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# WHAT DETERMINES THE PERCEIVED EASE OF THE USE OF AN ONLINE LEARNING SYSTEM

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**Keywords E-Learning System Self-Efficacy, Computer Experience, Perceived Ease of Use, China**

## ABSTRACT

**Purpose:** The study has examined the impact of the personal innovativeness, and computer learning on the e-learning system self-efficacy of university students during COVID-19. Meanwhile, the study has also examined the impact of e-learning system self-efficacy of university students on the computer experience. Finally, the study has also examined the impact of perceived ease of use of e-learning system by university students during COVID-19.

**Method:** The data is collected with the help of an adapted questionnaire. The SEM-PLS is employed for the data analysis. the response rate of the study is 45%.

**Results:** E-learning systems 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. Their relationship results in improved use of the e-learning system.

**Implications**: Several implications have been provided by the study from a theoretical perspective. The integrative understanding of the association between stable, situational, and dynamic individual differences related to their relationship with perceived ease of usage has been expanded by this study.

**Significance:** The study is among the few earlier studies on the issues related to e-learning system and perceived ease of use of e-learning system of university students during covid-19.

**Originality/Value:** The study has highlighted an important issue related to the E-learning system self-efficacy, computer experience and Perceived ease of use.

## BACKGROUND

With the emergence of COVID-19, authorities were prompted by the unexpected closure of educational institutions to recommend the adoption of alternatives methods of learning. In emergencies, the traditional learning methods result in loss of students in terms of educational gains. Thus, alternatives to traditional learning help in ensure the prevention of spreading epidemic and no loss to learning of students.

Electronic resources can aid the formal learning system, which is known as e-learning. The process of teaching can take place within or outside the classroom. The use of electronic resources, i.e. internet and computer support the process of learning and teaching, which is the key factor in e-learning (Aboagye et al. (2020; Naseem et al., 2021). When COVID-19 emerged, e-learning replaced the traditional methods of education as there was fear of virus spread in social gatherings. To prevent the spread of virus, e-learning was the best way. It helped in ensuring the spatial distancing. Students were facing challenges, but e-learning benefited them with the continuation of educational learning (Lizcano et al. (2020).

Research utilization and knowledge mobilization are the terms, which have been created mutually. One term was constituted in the field of healthcare and the other in management. There is a lack of clarity of concept in both terms. These terms are about the translation of evidence/knowledge into practical form. The absorptive capacity, along with the ability to identify new knowledge, its assimilation, and application, are crucial elements of the translation process (Shujahat, Sousa, & Hussain, 2019).

This knowledge in practice is based on various learning types, such as exploitative, transformative, and exploratory. However, the focus of most of the existing research is on the situated and relational nature of learning (Lyman, Hammond, & Cox, 2019). The cognitive and personal aspects of learning have not been emphasized by current researches. The online courses have grown dynamically, making the e-learning system (ELS) a flexible, convenient and easy way of sharing important information beyond political, economic and physical boundaries. Individuals have been equipped with learning opportunities anywhere and anytime. They can share their knowledge within and across institutions (Świgoń, 2017). The key individual characteristics have been explored in the current study, which interrelates and engage users successfully. In case users are not convenient with the technology, it is least possible that they engage themselves with new knowledge and its practical translation.

The acceptance behaviours of users for technology have been predicted by several models in the IS literature. The technology acceptance model (TAM) of Mugo, Njagi, and Chemwei (2017) is a widely recognized and accepted model. Two crucial variables are included in the model, which influence the intentions

of users to adopt a system. These variables include perceived usefulness (PUF) and perceived ease of use (PES). The significance of investigating variables influencing the two variables has been suggested by research. Therefore, different determinants have been proposed by research (Lai, 2017). The difference among individuals is a crucial factor, which influences the PUF and PES. The differences among individuals related to IT have been identified by researchers based on individual situational differences. These differences include individual differences related to IT, such as computer anxiety, computer self-efficacy (CSE), computer experience etc (Schlebusch, 2018; Li et al., 2021). Moreover, stable individual traits specific to IT include personal innovativeness and computer playfulness.

The dynamic difference among individuals relates to the characteristics, which are flexible over time, which is the key difference between stable and dynamic individual differences (Huang & Liaw, 2018). The PES is significantly affected by the individual difference related to IT (Shen, Ho, & Kuo, 2019). The results of previous research studies are either unclear or inconsistent (Agarwal & Dixit, 2020; Shen et al., 2019; Mohsin et al., 2021b; Naiwen et al., 2021). A clear need has been suggested by literature studies for further investigation on the above-stated relationships (Agarwal & Dixit, 2020).

