Examining the determinants of the intention of using E-learning among university students in China During COVID-19
Muhammad Naveed Jabbar

Abstract
The main objective of the study is to examine the intention of using E-learning among university students in China. The factors such as computer experience, personal innovativeness, computer self-efficacy, and performance expectations on the impact on the intention of using e-learning during COVID-19. PLS-SEM approach is used for analyzing the research models of complex nature, where there are numerous observed and unobserved variables in the model the response rate came out 77%, which is considered more than sufficient for further analysis. An empirical study based on e-learning was conducted in a developing country. It was found by the researcher that e-learning acceptance among the users is significantly influenced by CSE. The experience of using a computer has been regarded by previous studies as a strong determinant of attitudes toward using computers. E-learning systems are used by individuals when it is perceived that it will improve their effectiveness and productivity in learning education during COVID-19. Their intentions to use e-learning systems are influenced by these beliefs. As the high rate of attrition has become a key issue in e-learning, the main concern related to online teaching and learning is motivation. Their relationship results in improved use of the e-learning system. A computer self-efficacy construct was adapted in a study based on a specific implementation of e-learning. Computer self-efficacy was defined as the level with which people feel confidence in their skills for using online technology of learning and achievement of course-related tasks. The study has highlighted an important issue related to personal innovativeness, computer experience, and personal self-efficacy among students in China during COVID-19.

Keywords: computer experience, personal innovativeness, computer self-efficacy, China

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Introduction
In education, new opportunities are being created by Information and Communications Technology across the world (Kim & Park, 2018). The quality of learning and teaching is improving through the adoption of an education system based on computers and e-learning systems (Kent, Laslo, & Rafaeli, 2016; Nihuka, 2019). There has been a tremendous increase in the training programs based on e-learning rather than conventional face-to-face room-based education systems (Hill, Chidambaram, & Summers, 2017). Several institutions across the world have started implementing e-learning to develop a collaborative and effective environment for instructors and learners. In order to improve the quality of education, both developing and developed countries, including China, have implemented full or partial e-learning programs (Kim & Park, 2018;
Ngampornchai & Adams, 2016; Tawil, 2018). Several researchers have claimed that the e-learning system results in many benefits for instructors, learners, and educational institutions. Some of the potential benefits include improvement in methods of teaching and learning, interactivity, easy access to information, and successful delivery of content (Kim & Park, 2018; Zhu & Winkel, 2016). There has been a slow increase in e-learning programs, which is the key issue (Hussein, 2017). Moreover, the dropout rates are high in e-learning programs (Ali, Uppal, & Gulliver, 2018; Zhu & Winkel, 2016). Developing countries can face increased challenges in the implementation of e-learning courses in contrast to developed countries because of the lack of human and technical infrastructure. Moreover, lack of proper infrastructure, skills, computers, and ability to adhere to conventional methods of learning, lack of sharing information and cooperation of institutions are some other challenges in implementing e-learning courses (Ali et al., 2018).

The impact of COVID-19, on human lives are changing the global landscape. The pandemic has not only placed a significant impact on the course of activities rather has called for flexibilities and dynamism in different segment of society and sector of economy. Among these the mode of education is a serious concern popped up during pandemic. Lockdown is one of the most recognizable buzzword around the Globe. Since the early days of COVID-19 the countries around the world have been imposing partial or full lockdown. Closure of educational institute around the globe, forced the higher education institution to switch to online mode of teaching and learning. It is therefore now time to reconsider the urgent needs of the unparalleled status quo, to change our education system and to reinvent it. Though the online learning and subsequent concept of e-learning is not new and is in practice over the course of two decades. However, many of teachers and trainers it was a new task and required a lot of efforts from them for abrupt adjustment. Similarly, students who were engaged in physical mode of learning were not trained to be taught through online settings. Thereby the lack of acceptance for the technology is another issue in the achievement of benefits related to the utilization of online teaching during COVID-19. Thus, it is vital to consider the acceptance or rejection of technology by the user as a critical issue during covid-19. This challenge can be resolved by using different ways such as computer experience, computer self-efficacy and personal innovation.

