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RESEARCH PAPER

Developing E-Learning Attitude Scale: A Factor Analysis Approach

[1]Saira Niaz* [2]Niaz Hussain Soomro, [3]Zahid Hussain Pathan

1. Assistant Professor, Institute of English Language and Literature, University of Sindh, Jamshoro, Sindh, Pakistan
2. Assistant Professor, Department of Linguistics & Philology, University of Balochistan, Quetta, Balochistan, Pakistan
3. Assistant Professor, Department of Linguistics & Philology, University of Balochistan, Quetta, Balochistan, Pakistan

***Corresponding Author:** Saira.altaf@usindh.edu.pk

ABSTRACT

This study presents the development of an effective instrument to measure English language learners' attitudes towards e-learning in the context of a public sector university. This study used Davis' (1986) Technology Acceptance Model. The results of factor analysis revealed that five factors of the scale explained a total of 53.438% of the cumulative loading variance in the pattern of relationship among the items. Based on the loading values for each factor (sub scale), twenty-two items remained the final e-learning attitude scale for English language learners. These items were from five subscales- Student-teacher online interaction (6 items), Perceived benefits of e-learning (5 items), Student-student online interaction (4 items), Perceptions about e-learning (3 items), and Perceived challenges of e-learning (4 items). This scale can be used by teachers, educators, administrators in order to get a deeper understanding of e-learning attitudes of English language learners and to implement e-learning technology successful in the field of teaching and learning.

KEYWORDS E-Learning Attitudes, E-Learning, Factor Analysis, Scale Development

Introduction

Recent years have witnessed a phenomenal proliferation in the use of e-learning due to sudden outbreak of COVID-19 pandemic. E-learning changed its perspective with the pandemic particularly in the field of teaching and learning since it highly affected the world of education and consequently resulted the expedition of a process of "digitalization" in education (Cevik & Bakioglu, 2021). Although e-learning technology was integrated in Pakistan before the pandemic (though not taken seriously across disciplines until fairly recently), yet COVID-19 gave a boost to it. The pervasive situation compelled learners to make the effective use of digital devices, social media tools and technological applications, online resources and all other e-learning activities (Mulenga & Marban, 2020). This increased the need to know the e-learning attitudes of learners who were facing the metamorphosis in their learning phase. In this regard, it was essential to investigate the factors that are responsible for their attitudes towards e-learning. Therefore, this study aimed to design a more specified instrument that may measure the factors related to e-learning attitudes of learners. The development of the current e-learning attitude scale may be significant and beneficial for the future research in the field of e-learning.

The primary purpose of this study was to develop a valid and reliable scale to investigate e-learning attitudes of English language learners at a higher education institute in Pakistan. The upcoming scale that would be the product of this study is intended to provide reliable and valid measurement of English language learners' attitudes towards e-learning attitudes and its influencing factors. This may further be used by educators, policymakers, and researchers to inspect e-learning attitudes of individual learners or group of learners to implement e-learning technological practices in a better way or to increase the use of it in educational research. Secondarily, it aimed to investigate the factors related to e-learning attitudes of English language learners in the given context. This research also attempts to add the literature on e-learning attitudes in order to develop a holistic understanding of e-learning attitudes by incorporating its various aspects that include perceived benefits and perceived challenges of e-learning and online interaction.

Literature review

The term e-learning was considered as "an encompassing term that includes the full gamut of electronic tools by means of which we gather, record, and store information and by means of which we exchange and distribute information to others" (Anderson, 2010, p.4). Previous research has supported the importance of measuring learners' attitudes towards e-learning for its successful implementation (Liaw, Huang & Chen, 2007; Omidinia, Masrom & Selamat, 2011) for it has "a significant and an essential direct influence on meaning and goals to adopt e-learning" (kenan, 2015, p. 27).