Moreover, it is helpful to recognize the nature of individual differences of perceived ease of using ELSs for better understanding the perceived learning outcomes of users. An alternative mode of delivering course content is offered by e-learning. Therefore, this form of learning can be optimized by universities to ripe its benefits. Several advantages are offered by the use of e-learning and information technology in contrast to traditional modes of learning. The ELS offers a flexible learning pattern for users and instructors (Tratnik, Urh, & Jereb, 2019). A significant influence on the learning effectiveness of learners is created by these potential disadvantages. Resultantly, it is important to analyze learning outcomes in e-learning research studies.

The existing studies have given confusing results related to the influence of technology on learning outcome. It has been reported by some research studies that the learning outcomes of learners are improved by the use of computers (Söllner, Bitzer, & Janson, 2018; Tratnik et al., 2019). Some other research studies reveal that learning performance and effectiveness may not be improved or even reduced through the use of computers (Pickering, 2017). The PUF of TAM has been conceptualized as the level with which an individual perceives a system to improve his/her performance (Mugo et al., 2017).

When an individual considers that a system can yield greater benefits in contrast to other methods of performing a task, this concept is regarded as a relative advantage. In the context of ELS, PUF and perceived learning outcomes are considered similar concepts. Several studies have revealed that a positive influence is created by PES on individual difference and PUF (Mashroofa, Haleem, & Jahufer, 2020; Omar, Sarudin, & Aziz, 2020; Vaidyanathan, 2018). Altogether, it has been proposed that the inconsistent results in existing literature studies on e-learning can be explained through a better understanding of PES and individual differences.

## LITERATURE REVIEW

Different definitions and perspectives of e-learning have been given by researchers based on their epistemological backgrounds. Different theories have been offered by constructivist and objectivist researchers. It has been argued by constructivists that knowledge and meaning are generated by individuals based on their experience. The construction of knowledge is done in social contexts, and individual acquires this knowledge. Divergence occurs in constructivist theories based on the focus on cognitive or collaborative abilities of processing information. Sociocultural conceptions is another extension of constructivist theories, which place a high significance on cultural learning dimensions, including the values, beliefs, the norms within social interactions and contexts (Secore, 2017).

Aboagye et al. (2020) conducted a study on student challenges and the way to deal with e-learning during COVID-19. The researchers examined the preparedness of students in the outbreak of COVID-19 for e-learning (Aboagye et al. 2020; Sarfaz et al., 2021; Mohsin et al., 2021). It was found by the study that learners must be provided with a combination of e-teaching and traditional way of learning. Radha et al. 2020 tried to examine the e-learning process among learners having familiarity with internet technology to improve their skills. It was found by the study that during the COVID-19 pandemic due to lockdown e-learning has gained popularity in every educational institution.

From an objectivist perspective, learning is regarded as a passive process in which learners acquire knowledge from instructors uncritically (Awang, Zahurin, & Wan, 2018). The acquisition of knowledge is made from the external environment. Learning aims at acknowledging external reality and changing the behaviour of learners accordingly. Learners are obedient and passive receivers of knowledge (Cheng, Shu, & Zhou, 2016). Considering this aspect, ELSs aim at broadcasting the knowledge of instructors and instructional materials is delivered to learners in an effective and efficient way. The learning process is centred on the instructor, and they are able to control and monitor the learning processes of learners. Moreover, instructors are allowed by ELSs to understand the needs and knowledge levels of learners for developing effective activities of learning.

It has been argued by constructivists that knowledge is not passively acquired from the external world. Rather, a learner constructs knowledge by experiencing and exploring an object activity and constructing own meanings related to the object (Cheng et al., 2016). The pace of learning is controlled by the learner. However, a supporting role is played by the instructor (Awang et al., 2018). It is considered by constructivists that effective learning can be done by learners when they explore knowledge by themselves (Secore, 2017).

The ELSs aim at maximizing the accessibility and availability of knowledge and information for learners to develop their own information. There is a need for learners to engage themselves in the context of real-world for learning (Secore, 2017). For instance, forecasting can be done better by learners while doing the forecasting task. Therefore, learners and instructors must become able