The environment faced by developing countries such as China is unique. Therefore, it is important to understand the inclination of users towards the e-learning system. The Chinese universities are directed to complete 25 % of syllabus through conventional teaching and 75% through online teaching methods. To effectively and efficiently control the quality of teaching, the Chinese universities need to use the online teaching tools exclusively. The COVID-19 outbreak has made it realize to the educational institute to permanently adapt the online system or mix of an online and physical system and educational institutions must provide sufficient training to the students regarding the use of computer technology. This may increase the motivation level of users, offer them skills to use e-learning services and manage e-learning courses in a flexible manner (Nihuka, 2019). Literature on the issues related online learning during COVID-19 has identified that computer self-efficacy (CSE) is an important determinant of online learning, and CSE can be developed to improve the quality of e-learning courses. These may act as important elements in the adoption of ICT and expected outcomes (Yakubu, Dasuki, & Abubakar, 2020). Several parties or stakeholders are involved in e-learning, such as instructors, user, technical staff, faculty, administrative, supporter, etc. (Nihuka, 2019). Every stakeholder has a different perception regarding technology. Therefore, there is a need for a detailed investigation of important stakeholders, such as learners and instructors. A detailed analysis will help in taking suitable steps for every group having a significant influence on e-learning success. In this way, e-learning can benefit developing countries.

Therefore, the aim of the study is to develop a model of e-learning acceptance for developed countries through analyzing the association between individual dimensions, including personal innovativeness, the experience of computer, CSE, and expectations for performance as well as behavioural intention of an individual to use an e-learning system based on SCT (social cognitive
theory) (Boateng, Mbrokoh, & Boateng, 2016; Yakubu et al., 2020). Moreover, difference and similarity of perspectives between the users and instructors to adopt e-learning have been identified by this study through the use of structural equation analysis. An empirical investigation has been made on users of e-learning courses in China during COVID-19.

**Hypothesis**

Many prior studies have tried to explore the impact of various factors on the adopting of online learning during covid-19 (Martín, Jiménez, & Rodríguez, 2020). Majority of these studies have reported that the closure of higher education institutes has aimed COVID-19 can be seen as a paradigm shift. The shift from traditional method of teaching to online method of teaching is a need of time and indeed was a right option. However, computer experience, computer self-efficacy has been an issue of great importance. Different factors, including the satisfaction of education stakeholder, can be used to measure the successful implementation of e-learning systems during COVID-19. The principal participants in the field of education, including the users and instructors, along with post-adopter expectations, confirmation, social and individual influence, motivation and perceived behavioural control must be considered. Six dimensions were identified by Altholay, Abdullah, and Isaac (2019), including satisfaction of the user, usage intention for the system, quality of service, quality of information, quality of the system, and net benefit to have a potential influence on IS success model. The variables used in several research studies on e-learning have been examined in the present study. For instance, there is a correlation between individual CSE and learning performance, which improve e-learning adoption or usage during covid-19. Another concern is the implementation of e-learning systems by the stakeholders is Motivation, which includes intrinsic as well as extrinsic motivation (Martín, Jiménez, & Rodríguez, 2020). Different variables have been grouped into seven dimensions (based on similarity) in the present study using the previous studies based on measuring the success of e-learning. E-learning has been defined as a distance learning system, which uses internet technology for communication with users and delivering content using electronic models. The system aims at supporting universities and students, along with improving the transfer of knowledge (Kim & Park, 2018). The center of higher education is shifted from instructor to learner by e-learning during covid-19, which improves the quality of learning and teaching as a new paradigm. Students, during covid-19, are given an opportunity through the self-paced aspect of e-learning to access educational content from any place and any time. For this, suitable tools can be used in accordance with the needs. Students are able to organize and customize their performance learning course (Rezaee & Zahedi, 2018). Universities can achieve several benefits through the implementation of e-learning programs such as content standardization, personalized instruction, on-demand availability, and accountability, reduced time cycle, improved capabilities, low cost, and high convenience for students. Thus, during covid-19 the e-learning system becomes an alternative to the conventional classroom system. This system is growing fastly among institutions of higher education. Tutoring can be done at any time from the viewpoint of instructors (Peechapol, Sujiva, & Luangsodsai, 2018). Alternatively, serious challenges are posed by the current e-learning systems for instructors in developing countries. Most of the higher education institutions in developing countries are based on conventional teaching methods. Resultantly, there is a need to create e-learning awareness and alter users’ intentions and behaviour for using e-learning (Rezaee & Zahedi, 2018).