A number of factors influencing e-learning attitudes have been studied by various researchers. Volery and Lord (2000) identified ease of access, support, interaction as the critical success factors for e-learning attitudes. Zhu et al. (2013) concluded that students' motivation, benefits of e-learning such as flexibility and convenience, peer communication and student-teacher interaction were the main factors that maintained students' positive attitudes towards e-learning. Based on the literature review related to e-learning, this study discusses five important factors that influence English language learners' attitudes towards e-learning. These factors are Perceptions about e-learning, Online interaction, Perceived benefits of e-learning and Perceived challenges of e-learning.

It is defined as "the exchange of information between the various stakeholders in the course (e.g., peers, instructors, and other support staff)" (Johnson et al., 2008, p.360). Advanced technology in the field of e-learning has provided multiple opportunities for creating collaborative learning communities through online interaction and by exchanging information and experiences (Hajli et al., 2013). E-learning, with its interactive and participatory potential, has a significant impact on the interaction of second/foreign language learners. It provides opportunities of utilizing the conversation forums to the learners using e-learning dispenses.

E-learning has introduced significant enhancement in delivery of education. Therefore, considering the increasing demand of e-learning across the world, it becomes critical to understand the benefits of e-learning as perceived by learners. After studying a number of research studies on benefits of e-learning, this study has gathered almost all the benefits discussed in previous studies. The benefits of e-learning include enormous access to the e-learning resources (Al-Dosari, 2011; Dziuban et al., 2018; Al- Fraihat et al., 2020), convenience and self-pacing (Moody, 2004; You & Kang, 2014). Time and location flexibility (Kwofi & Henten, 2011), high level of learner engagement and involvement (Davidson & Amenkhienan, 2011), collaborative learning (2013), cost effectiveness (Verrshitskaya et al., 2020).

Almaiah et al. (2020) contended that challenges in an e-learning environment vary from country to country due to the contextual and cultural differences. Though Pakistan has been striving to implement e-learning in its educational institutes, it has been facing several issues such as access to the internet, poor infrastructure, lack of resources, lack of institutional support, and culture and policy (Nawaz, 2013). Qureshi (2012) divided the challenges faced by Pakistani students into three categories i.e., challenges related to (a) infrastructure, (b) instructional and (c) technical skills. Iqbal and Ahmad (2010) also reported electricity issue as one of the major challenges encountered by Pakistani learners. Some other challenges of using e-learning, as reported by researchers, were poor infrastructure (for instance, inaccessibility to latest technology, electricity breakdown, slow internet, lack of technological devices and support), digital literacy (Anderson & Gronulund, 2009; Nor & Mohamad, 2013), and lack of administrative support (Inglis, 2007).

Theoretical Framework

This study used Davis' (1986) Technology Acceptance Model as the foundational framework for the current research. This model is designed to inspect users' attitudes to accept or reject the new form of technology. Moreover, attitude is the prime component in the model that determines whether the use of technology will be preferred by the user or resisted. Attitude is further comprised of two key constructs of TAM i.e., Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) which are also called the determinants of attitude. PU is the degree of person's belief that the user perceives the particular system (for instance, e-learning in this case) useful while performing in a task (e.g., English language learning in this study). According to Granic and Marangunic (2019), PU is "the strongest determinant for the adoption of various technologies in educational context" (p.13). PEOU is defined as the degree to which one perceives that the use of the particular system (e-learning in this study) would cost the user (learner) either no effort or only a little effort (Devis, 1986; Marangunic & Granic, 2015). According to Zhao and Wang (2020), these two variables are used to measure and predict users' attitudes towards e-learning technology.