by information technology to integrate the contexts of real-world within the processes of learning (Foster, Colburn, & Briggs, 2018). It has been argued by collaborative learning theories that the creation of knowledge is done through the interaction of more than one people in a task, and they share different experiences. It is assumed by the collaborative learning model in line with constructivism that learners create their own knowledge. Learning of learners improves with a high level of sharing knowledge. The construction of knowledge, problem-solving, teamwork and active learning are involved in collaborative learning cooperation (Söllner et al., 2018). Different kinds of participation, interactions, problem-solving processes and discussions are supported by information technology based on these assumptions (Foster et al., 2018). As per cognitivism, the basis for learning is memory. In other words, the mental abilities and previous knowledge of a learner are important for learning (Foster et al., 2018). The input taken from the world is filtered by the mind a learner and interpretations are given based on the previous experiences of the learner. The informational processing ability of a student is limited. Thus, his/her attention might be selective. Better learning outcomes can be achieved through different methods of influencing the attention of learners, such as hypermedia usage, defining learning goals, and providing topic guidelines (Secore, 2017). Moreover, the memory of an individual is limited and reference aids should be accessed by learners through e-learning. The learning style must be consistent with the instruction for improved learning (Secore, 2017). The functions enabling a learner to gain access to related information, concentrate, and develop personal methods of learning should be provided by the ELSs. The focus of socio-cultural learning theory is on social contexts and the way learning occurs through modelling, observation and imitation. Social interaction, communication, and cognition results in higher-order learning functions. The ways of thinking are appropriated by the process of learning, such as gesture, language, which are transformed and internalized by the learner.

In line with constructivism, it is assumed by the theories of socio-culture that learners create knowledge, which is linked with the cultural and historical background of learners (Cilliers & Kruger, 2018). The process of learning occurs in a formal classroom environment as well as in society and environment. The interpretations are made by learners based on their culture and experiences. Therefore, different cultures must be respected and promoted for mutual existence without imposing any cultural domination (Cilliers & Kruger, 2018). Organizations need to mobilize knowledge resources for achieving and maintaining their competitive advantage (Ahmed & Sutton, 2017). A crucial role is played by ELSs (synchronous and asynchronous technology) in the mobilization of knowledge (Sprang, Swan, & Coker, 2020). The level with which an individual requiring the knowledge for a certain task is aligned with others possessing that information. Some important perspective on the mobilization of knowledge exists. The organizational efforts of mobilization of knowledge are based mainly on the transfer of knowledge (Ahmed & Sutton, 2017).

Both formal and informal processes can be used for the transfer of knowledge. Knowledge is regarded as a commodity or artefact by formalized knowledge sharing. This commodity can be transferred and structured using thoughtful

processes. Alternatively, the sharing of informal knowledge occurs through personal relationships developing in practical communities. Knowledge is constructed socially. For the mobilization of knowledge, knowledge is regarded in terms of the needs of the situation. For supporting decision making, the focus of knowledge is on the way of acquisition of accurate information at the right time to the right individual and in the right formation (Garrido & Requena, 2015). The effective utilization of knowledge must be based on the context of users. It has been argued based on the above-stated perspectives that knowledge mobilization should be supported by ELSs. ELSs enable the effective transfer of knowledge. Moreover, it allows learners to develop their knowledge through active social interactions than passive information assimilation (Sprang et al., 2020).

The current study is based on the integration of Self-efficacy theory and TAM (technology acceptance model). Moreover, different constructs such as computer experience, computer playfulness, personal innovativeness, and computer anxiety have been included. Different technologies of information, i.e. WWW, email, social network sites, and digital library, have been tested through the use of TAM. These information technologies are linked with ELSs in a significant way (Mugo et al., 2017). The ELSs have been investigated through the use of TAM (Omar et al., 2020). Moreover, it has been suggested by research that crucial roles are played by self-efficacy and TAM in predicting the use of e-learning (Rahmi, Yahaya, & Aldraiweesh, 2019). Therefore, the perceived ease of using ELSs and individual difference have been examined in the current study by using Self-efficacy theory and TAM as theoretical foundations.