In developing countries, the number of students having no enrollment in school is high since 1960. Moreover, the dropout rate is also high in developing countries. The allocation of budget is inefficient, along with the low quality of schooling, which creates a mismatch between the typical learning and the curriculum (Maloba, 2019; Rüth & Kaspar, 2017). However, China which is among the world leading economies are spending a huge budget on the education sector. During COVID-19, it was observed that instructors are not regular and usually absent from the classroom, which creates a lack of motivation among the students. For this reason, absentees are higher (Maloba, 2019). E-learning could act as a powerful tool for solving these issues in developing
countries. E-learning has a high potential to improve educational achievements in developing as well as developed countries (Ali et al., 2018; Rüth & Kaspar, 2017). It was found by Maloba (2019) that there is great potential possessed by the integrated technology for the education system in developing countries. Therefore, e-learning is being quickly adopted in developed and developing countries (Abbas & Rajiani, 2019; Ngampornchai & Adams, 2016). It was found that the adoption of ICT by firms and its usage involves complicated issues. It is complex but critical to understand the acceptance of e-learning systems among the users in developing countries (Hussein, 2017). In the growth of e-learning in developing countries, several obstacles exist, such as cost, infrastructure, training, information access and resources, etc. (Rüth & Kaspar, 2017).

It was pointed out by Singh and Mishra (2017) in a case study of users that the adoption of technology by instructors has some barriers. Some of these barriers include personal factors, lack of support, lack of awareness, lack of ability to use technology and resources. It was reported that skills, and knowledge of instructors, quality of the system, infrastructure, material conditions, staff support, and technical support are some main hurdles in the use of technology within the 26 developed and developing countries, which were investigated. It was pointed out that factors of e-readiness assessment include the external environment, human resource information, ICT readiness, are critical in developing economies. The changing instructor's role and technical support are some other main (Abbas & Rajiani, 2019).

A critical review of the challenges for e-learning was presented by Ali et al. (2018) in developing countries in comparison with the developed countries. It was highlighted that technology, characteristics of users, course, and organizational variables were the challenges. It was found by the previous investigations that developing countries experience several challenges in adopting e-learning. However, most of the previous research in developing economies are focused on course, technology and organizational issues. Alternatively, the focus of researchers was on individual characteristics in developed countries. Therefore, the focus of this study is on individual characteristics linked with e-learning to understand the adoption of e-learning.

The theoretical framework used for research is SCT drawn from research on social psychology for analyzing action, affect, through and personal motivation. The association between behavioural, personal, and environmental factors has been explained by SCT, as they are correlated with each other (Boateng et al., 2016). Outcome expectations and CSE are the key elements in the adoption of ICT. These elements reflect the effective responses and beliefs of individuals to determine the action or behaviour of an individual (Yakubu et al., 2020). It was stated that actions, decisions, and performance of individuals is based on outcome expectations and self-efficacy.

The theoretical framework of SCT has been adopted by researchers for conducting studies on career development, knowledge management, human resource development, IS research, and education (Akgün, Topal, & Duman, 2019; Hill et al., 2017; Vaidyanathan, 2018). It was found by Akgün et al. (2019) that there exists a strong correlation between usage of technology and self-efficacy. The researchers proposed that the adoption of IS by an individual can be predicted by SCT. However, it is important to understand the adoption of ICT by users for educational purposes (Kim & Park, 2018). The perception of users for using a computer is one of the challenges for technological integration in the education system (Singh & Mishra, 2017). It was found that when instructors are not confident about the use of computers in teaching processes, it is less likely to be adopted by them.

