and H10 are supported.

4.13. Conditional graphical depiction of moderation

Previous literature has highlighted the importance of illustrating moderation through diagrams (Ahmed et al., 2022; Hayes & Rockwood, 2020). Therefore, Figures A1(a–j) are presented in Appendix 5, show that technological innovation and service quality have a cogent moderation on the association of social isolation, facilitating conditions, social influence, effort expectancy, performance expectancy, and the outcome variable (Behavioral intention) to adopt mobile learning during COVID-19. Since the reading of the moderating factors (RED LINE) affects the GREEN LINE (behavioral intention), however, independent variables (BLUE LINE) are kept constant throughout the study period. Hence, it is established that technological innovation and service quality significantly impact behavioral intention.

Table 6. Hypothesized Moderation.

Hypotheses	Moderator	Moderation	Coefficient	SE	T	P*	LLCI	ULCI	Decisions
H9	SQ	PE x SQ	−0.2197	0.0123	−17.90	0.0000	−0.2438	−0.1956	Accepted
	SQ	EE x SQ	−0.0710	0.0109	−6.53	0.0000	−0.0923	−0.0497	Accepted
	SQ	SI x SQ	−0.1533	0.0127	−12.05	0.0000	−0.1782	−0.1283	Accepted
	SQ	FC x SQ	−0.1707	0.0120	−14.17	0.0000	−0.1943	−0.1471	Accepted
	SQ	SOI x SQ	−0.1523	0.0123	−12.42	0.0000	−0.1763	−0.1282	Accepted
H10	TI	PE x TI	−0.1757	0.0126	−13.90	0.0000	−0.2005	−0.1509	Accepted
	TI	EE x TI	−0.1095	0.0102	−10.77	0.0000	−0.1294	−0.0895	Accepted
	TI	SI x TI	−0.1490	0.013)	−11.49	0.0000	−0.1744	−0.1235	Accepted
	TI	FC x TI	−0.1232	0.0121	−10.15	0.0000	−0.1470	−0.0994	Accepted
	TI	SOI x TI	−0.1230	0.0121	−10.16	0.0000	−0.1467	−0.0992	Accepted

Note. Moderating variables: SQ: Service quality; TI: Technological innovation.
Source: Authors through their estimations.

5. Discussions

The current study's outcomes demonstrated that effort and performance expectancy have a significant and affirmative association with the outcome variable (Behavioral intention) to use m-learning during COVID-19. The outcomes are consistent with the previous studies (Faqih, 2020; Rahi et al., 2018; Kang et al., 2015). The study suggests that if the technology is user-friendly in the learning environment, the students are more likely to use m-learning technology. The current research also demonstrated that performance expectancy had the highest influence on behavioral intention; previous literature also exhibited similar outcomes, for example, Yang (2013) and Alasmari and Zhang (2019). This research also showed that social influence and facilitating conditions have an affirmative and cogent relationship with behavioral intention to use m-learning technology in an online atmosphere, which is lined with the previous studies (Alshurideh et al., 2020). Lastly, the study demonstrated that the extended dimension, for instance, social isolation, had a solid and affirmative association with behavioral intention to adopt mobile-based learning. The outcomes are also persistent with previous studies that demonstrated that social isolation had a significant and affirmative association with behavioral intention (Faqih, 2022a; Aliaño et al., 2019; Nassuora, 2013). The study also found that the mediation of perceived anxiety significantly but adversely influences the extended UTAUT dimensions and behavioral intention. Previous literature has also suggested that perceived anxiety is a negative mediating variable discouraging people from using technology-related gadgets (Raza et al., 2021; Almisad & Alsalim, 2020; Imran et al., 2016). Moreover, this research found an affirmative and significant impact of perceived compatibility and perceived value as mediators on the relationship between exogenous and endogenous variables. Previous literature has also steadily shown that perceived value and perceived compatibility have a cogent influence on the dimensions of an extended UTAUT model and behavioral intention (Hsu & Lin, 2016; Tout et al., 2019; Nguyen et al., 2020). Finally, we measured the moderation of service quality, which showed a significant influence between the dimensions (EE, SI, PE, FC, and SOI) of an extended UTAUT model and behavioral intention. The primary literature also demonstrated similar outcomes and showed that service quality had a cogent impact on the dimensions of the UTAUT model and behavioral intention (Baccari & Neji, 2016; Akter et al., 2013). Lastly, the researchers evaluated the impact of technological innovation as a moderating construct, and the findings concluded a significant moderation of technological innovation between the dimensions (EE, SI, PE, FC & SOI) of an extended UTAUT model and behavioral intention. It is consistent with previous literature supporting this research's findings (Huang et al., 2020; Hussain et al., 2019; Almaiah & Alismaiel, 2019; Makki et al., 2016).