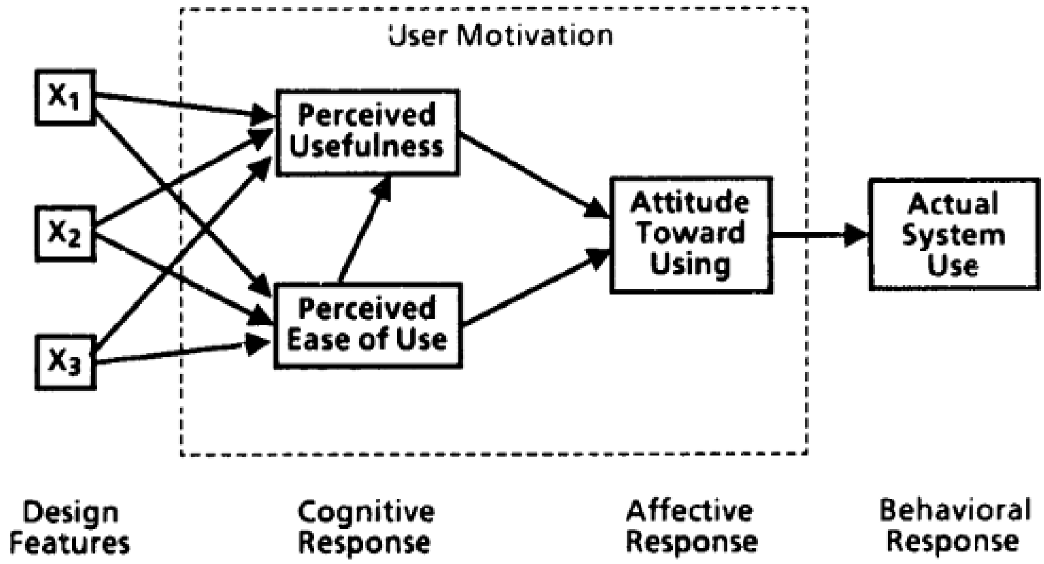

Figure 1: Technology Acceptance Model (Davis, 1986)

Material and Methods

This study used existing literature related to learners' attitudes towards e-learning as a guide to the current study afterwards based on the guide, a new scale was developed to investigate the factors related to e-learning attitudes of English language learners. Based on the literature review, five subscales were considered to represent five different dimensions of English language learners' attitudes towards e-learning. The approach in this study was adopted in a way that each subscale could produce significant and reliable information about that particular aspect of e-learning attitudes of English language learners. Afterwards, confirmatory factor analysis was used to confirm the factors that was "to test the hypothesis that relationship between observable variables and their underlying latent construct(s) exists" (Suhr, 2006, p. 1). It inspected whether or not there was any relationship between the observed variables (each variable represented by an item in a scale) and their underlying factor. This statistical method, originally developed by Joreskog (1973), was to check how well the measured factors represented a number of constructs. Prior to test the hypothesis statistically, researchers postulated a relationship pattern by using their knowledge of theory or/and empirical research. In CFA, selecting the number for factors was dependent on the number of the theoretical processes used in a research area. Suhr (2006) suggested a procedural approach to CFA that it required the researcher to review the literature and the relevant theory to specify and support a model, determine model identification, gather data, compute preliminary descriptive statistical analysis test, to test the model fit and to present and interpret the results. It then proceeded to fit these loaded items in the target matrix as closely as possible. Using CFA, researchers of the current study also specified the number of variables (factors) required in the data and showed that which measured factor was related to which latent factor.

A convenience sampling method was used to select 440 participants from the undergraduate students of BS part 2 enrolled in remedial English course at a higher education institute in Pakistan. Participants represented various majors that included English linguistics (n= 89), English literature (n= 83), English language and literature (n= 99), Political science (n= 47), Criminology (n=42), Business Administration (n= 37), Islamic Studies (n= 18), and Psychology (n= 25).

Statistical steps to run factor analysis

The current study followed the statistical steps as explained by Tabachnick and Fidell (2019) and Pallant (2016) to run the factor analysis on the collected data. Explained below in detail, the first step was to check the suitability to perform factor analysis by inspecting some considerations and assumptions. The second step was to extract the factors. Finally, the third step was to rotate the factor and to interpret them.