The organizational structures are not just the fundamental challenges in the implementation of e-learning. However, the mind and beliefs of users, support, and access to a computer are also some key challenges (Abbas & Rajiani, 2019). The influence of CSE on the adoption of e-learning in developed and developing countries has been investigated by previous research studies (Hussein, 2017; Kim & Park, 2018; Peechapol et al., 2018; Shah & Attiq, 2016; Tawil, 2018). The studies found that the adoption of e-learning can be determined by the CSE construct. It has been found by the current study that individual performance, real technology usage, and technology acceptance are influenced by self-efficacy (Kim & Park, 2018; Shah & Attiq, 2016).
In SCT, a crucial role is played by self-efficacy (Akgün et al., 2019; Rezki, 2018). Thus, SCT has been applied to analyze the adoption of e-learning in the current study. Three main dimensions, including personal behaviour, characteristics, and e-learning environment, have been examined based on SCT by the current study. These three dimensions are linked with the e-learning acceptance by the learners and instructors. The relationship between variables within the dimensions has been discussed by the study to the hypotheses of the study.

E-learning might be perceived differently by individuals because of the difference in their attributes that is linked with the use of technology. Thus, effective implementation of e-learning can be achieved through consideration of users’ characteristics. A potential influence is created on the use of e-learning system by different characteristics of end-users of the system (Kim, Russell, & Schroeder, 2017).

With reference to developing countries, crucial roles are played by beliefs and motivation in learning (Ngampornchai & Adams, 2016). The acceptance of technology in the IS domain is influenced by personal factors in the e-learning system (Akgün et al., 2019; Peechapol et al., 2018). Students with effective skills in using a computer are likely to utilize this technology for education purpose and achievement of educational obligations. The key variables of user characteristics for accepting technology are self-efficacy and computer experience (Akgün et al., 2019).

As per the previous research studies, the focus of this study is on individual characteristics such as personal innovativeness in ICT, CSE, expectations of users, the experience of the computer. These variables are categorized as four personal attributes, which are likely to have an impact on the adoption of e-learning in developing countries. The experience of using a computer has been defined by Khaloufi and Laabidi (2017) as the level of an individual in understanding the use of a computer. The experience of using a computer has been regarded as a crucial variable in the difference among individuals that determines their individual confidence, beliefs, and behaviour (Peechapol et al., 2018). The experience of using a computer has been regarded by previous studies as a strong determinant of attitudes toward using computers. Thus, a positive influence is created on CSE by computer experience.

Different sources influence self-efficacy in SCT, including previous mastery experience and vicarious experience (Boateng et al., 2016). Moreover, the performance expectations of an individual are influenced by various experience influences. Moreover, the most crucial information source for the development of individual self-efficacy is provided by individual experience (Boateng et al., 2016). In a similar way, the experience of using computer act as a key source of information for the users of technology in determining their level of general CSE. It was strongly argued by Boateng et al. (2016) that the previous experience of using a computer creates an influence on judgments of self-efficacy. A key variable influencing the performance expectation and perceived usefulness in the field of IS is computer experience. In general, the use of computers is increased by users; a positive attitude is developed among them for computers. This is likely to have a positive CSE because of individual perception for dealing with computer technology. They may enrol themselves in e-learning courses in the future. A high CSE level is shown by individuals who spend more time using a computer, which influences their performance expectations related to computer skills. Based on the above discussion, the following hypotheses have been developed:

CSE has been defined in the IS domain as the perceptions of an individual for his ability to use computers in achieving a specific task. Both specific and general CSE are included in it (Rezki, 2018). The positive attitudes are less among individuals with less self-confidence in using technology. Moreover, they are less inclined to use e-learning (Chopra, Madan, & Jaisingh, 2019). A CSE construct was adapted in a study based on a specific implementation of e-learning. CSE was defined as the level with which people feel confidence in their skills for using online technology of learning and achievement of course-related tasks.

It has been found by previous studies that the use of technology and performance expectation can be determined through self-efficacy (Akgün et al., 2019; Kim & Park, 2018; Shah & Attiq, 2016; Vaidyanathan, 2018). There is a positive association between CSE and acceptance and intention
of individuals for using e-learning (Chopra et al., 2019). In a similar way, specific CSE was analyzed by Kim and Park (2018) in a study based on e-learning. It was found by the researchers that the perceptions of users for using an e-learning system, real usage, and outcome expectations are influenced by CSE within developed countries.