***Hypothesis***

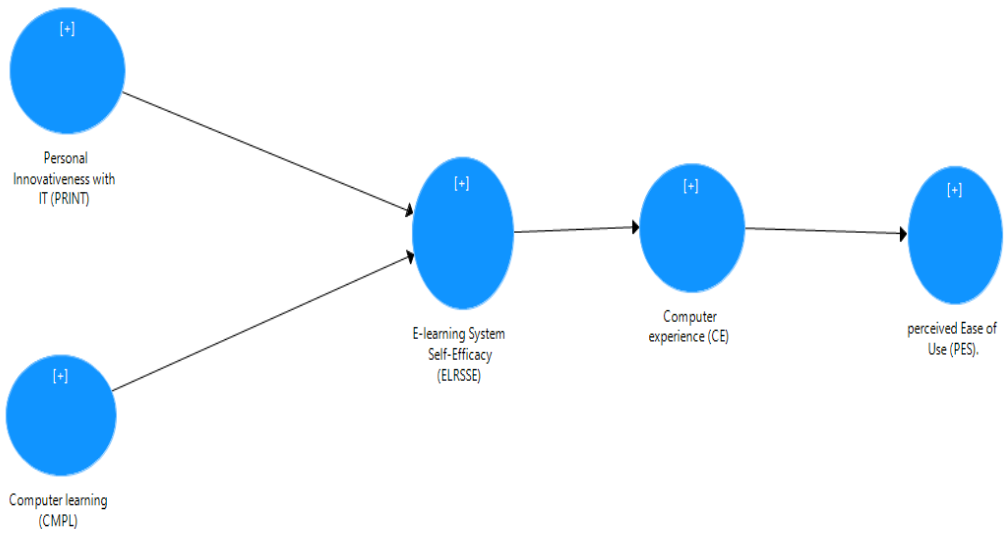


**Figure 1:** Conceptual framework

An individual difference variable is CSE, which includes the judgment of an individual about his/her ability to using a specific system or computer (Yorganci, 2017). Since there is no stable disposition of self-efficacy, it is

suggested by research that CSE is a multifaceted and multileveled construct. Moreover, it can be divided into two different categories such as self-efficacy specific to system and self-efficacy related general computer (Mensah & Mi, 2019). The use of a particular information system is regarded as system-specific self-efficacy. TAM can be used to associate PES with general CSE. This reflects that there is a similarity between PES and self-efficacy (Mugo et al., 2017). Moreover, TAM suggests that feelings, thinking, self-motivation, and actions of an individual are influenced by self-efficacy. In line with the theories, several empirical studies, including the research studies on ELSs, have supported the relationship (Ayub, Zaini, & Luan, 2017; Lai, 2017).

A study was conducted by Rahmi et al. (2019), in which 140 engineers were surveyed. The researchers proposed that there is an influence of general CSE on the perceived ease of using an ELS. Both the specific and general self-efficacy has been evaluated empirically by Latikka, Turja, and Oksanen (2019). It is revealed by the findings that there is a strong potential influence of system-specific self-efficacy on PES as compared with general self-efficacy related to computer. It was verified by Latikka et al. (2019) that PES is significantly influenced by system-specific self-efficacy.

The ability of an individual to become fearful, apprehensive, and uneasy regarding the general use of computers in the future is referred to as computer anxiety. Worries related to the use of computers, including fear, hostility, and intimidations, are the anxieties. It is feared by individuals that they will damage computers and would not be able to use them wisely (Wang & Wang, 2019). A high level of rigidity might be shown by people who are computer anxious as compared with those having no anxiety. The reactions of individuals towards an information system may result in moderate discomfort for using a computer or complete avoidance. In the case of choice availability, computer anxiety may not let individuals use computers. It is a type of state anxiety, which can be enhanced through suitable conditions and interventions (Huang & Liaw, 2018; Nand, Pitafi, & Kanwal, 2020).

The classical theories support the suggested association between PES and computer anxiety. Moreover, these theories suggest that anxiety has a negative influence on cognitive responses (Shen et al., 2019). In line with the theoretical background, it has been reported by empirical studies that computer anxiety has a significant influence on PES (Nand et al., 2020). When a person highly believes that he has low computer anxiety, the ELS is perceived to be easy to use.

It has been found by research that computer playfulness and personal innovativeness with IT are well-recognized traits of individuals specific to IT (Huang & Liaw, 2018; Li, Xu, & Xu, 2018; Vaidyanathan, 2018). Based on the theory of Innovation Diffusion, the individual willingness to try any new technology or system is regarded as personal innovativeness with IT (Vaidyanathan, 2018).

Innovations are accepted by some individuals in an institution in contrast to others. Innovative individuals have been conceptualized by research as the ones

who adopt an innovation or technology before others do (Ayub et al., 2017). Innovative individuals are classified based on the relative adoption speed for innovation. Moreover, the internal disposition of an individual for bringing a playful quality to an artefact and interpret it is referred as playfulness. Computer playfulness in the field of IS is regarded as the level of cognitive spontaneity in interacting with the computer (Li et al., 2018). As mentioned earlier, intrinsic and extrinsic are two types of motivation. However, computer playfulness is regarded as intrinsic motivation.