6. Conclusion and implications

The conclusion of this study showed that smartphone technology has transformed the online education ecosystem and proficiency. This study found that dimensions of the UTAUT model, social isolation, performance expectancy, social influence, effort expectancy, and facilitating conditions, are essential constructs that significantly enhance behavioral intention to use mobile learning in technologically advanced countries during COVID-19. It is imperative to generate an effective mobile learning online education platform that improves awareness of the dimensions of an extended UTAUT theory. The current study's findings demonstrated that effort expectancy substantially impacted the behavioral intention to use mobile-based learning in an online education ecosystem during COVID-19. This research also demonstrated that perceived anxiety adversely impacts effort expectancy and cognitive capacity for innovation. The current study also suggested that mobile manufacturers should introduce more user-friendly gadgets to reduce perceived anxiety and improve behavioral intention to use mobile learning in online education. The undertaken research also exhibited that perceived value and perceived compatibility enhance students' intention to use mobile learning. Finally, this research showed that service quality and technological innovation significantly affect the association between exogenous and endogenous constructs, enhancing the behavioral intention to use mobile learning (m-learning). The current research model is empirically valid and reliable and provides critical theoretical implications for the knowledge body. This research developed a novel conceptual framework to evaluate the technology adoption-related problems, specifically mobile-based learning for online education. The outcomes of the current study successfully tested the relevance and pertinence of m-learning with the extended dimensions of the UTAUT theory from the perspective of developed economies. The proposed conceptual framework offers theoretical utility to future research scholars to replicate the study in different industries and geographical regions. The findings of the current study have significant practical repercussions; for instance, it is imperative to advance a mobile learning environment, which should be friendly and consider learners' preferences, teaching orientation, experience, needs, and values. It includes providing a personalized learning journey tailored to the learner's preferred form and learning mode. Thus, managers must consider attitudes that improve cognitive perception to adopt mobile learning towards online education. Higher educational institutes and universities should also prioritize the quality of service and technological innovation when developing learning management systems for online education.

7. The limitations of the research and potential areas for future researchers

The current research has beneficial practical and theoretical implications but has certain limitations. The study only focuses on technologically advanced countries with rich resources, so the results cannot be generalized. Future researchers should replicate the study for developing nations and collect a larger sample size for more accurate and vigorous outcomes. The sample size of the study is not significant; thus, it is recommended to the future researchers to increase the sample size for more robust results. The study has not incorporated the cause and effect model between the variables, hence, the cause and effect of variables could not be measured. Future researchers should consider the cause-and-effect model in their studies (Štreimikienė & Ahmed, 2021). The research has further restrained; for instance, the current study should have incorporated other constructs that might influence the acceptance of mobile-based learning. Hence, it is suggested to future research scholars to study these constructs while they will conduct their studies. Lastly, the study used a cross-sectional survey method; thus, holistic outcomes could not be achieved. Therefore, it is recommended that future researchers carry out their studies using a longitudinal survey method for more robust and generalizable results.

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Appendix 1. Modified questionnaire (measurement scales)

Table A1. Modified Measurement Scales.