It was found by Vaidyanathan (2018) that there is a positive association between high individual CSE and high learning performance. Their relationship results in improved use of the e-learning system. An empirical study based on e-learning was conducted in a developing country. It was found by the researcher that e-learning acceptance among the users is significantly influenced by CSE. It was indicated by Yakubu et al. (2020) that there is a significant influence of self-efficacy related to the web on actual usage and behavioural intention to use e-service. Therefore, a high level of specific CSE among users’ results in a higher ability for IS control and perceived usefulness for a certain technology, which in turn influences the behavioural intention for IS usage. Alternatively, when a computer is considered too complex for usage, individuals are not able to deal with the system because of a lack of achieving its usefulness. The following hypotheses have been developed based on the above discussion:

H1: Computer Experience (CDMEX) has significant impact on the computer self-efficacy (CSE).
H2: Personal innovativeness (PERIN) has significant impact on the computer self-efficacy (CSE).
H3: Computer self-efficacy (CSE) has significant impact on the performance expectations (PREX).
H4: Performance expectations (PREX) has significant impact on the intention of using e-learning.

**Methodology**

The researcher formulated a questionnaire survey for the collection of data from the target sample. The data were subjected to analysis through the use of different processes and tools of statistics. For analysis of data, statistical and inferential procedures were used. For inferential statistics, PLS-SEM was adopted, which refers to the Partial Least Square Structural Equation Modeling. Thus, the PLS-SEM approach was used to test the formulated hypotheses. PLS-SEM approach is used for analyzing the research models of complex nature, where there are numerous observed and unobserved variables in the model (Hair, Hult, and Ringle, 2016). Most of the researchers have considered the PLS-SEM approach the most suitable for testing research hypotheses, prediction, and developing a research model (Akter, Fosso Wamba, & Dewan, 2017; Hair et al., 2016; Henseler, Hubona, & Ray, 2016). Resultantly, the PLS approach is better than other approaches of data analysis because of its superior power and flexibility.

Some considerable efforts have been made by the research for achieving maximum response rate in the questionnaire survey. A total of 310 questionnaires were distributed among the target sample during covid-19. Out of 310, total 220 were received back. Almost 25 questionnaires were omitted and discarded because of missing information. Therefore, the response rate came out 74%, which is considered more than sufficient for further analysis.

**Results**

Two steps are involved in PLS analysis, outer model assessment and inner model assessment. The first step is the determination of the measurement model or the outer model. However, the second step is the determination of the structural model or the inner model. The association between the dependent unobserved variables and their reflectors is assessed in the outer model (Hair, Matthews, Matthews, and Sarstedt, 2017). However, the association between dependent and independent unobserved variables is determined in the inner model assessment.
Therefore, the PLS-SEM method has been employed for this research, and PLS3 software has been utilized (Ringle, Sarstedt, & Mitchell, 2018). Some important measures are determined in estimating the outer model, which includes the reliability of variables, the validity of variables, and internal reliability consistency (Hair et al., 2017; Henseler et al., 2016). The outer loadings values for every variable has been determined that were in the range of 0.40-0.70 (Hair, Sarstedt, & Ringle, 2019). All the values were in the standard range of acceptance (Henseler et al., 2016). When the values of item loadings lie in the range 0.81-1.00, these are considered to be strong.
It has been suggested by Shuhaiber (2018) that loadings are moderate when they lie in the range of 0.5-0.8. For the acceptance of the item loadings, the values must be greater than 0.3 (Akter et al., 2017). It is assumed by the coefficient of Cronbach alpha that every item has an equal contribution to the corresponding variable. The composite reliability measures the changes in outer loadings of an indicator (Hair et al., 2017). Therefore, the outer loadings values and AVE values have been calculated for determining convergent validity (Richter, Cepeda, and Roldán, 2016). The square loadings value is provided by AVE for every indicator. The level of empirical uniqueness of a specific measure from others is referred to as convergent validity (Singh & Prasad, 2018). Achieving discriminant validity reflects that a specific variable is unique and measures the process within the boundaries (Ramayah, Cheah, & Memon, 2018).