Less effort is required by an individual for performing a task who has a high level of computer playfulness as compared with the one having a low level of computer playfulness (Shen et al., 2019). The association between self-efficacy and stable individual difference specific to IT emerged from the self-efficacy theory of Stajkovic, Bandura, and Locke (2018). According to this theory, the influence of individual personality on performance has based the influence created on self-efficacy. Moreover, it has been revealed by empirical research that computer anxiety is negatively influenced by computer playfulness. However, CSE is positively influenced by computer playfulness (Li et al., 2018). In a similar way, there is a strong negative relationship between personal innovativeness with IT with computer anxiety. Personal innovativeness is positively associated with CSE (Agarwal & Dixit, 2020; Huang & Liaw, 2018). Therefore, the following hypotheses have been proposed in this regard:

The level with which an individual perceives the way of using a computer is referred to as computer experience. Users who are experienced have sufficient information about using a specific system or computer. Thus, this construct has been reflected as an important difference variable of individuals in determining their behaviour, skills, ability to use a computer, knowledge of computer, usage, and beliefs (Mashroofa et al., 2020). An individual with experience of using a computer may be efficient (Mashroofa et al., 2020). The association between self-efficacy and experience is based on strong theories. The idea of self-efficacy to be based on four aspects, including vicarious experiences, enactive mastery experiences, allied types of social influence and verbal persuasion, affective and physiological states, was identified by Stajkovic et al. (2018). There has been empirical support for the association between computer experience and self-efficacy specific to the system (Postma & Babo, 2019). Moreover, it was found that there is a strong influence of computer experience on computer anxiety than any other determinants of computer anxiety. Differences in the personality of individuals influence the efficacy perceptions as per the theory of self-efficacy (Stajkovic et al., 2018). The positive influence of personality on self-efficacy related to a system has been confirmed by empirical research (Postma & Babo, 2019).

The theory of self-efficacy reveals a relation between anxiety and personality (Stajkovic et al., 2018). The individual difference specific to IT is regarded as a trait related to a situation. However, personality is regarded as a broader trait (Huang & Liaw, 2018). The self-efficacy perception of an individual is shaped by specific as well as broad traits. The influence of individual difference specific to IT is more pervasive on CSE as compared with personality. This pervasive influence is because of the lack of specific targets by the personality (Huang &

Liaw, 2018). An empirical study reflects that there is less computer anxiety among online learning students as compared with traditional classroom learning students, which verify the above-stated relationship. Therefore, the following hypotheses have been proposed:

H1: Personal Innovativeness with IT (PRINT) has significant impact on the ELS Self-Efficacy (ELRSSE).
H2: Computer learning (CMPL) has significant impact on the ELS Self-Efficacy (ELRSSE).
H3: ELS Self-Efficacy (ELRSSE) has significant impact on the computer experience (CE).
H4: Computer experience (CE) has significant impact on the perceived ease of use (PES).

## METHODOLOGY

The stud has employed the survey-based methodology (Hair, Hult, & Ringle, 2016; Naala, Nordin, & Omar, 2017). The data is collected with the help of an adapted questionnaire. The SEM-PLS is employed for the data analysis (Akter, Wamba, & Dewan, 2017; Hair et al., 2016; Ramayah, Cheah, & Memon, 2018). SEM models comprise of latent variables having cause and effect association (Akter et al., 2017; Shiau, Sarstedt, & Hair, 2019). In addition, PLS-SEM is a powerful and a flexible tool that is used for developing models as well as estimating the relationship among the set of variables (Ringle, Sarstedt, and Mitchell, 2018). The items of variables are taken from the prior studies. The researchers select the sample size by using the recommendations of Kyriazos (2018). According to the suggestion of Kyriazos (2018), the sample size of respondent should be three hundred because it is assumed a good sample, however, the fifty respondents is supposed a weaker sample, one hundred respondent is reflected a weak sample while a sample of two hundreds respondents consider an adequate. Thus, this research study choose a three hundreds respondents as a sample. A total of 500 survey questionnaires were disseminated among the selected population. Out of 500 distributed questionnaires only 312 questionnaires were returned and usable for the purpose of analysis. It shows that the response rate was 62.4%. According to Sabir, Mohammad, and Shahar (2019), the average response rate in the management sciences study is 56% and this study achieved the adequate level of response rate.

## RESULTS

The research model was being analyzed by employed “Partial Least Squares” technique through statistical software the Smart PLS 3 (Ringle, Wende, & Becker, 2015). The two level analyses method suggested by Henseler et al. (2014) and Ramayah, Yeap, and Ahmad (2017) was used for the analysis of data. The measurement model was assessed in first stage and then structural model was estimated by this study (Hair, Risher, & Ringle, 2019; Shehzadi et al., 2020; Zia-ur-Rehman et al., 2021).

The SEM-PLS is a two step procedure comprises of measurement model and structural model. The Measurement model of the current study is shown in the figure 2 below.