Factors	Items	Statement	Citations
	EE1	1) Mobile-based learning technology is user-friendly.	
	EE2	2) Mobile-based learning technology can enhance the students' productivity. productivity.	
Effort Expectancy	EE3	2) The mobile-based learning technology is easy to use and user-friendly.	Thomas et al. (2020); Venkatesh et al. (2012, 2003); Alawani & Singh (2017)
	EE4	4) Mobile technology operations are easy to learn and use.	
Performance Expectancy	PE1	1) In online education, mobile-based technologies are helpful.	Thomas et al. (2020); Venkatesh et al. (2012, 2003); Al-Adwan et al. (2018)
	PE2	2) Mobile technologies facilitate the students to accomplish their assignments in a very swift manner.	
	PE3	3) Mobile technologies would improve students' performance.	
Social Influence	SI1	1) I am a source of inspiration to others because of using mobile-based learning.	Venkatesh et al. (2012); Thomas et al. (2020); Venkatesh et al. (2003)
	SI2	2) I always advocate for my peers to use mobile-based learning.	
	SI3	3) University teachers should be in favor of using mobile-based technologies.	
	SI4	4) My peers and classmates always influence me to use mobile-based learning.	
Facilitating Conditions	FC1	1) Resources are necessary to adopt mobile learning.	Thomas et al. (2020); Venkatesh et al. (2003, 2012)
	FC2	2) The important skills are necessary to adopt mobile-based learning	
	FC3	3) When I encounter a problem with the IT services to adopt m-learning, I always have support.	
Social Isolation	SOI1	1) Social isolation always creates panic and loneliness for me.	Raza et al. (2021); Ahmed et al. (2022); Kang et al. (2015)
	SOI2	2) Mobile-based learning platform comforts me from social isolation during COVID-19.	
	SOI3	3) Mobile-based learning in an online environment provides an opportunity to intermingle with classmates and eradicates feelings of social isolation.	
Perceived anxiety	PA1	1). I am usually hesitant to use mobile-based technologies in online education.	Faqih (2022b); Nagar (2016) Imran et al. (2016)
	PA2	2). I always have fear and anxiety when I use mobile-based learning. I always have a fear of making mistakes.	
	PA3	3). Since, I am not well-versed with the mobile-based technology. Therefore, I try to avoid it.	
Perceived Value	PV1	1) Mobile-based learning is a sign of status when I use m-learning.	Faqih (2022b); Moore and Benbasat (1991); Tout et al. (2019)
	PV2	2) Society always praises those people who use mobile technology.	
	PV3	3) I use mobile-based learning due to high productivity and social symbol.	
Perceived Compatibility	PC1	1). I restrain myself from mobile technology for learning due to a lack of skills.	Faqih (2022b); Nguyen et al. (2020); Hsu and Lin (2016)
	PC2	2). Mobile-based learning is helpful because of my job description.	
	PC3	3). My learning curve can cater to the necessary skills for using mobile learning.	
	PC4	4). Mobile-based learning is an unavoidable technology in the future.	

(*continued*)

Table A1. Continued.

Factors	Items	Statement	Citations
Service Quality	SQ1	1) I prefer to select a digital platform due to the augmented service quality.	Akter et al. (2013); Baccari & Neji (2016)
	SQ2	2) The mobile-based learning provides an enormous service quality in online education.	
	SQ3	3) Service quality is paramount while using online digital education platforms.	
Technological Innovation	TI1	1). Technological innovation provides novel opportunities in an online learning environment.	Huang et al. (2020); Almaiah & Alismaiel (2019); Al-Nassar (2020)
	TI2	2). Technological innovation enhances the efficiency of mobile-based learning for online education.	
	TI3	3). Technological innovation always inspires me to adopt new technological platforms.	
	TI4	4). Technological innovation has played a vital role during COVID-19 in mobile-based learning.	
Behavioral Intention	BI1	1). I am always ready to use mobile learning in online education.	Ahmed et al. (2022); Raza et al. (2021); Yang (2013)
	BI2	2). Whenever there is an emergency, I am ready to use m-learning.	
	BI3	3). I always recommend using m-learning in a routine university education.	
	BI4	4). The online learning environment compels me to adopt mobile-based learning during COVID-19.	

Source: Authors through their estimations.

Appendix 2. Demographic statistics of respondents

Table A2. Demographic analysis.

Demographics		Frequency	Percent
Gender	Male	505	56.2%
	Female	393	43.8%
Marital Status	Single	518	57.6%
	Married	354	39.4%
	Divorced	26	2.9%
Age (In Years)	18–30	320	35.6%
	30–40	204	22.7%
	40–50	124	13.8%
	50–60	141	15.7%
	More than 60	109	12.1%
Education	Under-Graduation	388	43.2%
	Graduation	286	31.8%
	Post-Graduation	144	16.0%
	Ph.D. degree and Post-doctoral research fellows	80	8.9%
Experience (In Years)	1–5	382	42.5%
	5–10	271	30.2%
	10–15	176	19.6%
	More than 15 years	69	7.7%
Income (In USD 000)	30–60	156	17.4%
	60–90	399	44.4%
	90–120	182	20.3%
	120–150	97	10.8%
	More than 150	64	7.1%
Total—*N*		898	

Source: Authors through their estimations.