Step 1: Suitability to perform factor analysis

KMO and Bartlett's Test

The first consideration to test the suitability of factor analysis in a study was computation of two statistical measures that signified the suitability of the data for running the factor analysis. These two measures were Kaiser-Meyer-Olkin (KMO) and Bartlett's test of sphericity (Hair et al., 2019; Pallant, 2016; Tabachnick & Fidell, 2019). The tests were computed to measure the adequacy of sampling and data where the minimum value of KMO must be .6 to run the factor analysis and the value of Bartlett's test of sphericity should be significant ($p < .05$) for it (Hair et al., 2019; Pallant, 2016). As Table 1 shows that in the current research data the KMO value at .765 that was considered as an excellent sampling adequacy measuring value and Bartlett's Test of Sphericity value is .000 ($p = .000$) which was smaller than .05 and was highly significant. Therefore, it was adequate to compute factor analysis on this study.

Table 1
KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.777
Bartlett's Test of Sphericity	Approx. Chi-Square	2775.366
	Df	276
	Sig.	.000

Sample size for Factor Analysis

Second consideration to check the adequacy of factor analysis was the sample size. Pallant (2016) explained that the larger sample was the better sample to make more reliable correlation coefficients among the variables. It was suggested that "it is comforting to have at least 300 cases for factor analysis" (Tabachnick & Fidell, 2019, p. 613). Thus, the sample size for the current study was 440 cases indicating the good number.

Strength of intercorrelations among the items

The third consideration relates to the strengths of intercorrelations among the items that was measured from the inspection of correlation matrix. It was defined as "set of correlation coefficients among a number of variables" (Kline, 1994, p. 4). Tabachnick and Fidell (2019) have recommended that the evidence of coefficients value for should be greater than .3 for correlation matrix. The SPSS outcome of this study showed the interrelationships among the scale items as many of them exceeded .30 indicating the need to run factor analysis and supported the factorability of the correlation matrix. They have also argued that in order to produce the correlation matrix, eigenvalues for all the items are also necessary.

This study has used FA to extract the factors and the items were inspected to check the high and low factor loadings. Prior to compute factor analysis, assessment was done for the suitability of the data. An estimation of the number of factors was obtained from the eigenvalues reported in the table. Using KMO value (.777), only those components were extracted which had the eigenvalue of 1 or more. Eigenvalue**s** represented variance (Tabanchnick & Fidell, 2019). The outcome also showed the extracted factors with their eigenvalue**s** and variance percentage for each variable in addition to the cumulative variance of the extractable factors.

Step 2: Factor extraction

Step 2 was to determine the number of factor(s) by preparing a correlation matrix to perform factor analysis and extract a group of factors from the correlation matrix. One of the major goals of factor extraction was to discover the minimum number of factors with their reliably positioned variables. The other goal included discovering the meaning of the factors that is situated in connection to observed variables (Tabachnick & Fidell, 2019). According to Pallant (2016), there were various statistical techniques for extracting factors or dimension. Among them we followed screeplot as a reference point for extracting the factors for the current research study. This screeplot was utilized to extract the number of factors. It showed the factors in descending order along with the eigenvalues as the ordinate. It inspected the plot to find out the changing point where the plot shaped the curve. Cattell (1966) called it the changing point as elbow point and he further explained that the factors above the elbow point should be retained because these factors were highly contributing to the variance of the data set. Gorsuch (1983) added that the outcome of the scree test was more vivid and thus reliable particularly when communalities were high and sample size was large, and each factor in a tool had several observed variables with high loadings.