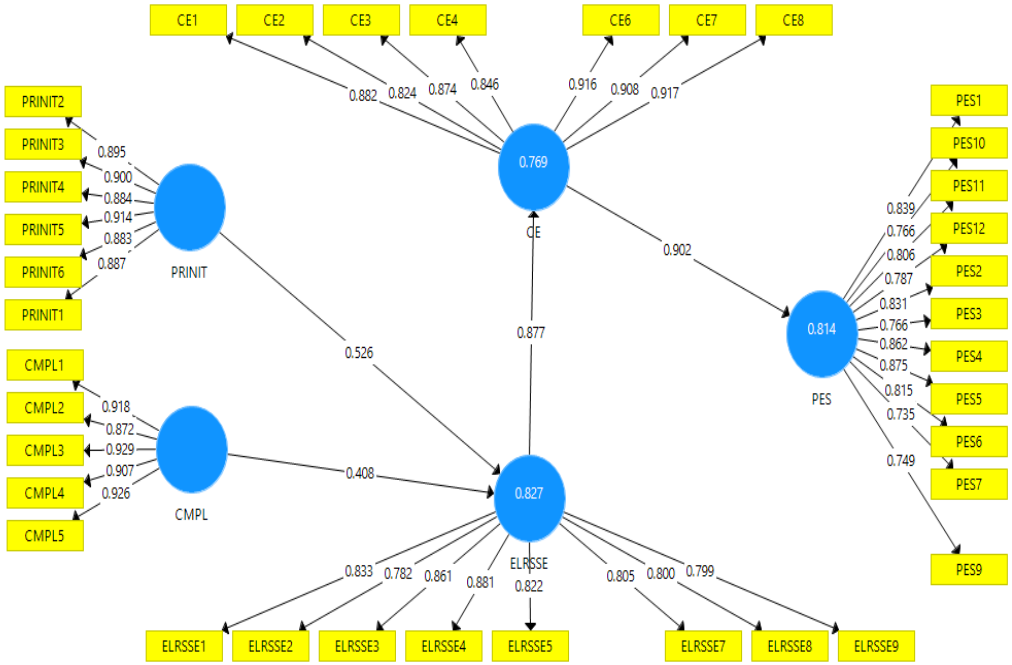


**Figure 2:** Measurement Model

The outer loading is used to determine the individual item reliability (Naala et al., 2017; Ramayah et al., 2018; Shuhaiber, 2018). Following the rule of thumb suggested by Hair, Matthews, Matthews, and Sarstedt (2017), items with loading above 0.70 is deleted from the final analysis. The outer loadings are shown in the following table.

**Table 1:** Cross Loadings

| | CE | CMPL | ELRSSE | PES | PRINIT |
|---|---|---|---|---|---|
| **CE1** | **0.882** | 0.599 | 0.777 | 0.760 | 0.633 |
| **CE2** | **0.824** | 0.530 | 0.700 | 0.724 | 0.572 |
| **CE3** | **0.874** | 0.572 | 0.754 | 0.754 | 0.586 |
| **CE4** | **0.846** | 0.531 | 0.734 | 0.791 | 0.553 |
| **CE6** | **0.916** | 0.669 | 0.801 | 0.849 | 0.661 |
| **CE7** | **0.908** | 0.636 | 0.819 | 0.821 | 0.623 |
| **CE8** | **0.917** | 0.667 | 0.817 | 0.858 | 0.653 |
| **CMPL1** | 0.637 | **0.918** | 0.828 | 0.675 | 0.830 |
| **CMPL2** | 0.549 | **0.872** | 0.734 | 0.588 | 0.781 |
| **CMPL3** | 0.653 | **0.929** | 0.812 | 0.669 | 0.821 |
| **CMPL4** | 0.607 | **0.907** | 0.796 | 0.637 | 0.815 |
| **CMPL5** | 0.659 | **0.926** | 0.822 | 0.676 | 0.813 |
| **ELRSSE1** | 0.649 | 0.796 | **0.833** | 0.642 | 0.777 |
| **ELRSSE2** | 0.602 | 0.766 | **0.782** | 0.657 | 0.786 |
| **ELRSSE3** | 0.686 | 0.797 | **0.861** | 0.681 | 0.808 |
| **ELRSSE4** | 0.690 | 0.815 | **0.881** | 0.705 | 0.831 |
| **ELRSSE5** | 0.603 | 0.852 | **0.822** | 0.653 | 0.800 |
| **ELRSSE7** | 0.857 | 0.571 | **0.805** | 0.793 | 0.636 |
| **ELRSSE8** | 0.861 | 0.598 | **0.800** | 0.796 | 0.624 |