Appendix 3. Principal component analysis, convergent and discriminant validities

Table A3. Convergent and discriminant validities.

Factors	Items	FL	CA	CR	AVE
Dependent Variable:					
Behavioral Intention	BI1	0.936	0.916	0.943	0.841
	BI2	0.883			
	BI3	0.937			
	BI4	0.898			
Independent Variables:					
Performance Expectancy	PE1	0.928			
	PE2	0.901	0.919	0.944	0.842
	PE3	0.947			
	PE4	0.871			
Effort Expectancy	EE1	0.929			
	EE2	0.905	0.928	0.949	0.860
	EE3	0.946			
Social Influence	SI1	0.932			
	SI2	0.904	0.924	0.949	0.858
	SI3	0.946			
	SI4	0.891			
Facilitating Conditions	FC1	0.926			
	FC2	0.906	0.921	0.944	0.849
	FC3	0.932			
Social Isolation	SOI1	0.931			
	SOI2	0.892	0.913	0.937	0.834
	SOI3	0.948			
Mediating Variables:					
Perceived Anxiety	PA1	0.922			
	PA2	0.894	0.925	0.946	0.853
	PA3	0.925			
Perceived Compatibility	PC1	0.930			
	PC2	0.906	0.924	0.964	0.854
	PC3	0.876			
	PC4	0.938			
Perceived Value	PV1	0.930			
	PV2	0.903	0.921	0.943	0.848
	PV3	0.932			
Moderating Variables:					
Service Quality	SQ1	0.929			
	SQ2	0.901	0.919	0.942	0.844
	SQ3	0.928			
Technological Innovation	TI1	0.926			
	TI2	0.895	0.913	0.937	0.833
	TI3	0.865			
	TI4	0.918			

Source: Authors through their estimations.

Appendix 4

Table. A4. Cross-loading statistics.