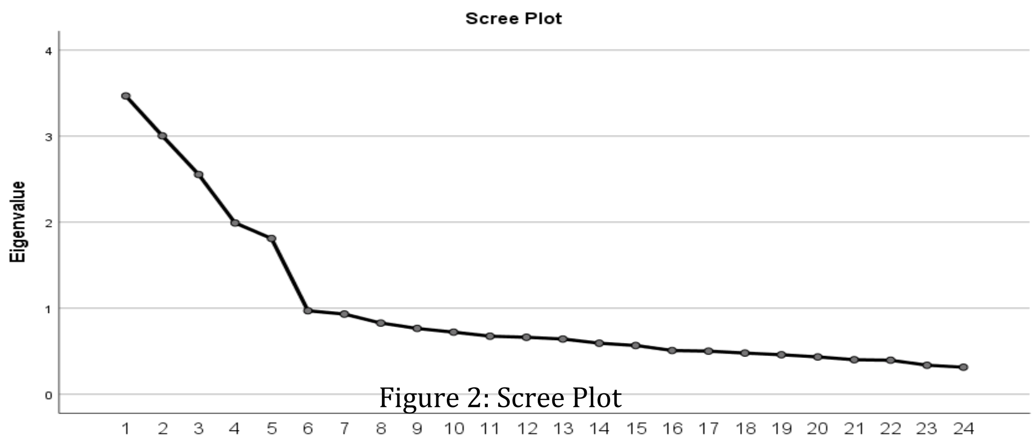

Figure 2: Scree Plot

The scree plot shown above extracted five factors which had greater than one eigenvalue. However, the sixth factor, along with other remaining factors, had less than 1 eigenvalue. After indicating five factors, the shape of the plot turns curved (elbow shape). Therefore, only five factors were retained for further analyses. Moreover, the Total Variance table was also examined to know the number of the factors meeting the criterion. Factor analysis in the present study revealed five factors recorded above 1 eigenvalue (12.425, 11.477, 10.718, 10.226, and 8.592 respectively). These five factors explained a total of 53.438% of the cumulative loading variance (see Total Variance Explained in Table 2).

Step 3: Factor Rotation and Interpretation

After the factor extraction, the rotation process was followed to enhance the interpretability and scientific utility of the solution. According to Tabachnick and Fidell (2019), "rotation of the factors is a process by which the solution is made more interpretable without changing its underlying mathematical properties" (p. 478). After an extraction, this process was followed to magnify high correlations between the variables and the factors. It determined the number of the factors to increase the interpretability in order to interpret the final results. The naming and interpretation of the factors (sub scales) depended on the meaning of the specific combination of observed variables correlating highly with each other. Factor rotation repositioned the factor axes to facilitate the interpretation of the data. The researcher could easily interpret the particular factor when several observed variables may have high correlation with it and they do not correlate with any other with the same correlation value (Tabachnick & Fidell, 2019). In orthogonal (uncorrelated) rotation – as compared with oblique (correlated) rotation – all the factors are uncorrelated to each other and hence contain the independence among the factors even after rotating them. Orthogonal rotation produces a loading matrix that presents the correlation between items (observed variables) and factors. On the other hand, oblique factor analysis shows the factors that contain the correlation among each other and therefore they do not remain independent after rotation (Pallant, 2016). Within these two broad approaches, there are various statistical techniques offered by SPSS software.

In orthogonal rotation, the techniques to be followed Varimax, Quartimax, and Equamax. Among them, the varimax is most commonly used in the rotation process (Hair et al., 2019; Pallant, 2016). Varimax is "a variance-maximizing procedure" (Tabachnick & Fidell, 2019, p. 487) which simplifies factors by maximizing the variance of factor loading that displays high loading higher and consequently reducing the number of variables by making low loading lower for each factor. This technique facilitated the researcher to interpret each of the variable that loads strongly only on one component or factor and not on others. By adopting this technique, researchers felt easy to interpret factors as the correlation between factor and variable is quite obvious.

Quartimax does the same action for variables what Varimax does for factors. It maximizes the dispersion of the loadings within variables across factors and thus simplifies them. It differs from Varimax in a way that it operates on the rows rather than columns. It is less popular than varimax as researchers are more interested in simple factors as compared to simple variables. Equamax is the hybrid version of above-mentioned techniques i.e., Varimax and Quartimax as it simplifies simultaneously both- the factors and the variables. The current study used Orthogonal extraction method Varimax rotation as it is most commonly used in attitude studies when researchers aim to extract unrelated and independent factors.