| | | | | | |
|---|---|---|---|---|---|
| **ELRSSE9** | 0.824 | 0.581 | **0.799** | 0.771 | 0.598 |
| **PES1** | 0.808 | 0.611 | 0.750 | **0.839** | 0.587 |
| **PES10** | 0.612 | 0.541 | 0.626 | **0.766** | 0.550 |
| **PES11** | 0.659 | 0.603 | 0.697 | **0.806** | 0.614 |
| **PES12** | 0.606 | 0.587 | 0.647 | **0.787** | 0.545 |
| **PES2** | 0.775 | 0.651 | 0.730 | **0.831** | 0.591 |
| **PES3** | 0.753 | 0.533 | 0.686 | **0.766** | 0.553 |
| **PES4** | 0.856 | 0.585 | 0.767 | **0.862** | 0.611 |
| **PES5** | 0.838 | 0.627 | 0.773 | **0.875** | 0.638 |
| **PES6** | 0.807 | 0.576 | 0.757 | **0.815** | 0.584 |
| **PES7** | 0.569 | 0.469 | 0.560 | **0.735** | 0.503 |
| **PES9** | 0.561 | 0.507 | 0.591 | **0.749** | 0.506 |
| **PRINIT2** | 0.624 | 0.764 | 0.792 | 0.607 | **0.895** |
| **PRINIT3** | 0.589 | 0.798 | 0.790 | 0.618 | **0.900** |
| **PRINIT4** | 0.611 | 0.752 | 0.777 | 0.626 | **0.884** |
| **PRINIT5** | 0.684 | 0.834 | 0.846 | 0.695 | **0.914** |
| **PRINIT6** | 0.611 | 0.809 | 0.776 | 0.637 | **0.883** |
| **PRINIT1** | 0.603 | 0.824 | 0.792 | 0.635 | **0.887** |

The average variance extracted, composite reliability and cronbach's alpha are sued to determine reliability of measurement model (Hair et al., 2016; Henseler, Hubona, & Ray, 2016; Naala et al., 2017). The reliability analysis of the current study is shown the table 2 below.

**Table 2:** Reliability

| | **Cronbach's Alpha** | **rho_A** | **Composite Reliability** | **Average Variance Extracted (AVE)** |
|---|---|---|---|---|
| **CE** | **0.952** | **0.954** | **0.961** | **0.777** |
| **CMPL** | **0.948** | **0.950** | **0.960** | **0.829** |
| **ELRSSE** | **0.932** | **0.932** | **0.944** | **0.678** |
| **PES** | **0.945** | **0.952** | **0.952** | **0.646** |
| **PRINIT** | **0.950** | **0.950** | **0.960** | **0.799** |

In view of Hair et al. (2017), and Shuhaiber (2018), to achieve adequate discriminant validity, the AVE square roots must exceed the squared correlation estimates. In our case the diagonal values of validity matrix are higher than the other values (Table 3)

.

| | **CE** | **CMPL** | **ELRSSE** | **PES** | **PRINIT** |
|---|---|---|---|---|---|
| **CE** | 0.892 | | | | |
| **CMPL** | 0.884 | 0.891 | | | |
| **ELRSSE** | 0.877 | 0.878 | 0.893 | | |
| **PES** | 0.702 | 0.714 | 0.865 | 0.804 | |

| | | | | | |
|---|---|---|---|---|---|
| **PRINIT** | 0.700 | 0.712 | 0.810 | 0.713 | 0.894 |

After the assessment of measurement model the next step is to establish the links between and among the variable through structural model. The structural model of the current study is shown in the figure 3 below