	Components										
Items	1	2	3	4	5	6	7	8	9	10	11
BI1	0.021	0.038	−0.015	−0.019	0.019	0.009	−0.005	−0.019	−0.030	−0.030	0.936
BI2	−0.024	0.001	0.011	0.012	−0.016	0.007	0.037	0.002	−0.021	−0.005	0.883
BI3	−0.007	0.022	−0.024	−0.011	−0.016	−0.013	0.008	0.018	−0.016	−0.034	0.937
BI4	0.043	0.009	−0.008	0.014	−0.015	0.008	0.039	0.077	−0.006	−0.052	0.898
PE1	−0.004	0.058	−0.002	0.928	0.013	0.055	−0.014	0.033	−0.021	−0.036	−0.016
PE2	0.042	0.008	−0.009	0.901	−0.022	0.078	−0.006	−0.051	−0.035	0.017	−0.014
PE3	0.000	0.018	−0.036	0.947	0.004	0.024	−0.010	−0.005	−0.015	−0.047	0.013
PE4	0.001	0.026	−0.006	0.871	−0.019	0.042	0.035	0.022	−0.021	−0.006	0.016
EE1	0.007	0.000	0.929	−0.006	−0.006	0.054	0.004	0.026	0.038	0.048	−0.050
EE2	−0.031	−0.010	0.905	0.009	0.016	0.044	0.068	0.002	−0.004	0.003	0.044
EE3	0.039	−0.037	0.946	−0.050	−0.008	0.026	0.007	−0.004	0.023	0.019	−0.023
SI1	0.000	0.932	−0.007	0.026	−0.015	0.040	0.034	0.020	−0.022	−0.007	0.017
SI2	0.024	0.904	0.011	0.042	0.005	−0.079	−0.032	−0.004	0.025	−0.029	0.028
SI3	−0.025	0.946	−0.052	0.015	−0.009	−0.005	0.037	0.026	−0.025	−0.022	0.016
SI4	0.038	0.891	−0.035	−0.051	−0.003	0.024	0.006	−0.004	0.024	0.018	−0.024
FC1	−0.012	−0.010	0.010	−0.020	0.052	−0.008	0.926	0.031	0.008	−0.055	0.019
FC2	−0.002	0.012	0.045	0.008	0.003	−0.002	0.906	−0.012	−0.009	−0.015	0.035
FC3	−0.044	0.035	0.025	−0.018	0.024	0.030	0.932	0.027	−0.045	−0.003	−0.013
SOI1	0.932	0.024	−0.015	−0.007	0.032	−0.028	−0.009	−0.021	0.033	0.015	−0.005
SOI2	0.892	−0.026	0.008	0.040	−0.055	−0.015	−0.003	−0.015	−0.033	0.007	0.008
SOI3	0.948	0.002	0.021	0.005	−0.004	−0.017	−0.047	−0.014	0.004	−0.014	−0.015
PA1	−0.030	0.035	0.048	0.066	−0.009	0.922	0.003	−0.017	0.095	−0.024	−0.006
PA2	−0.007	−0.051	0.045	0.049	0.046	0.894	−0.006	0.025	0.127	−0.002	−0.003
PA3	−0.025	−0.029	0.033	0.046	0.036	0.925	0.023	−0.031	0.131	−0.022	0.013
PC1	0.028	−0.019	−0.017	0.007	0.930	0.043	0.015	−0.004	0.012	−0.041	0.001
PC2	−0.048	0.012	0.026	0.005	0.906	0.001	0.031	0.014	0.005	−0.019	−0.002
PC3	−0.006	−0.013	−0.008	−0.018	0.876	0.028	0.033	−0.033	−0.003	0.030	−0.012
PC4	−0.007	−0.002	0.025	−0.036	0.938	0.086	−0.008	0.005	−0.027	0.013	−0.017
PV1	−0.025	0.033	0.027	0.037	−0.001	0.011	−0.007	0.930	0.019	0.040	−0.021
PV2	−0.019	0.009	−0.002	−0.037	−0.004	−0.036	0.021	0.903	−0.007	0.009	0.025
PV3	−0.005	−0.001	−0.001	−0.022	−0.017	0.005	0.030	0.932	0.012	0.026	−0.004
SQ1	0.004	−0.008	0.004	−0.053	−0.004	−0.023	−0.026	−0.006	0.009	0.929	−0.022
SQ2	−0.020	−0.039	0.001	−0.009	−0.020	−0.029	−0.043	0.045	0.002	0.901	−0.027
SQ3	0.024	−0.010	0.064	−0.003	−0.008	0.007	−0.003	0.036	−0.019	0.928	−0.020
TI1	−0.008	−0.002	0.021	−0.033	−0.005	0.086	−0.009	0.003	0.926	0.014	−0.018
TI2	0.004	−0.008	0.013	−0.019	−0.005	0.129	0.002	−0.009	0.895	−0.007	−0.036
TI3	0.008	−0.012	0.023	−0.020	0.025	0.133	−0.040	0.031	0.865	−0.015	−0.014
TI4	−0.006	−0.052	0.044	0.048	0.047	0.127	−0.006	0.025	0.918	−0.003	−0.002

Source: Authors through their estimations.

Appendix 5. Graphical presentation of moderation of service quality and technological innovation from Figure A1(a–j)