Furthermore, it was important to assess the sample size while estimating the measurements of reliable correlation coefficient in order to interpret the rotated component matrix. Tabachnick and Fidell (2019) have argued that "at least 300 cases are needed with low communalities, a small number of factors, and just three or four indicators for each factor" (p. 482). Hair et al. (2019) have also elaborated that minimum value for a factor loading should be .30 for a sample size of 350 to identify significant factor loadings. The sample size of this study was 440 that indicated statistically significant factor loadings. This research followed the Orthogonal approach to extract the factors with Varimax rotation because there were different and uncorrelated aspects of the e-learning attitude scale.

Tabachnick and Fidell (2019) expound about the reliability of the factors that if only one observed variable loads highly on a factor, then the factor is poorly defined. If two variables have high loadings on a factor, then its reliability depends on their pattern of correlation with each other and with other variables. If there is high correlation between these two variables (for instance, r > .70) and these two variables may simultaneously uncorrelated with other variables then the factor may be reliable. The component matrix above showed on each factor more than two variables were loading indicated that the extracted factors were reliable. Concerning the fact that the higher the loading, the more the variable is a measure of the factor, all the variables were inspected to check the loading values. The loadings above .71 are considered excellent loadings, .63 loading as very good, .55 loading as good, .45 as fair, and .32 as poor factor loading (Comrey & Lee, 1992). However, some other researchers think .3 factor loading value as the acceptable one (Pallant, 2016; Mvuddu & Sink, 2013).

Considering this criterion, factor analysis was computed on all 24 items for a sample of 440 English language learners. All the variables were rotated using Orthogonal Varimax approach as shown in the Rotated Component Matrix (see Table 3). Pallant (2016) recommend that "removing the items if they had low communality values (e.g., less than .3) as indicates that the item does not fit well with the other items in its component" (p. 220). Therefore, two variables having the low communality values were deleted for further analysis of inferential statistics that condensed the scale to 22 items (variables) in total.

- I feel comfortable using LMS for learning English. (Communality value = .297)
- E-learning helps me to learn English anytime (Communality value = .268)

Table 2
Total variance explained

omponent	Initial Eigenvalues			traction Sums of Squared Loadings			otation Sums of Squared Loadings		
	otal	% of Variance	nulative %	otal	% of Variance	nulative %	otal	% of Variance	nulative %
1	467	14.447	14.447	.467	4.447	14.447	982	2.425	12.425
2	004	12.515	26.962	.004	2.515	26.962	754	1.477	23.901
3	554	10.640	37.602	.554	0.640	37.602	572	0.718	34.620
4	991	8.294	45.896	.991	8.294	45.896	454	0.226	44.846
5	810	7.542	53.438	.810	7.542	53.438	062	8.592	53.438

Table 3
Rotated Component Matrix

	Component				
	1	2	3	4	5
I find my teachers very interactive in online groups.	.758				
My teachers do not provide me feedback on my work in online groups.	.735				
I find limited response of teachers to my English language related queries in online groups.	.724				
E-learning increases my interaction in English with my teachers in online groups.	.707				
My teachers share course material in online groups.	.637				
My teachers always encourage me to use e-learning.	.601				
E-learning is cost effective for learning English.		.783			
E-learning for learning English requires little effort on my part.		.765			