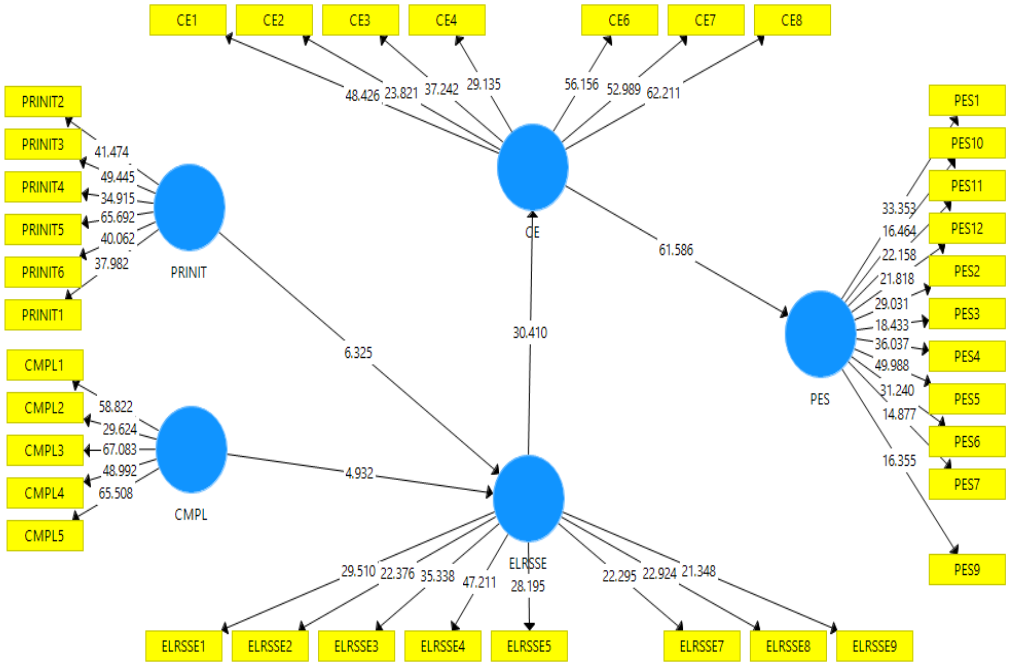


**Figure 3:** Structural model

It has been confirmed by findings of the research that mediating role is played by computer anxiety and self-efficacy for an ELS. The influence created on perceived ease of usage by computer experience is not mediated by computer anxiety, which is inconsistent with a previous research study (Gamble, 2018).

**Table 4:** Structural Results

| | **Original Sample (O)** | **Sample Mean (M)** | **Standard Deviation (STDEV)** | **T Statistics (\|O/STDEV\|)** | **P Values** |
|---|---|---|---|---|---|
| **CE -> PES** | 0.902 | 0.904 | 0.015 | 61.586 | **0.000** |
| **CMPL -> ELRSSE** | 0.408 | 0.416 | 0.083 | 4.932 | **0.000** |
| **ELRSSE -> CE** | 0.877 | 0.877 | 0.029 | 30.410 | **0.000** |
| **PRINIT -> ELRSSE** | 0.526 | 0.518 | 0.083 | 6.325 | **0.000** |

The value of R-Square is shown in the table 5 below.

**Table 5:** R-Sqaure

| | **R Square** |
|---|---|
| **CE** | 0.769 |
| **ELRSSE** | 0.827 |
| **PES** | 0.814 |

## DISCUSSION AND CONCLUSION

The role of dynamic individual differences as a mediator between PES and determining variables has been identified by the study. Evidence has been provided by a previous research study related to the role of beliefs as a mediator between behaviour and individual differences. The beliefs include both ease of use and usefulness of a system (Vaidyanathan, 2018). The understanding related to self-efficacy for a specific system and computer anxiety as mediators on the association of easy of usage and individual differences has been improved by the current research. Moreover, the research found a relatively low computer playfulness level (mean = 4.44). It reflects that it was partially agreed by respondents that they felt original, imaginative, and inventive during their interaction with an ELS. Moreover, it was revealed by findings that there are several potential challenges for creatively using an ELS. This research can be expanded by exploring the influence of ELS design on the creative thinking of students.

Several advantages can be attained by learning and teaching in e-learning environment. The most important advantage is reduced expenses both for teachers and students. Several students have return to educational institutions because of ELS. During the COVID-19 pandemic, irrespective of social challenges, students have successfully continued their learning through e-technology. Based on the outcomes of literature studies, it is important to specify the challenges, issues, and advantages of adopting ELS in the higher education sector.

The study has found association between computer experience and PES. The results are consistent with some studies (Oyadeyi, 2018; Sultan & Kanwal, 2017) and inconsistent with others. A high level of computer experience was revealed by the sample used in the research. Thus, it can be assumed that computer anxiety is not determined by computer experience. A crucial variable in determining computer anxiety is computer experience when users are not familiar with the use of computers. In the case of users' familiarity with computers, computer experience does not act as a key variable in determining computer anxiety. The results of a survey study are confirmed, which reveal that students reflect average to a low level of computer anxiety. Over the last seven to fifteen years, the situation of computer anxiety has not changed (Khoshsima, Toroujeni, & Thompson, 2019; Mastuti & Handoyo, 2018). There is a need for further research on exploring the way in which anxiety changes with time. It is important to understand the differences among individuals from a practical aspect in delivering an effective strategy of e-learning. Specifically, the focus of this research is on ELSs rather than on computers in general. The results of the research are crucial for developers and practitioners of ELSs.

## DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

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