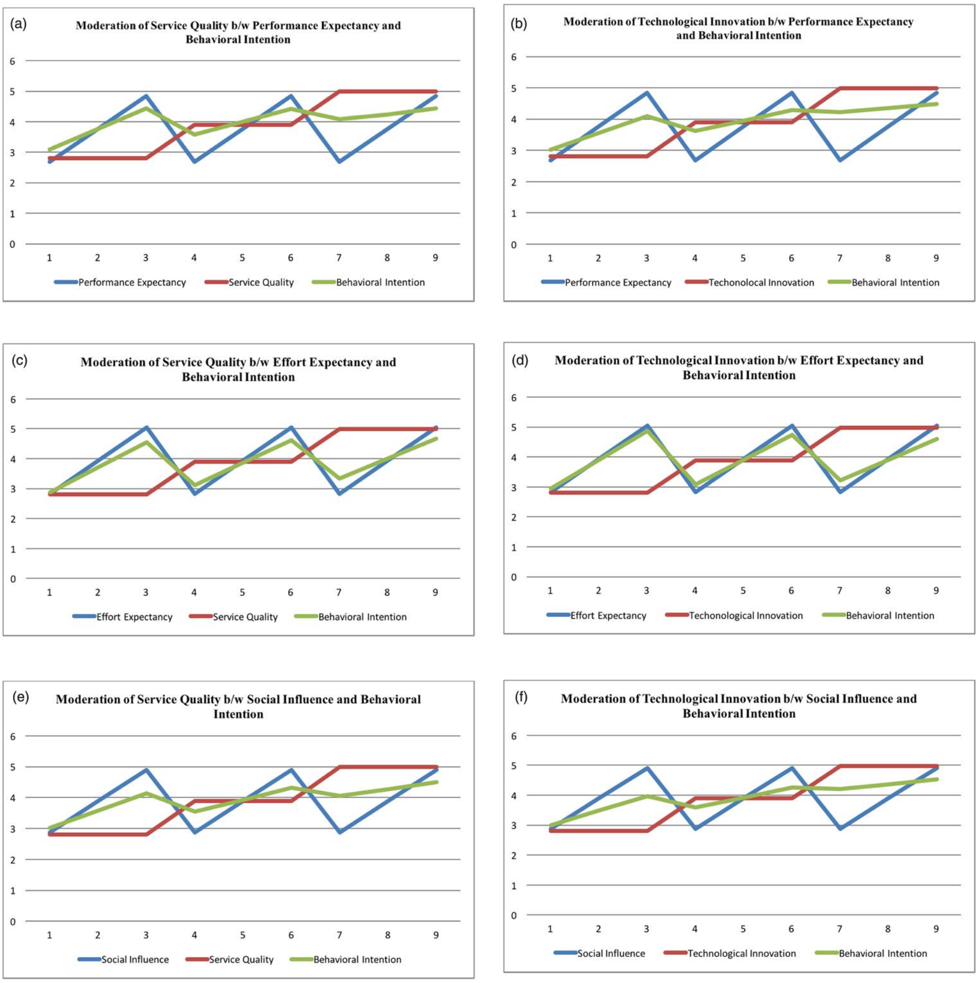

Figure A1. (a) Moderation of Service Quality between PE & BI, (b) Moderation of Technological Innovation between PE & BI, (c) Moderation of Service Quality between EE & BI, (d) Moderation of Technological Innovation between EE & BI, (e) Moderation of Service Quality between SI & BI, (f) Moderation of Technological Innovation between, (g) Moderation of Service Quality between FC & BI, (h) Moderation of Technological Innovation between FC & BI, (i) Moderation of Service Quality between SOI & BI, (j) Moderation of Technological Innovation between SOI & BI.
Source: Authors through their estimations.

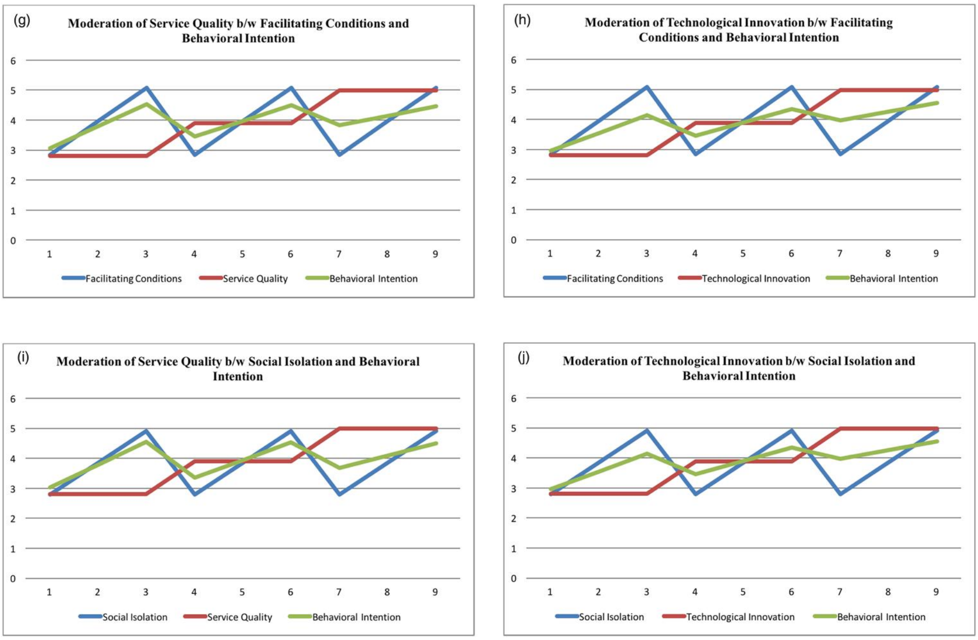

Figure A1. Continued.