Table 2: Reliability

<table>
<thead>
<tr>
<th></th>
<th>Cronbach's Alpha</th>
<th>rho_A</th>
<th>Composite Reliability</th>
<th>Average Variance Extracted (AVE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CDMEX</td>
<td>0.902</td>
<td>0.904</td>
<td>0.939</td>
<td>0.837</td>
</tr>
<tr>
<td>CSE</td>
<td>0.948</td>
<td>0.949</td>
<td>0.960</td>
<td>0.829</td>
</tr>
<tr>
<td>IUEL</td>
<td>0.967</td>
<td>0.969</td>
<td>0.971</td>
<td>0.771</td>
</tr>
<tr>
<td>PERIN</td>
<td>0.902</td>
<td>0.904</td>
<td>0.939</td>
<td>0.836</td>
</tr>
<tr>
<td>PREX</td>
<td>0.926</td>
<td>0.928</td>
<td>0.944</td>
<td>0.773</td>
</tr>
</tbody>
</table>

The cross-loadings and Fornell-Larcker criterion has been used for determining discriminant validity. The AVE analysis has been used to compare the correlation values among the latent variables and squared values of AVE. Thus, a suitable level of discriminant validity has been achieved in the current study.

Table 3: Validity

<table>
<thead>
<tr>
<th></th>
<th>CDMEX</th>
<th>CSE</th>
<th>IUEL</th>
<th>PERIN</th>
<th>PREX</th>
</tr>
</thead>
<tbody>
<tr>
<td>CDMEX</td>
<td>0.900</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CSE</td>
<td>0.870</td>
<td>0.900</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IUEL</td>
<td>0.671</td>
<td>0.680</td>
<td>0.878</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PERIN</td>
<td>0.610</td>
<td>0.875</td>
<td>0.697</td>
<td>0.900</td>
<td></td>
</tr>
<tr>
<td>PREX</td>
<td>0.883</td>
<td>0.716</td>
<td>0.730</td>
<td>0.896</td>
<td>0.879</td>
</tr>
</tbody>
</table>

The structural or inner model has been determined by analyzing the relation between the model's predictive ability and dependent and independent unobserved variables (Hair et al., 2017). Moreover, the path-coefficient analysis has been performed for determining the hypothesized association between dependent and explanatory unobserved variables in the research model. The bootstrapping method with 5000 samples and 360 cases has been used for determining path coefficient significance. The significance of path coefficients, t-statistics, beta-coefficients, and standard errors have been obtained for checking the formulated research hypotheses (Hair et al., 2017; Henseler et al., 2016).
The coefficient of determination has been used for determining the structural model. The value of R-square is considered the most strong and commonly adopted measure (Henseler et al., 2016). There are some similarities between the correlation coefficient and coefficient of determination. The values of R-square have been signified in percentage form, which reflects the model’s predictive ability (Richter et al., 2016).

Table 5: R-Square

<table>
<thead>
<tr>
<th></th>
<th>R Square</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSE</td>
<td>0.797</td>
</tr>
<tr>
<td>IUEL</td>
<td>0.533</td>
</tr>
<tr>
<td>PREX</td>
<td>0.839</td>
</tr>
</tbody>
</table>

The changes in the R-square values can be determined by effect size ($f^2$). When some of the explanatory variables are omitted from the research model, the change in the R-square value is determined by the effect size. When the value of effect size comes out 0.02, 0.15, and 0.35, it is considered small, medium, and large, respectively.
The goodness of fit has been determined by using Stone-Geisser’s $Q^2$ test in the PLS-SEM method. Resultantly, the predictive relevance of the model has been determined by using the blindfolding procedure and Stone Geisser’s test. The Q-square value should be positive for achieving predictive relevance. Alternatively, the model has no predictive relevance.

**Table 6: Q-Square**

<table>
<thead>
<tr>
<th></th>
<th>SSO</th>
<th>SSE</th>
<th>$Q^2 (=1-SSE/SSO)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>CDMEX</td>
<td>651.000</td>
<td>651.000</td>
<td>0.654</td>
</tr>
<tr>
<td>CSE</td>
<td>1085.000</td>
<td>375.185</td>
<td>0.654</td>
</tr>
<tr>
<td>IUEL</td>
<td>2170.000</td>
<td>1294.988</td>
<td>0.403</td>
</tr>
<tr>
<td>PERIN</td>
<td>651.000</td>
<td>651.000</td>
<td>0.642</td>
</tr>
<tr>
<td>PREX</td>
<td>1085.000</td>
<td>388.835</td>
<td>0.642</td>
</tr>
</tbody>
</table>

**Discussion and Conclusion**

It has been clearly stated by previous studies that extrinsic motivation, performance expectation, and perceived usefulness are similar concepts (Akgün et al., 2019). Extrinsic motivation or perceived usefulness during covid-19, is represented by performance expectation in the current study. The performance enhancement of individuals by using a specific technology is linked with performance expectation (Vaidyanathan, 2018). External variables, including services, personal characteristics, system characteristics, affect this construct (Huang et al., 2020). Individual performance is improved by favourable beliefs of users regarding an e-learning technology, which is regarded as performance expectation in e-learning (Chopra et al., 2019). In order to explain the acceptance of technology, its use, and intention to continue with it, performance expectation is an important variable (Akgün et al., 2019; Simarmata & Hia, 2020; Vaidyanathan, 2018; Yakubu et al., 2020).

E-learning systems during covid-19, are used by individuals when it is perceived that it will improve their effectiveness and productivity in learning education. Their intentions to use e-learning systems are influenced by these beliefs. As the high rate of attrition has become a key issue in e-learning, the main concern related to online teaching and learning is motivation. It is not sufficient to concentrate on learning context and course design for implementing e-learning successfully. However, it is important to understand the motivation of users in e-learning success (Martín et al., 2020). It has been empirically tested that motivation creates a positive influence on the behavioural intention of learners, instructors, and engineers for adopting e-learning (Hussein, 2017; Shah & Atiq, 2016).

In the information technology field, personal innovativeness is referred to as the individual’s willingness to use any new information technology (Simarmata & Hia, 2020). It was believed by Simarmata and Hia (2020) that for accepting technological and informational innovation,
personal innovativeness is a crucial factor. In a similar way, it was suggested that the usage behavior of individuals and new IT diffusion can be understood through personal innovativeness. The more positive beliefs and usage intention for a specific technology are developed among people with greater personal innovativeness in contrast to individuals with low personal innovativeness. Alternatively, when low motivation is possessed by end-users of the system, traditional methods of teaching are considered to be more efficient as compared with e-learning methods. Technological anxiety is high among individuals with a low level of motivation for using new technology (Peechapol et al., 2018).

A study based on IS identified CSE and personal innovativeness as key variables in determining performance expectation and perceived usefulness during covid-19. The role of personal innovativeness in influencing the CSE beliefs among individuals as been examined empirically by previous e-learning research studies (Peechapol et al., 2018). It was found by researchers that perceptions of self-efficacy and performance outcomes in the e-learning system can be determined by personal innovativeness during covid-19. The adoption of an e-learning system is also influenced by personal innovativeness during covid-19. It was claimed by Huang, Teo, and Zhou (2020) that there is no significant influence of personal innovativeness on the perceived usefulness of e-learning in developing countries like China during covid-19. The focus of the current study is to analyze the role of personal innovativeness in e-learning with reference to developing countries during covid-19.

One of the important variables in determining individual behaviour is the behavioural intention, which directly influences the usage behaviour of an individual during covid-19. The level with which a user is likely to reuse a web in the future is referred to as an intention by the studies based on web usage during covid-19. The frequent use of a system in a specific period is related to the behavioural intention to use during covid-19. In this research, performance expectation and CSE are influenced behavioural intention (endogenous variable) as per the previous research studies.

REFERENCES