E-learning helps me learn English anywhere.		.760			
E-learning environment enhances my English language skills.		.634			
E-learning helps me learn English anytime.		.507			
E-learning helps me learn English effectively.		.447			
I like to interact in English with my peers in online groups.			.806		
I share my English learning experiences with other students in online groups.			.800		
Interaction in English with fellow students in online groups helps me learn better.			.773		
I like to share material for learning English with my peers in online groups.			.750		
I prefer e- learning instead of physical classroom for learning English.				.844	
I prefer to read an e-book rather than a print-book.				.837	
I do not like e-learning for learning the English language.				.807	
I feel comfortable using LMS for learning English.				.426	
It is not affordable for me to have a reliable internet connection at my home.					.754
I do not have access to the internet connection at my institute/department.					.730
I think I do not have enough skills to use LMS for learning English.					.663
Repeated electricity failures discourage me to use e-learning.					.655

Factor one was represented by 6 items and was labeled as "Student-Teacher Online Interaction". It carried 12.425% variance and factor loading values were ranging from .758 to .601 indicating excellent to good loadings. Factor two reflected the and ease of use as well as the usefulness of e-learning that explained 11.477% of the variability and was represented by 5 items. The factor loading value ranged from .783 to .447. It was named as "Perceived Benefits of E-learning" as all observed variables were addressing the various benefits of e-learning such as cost saving, ease of use, effective learning, access and flexibility of e-learning material. Factor three was comprised of 4 items which were addressing the concept of peer interaction in online groups hence it was labeled as "Student-Student Online Interaction". It was accounted for 10.718% of the variance. All the four variables had excellent factor loading values ranging from 0.806 to 0.750. Factor four with 10.226% of the variance was composed by 3 items that dealt with learners' perceptions (preferences, feelings and likes) for e-learning. Thus, this factor was termed as "Learners' Perceptions for E-learning". The variables were loading from excellent to very good with 0.844 to 0.426. Factor five was related to the challenges faced by learners in adopting e-learning and explained 8.592% of the variance. The challenges included the internet access, affordability of internet, technology skills and electricity failures. This factor, named as "Perceived Challenges of E-learning" was represented by 4 variables ranging from 0.754 to 0.655 factor loading value.

Reliability of Factors

Overall, the 22-item based scale generated a Cronbach alpha was 0.733 (see Table 4). Alpha coefficients were also computed on an individual factor of the e-learning attitude scale. Factor 1 (Student-Teacher Online Interaction) produced a Cronbach alpha of .785. The reliability coefficient for factor 2 (perceived benefits of e-learning) was also adequate with

.738 alpha value. Factor 3 (Student-Student Online Interaction) also yielded a high reliability of .799. Factor four (that was named as perceptions about e-learning) had the highest Cronbach alpha value among all the factors with .811 Cronbach alpha. Finally, the Cronbach alpha for factor five (Perceived Challenges of E-learning) was also computed that displayed low but acceptable value with .669 alpha. This alpha value was supported by the fact that Cronbach alpha value is very sensitive to the number of items. Although the minimum level of 0.7 is recommended, yet it is difficult to get the decent Cronbach alpha value if there is a small number of items (less than 10) in the scale. In such case, the mean inter-item correlation should be reported that should range from .2 to .4 (Hair et al. 2019; Pallant, 2020). In this case, the mean inter-item correlation of factor five is .333 suggesting a strong relationship among the items.

Table 4
Reliability of E-learning Attitude Scale

Scale	Cronbach Alpha Value
E-learning attitude scale	.733
Reliability of Individual Factors of E-learning Attitude Scale	
Student-teacher online interaction	.785
Perceived benefits of e-learning	.738
Student-student online interaction	.799
Perceptions about e-learning	.811
Perceived challenges of e-learning	.669 (mean inter-item correlation = .333)

Conclusion

As a result of confirmatory factor analysis, five factors were confirmed in the scale of e-learning attitudes of English language learners namely Student-teacher online interaction, perceived benefits of e-learning, student-student online interaction, perception about e-learning, and perceive challenges of e-learning. Almost all the factors had acceptable Cronbach alpha value as well. The final questionnaire had 22 items after deleting two items for having communality value. As a result, five- factor structure of the E-learning attitude scale has been confirmed through the factor analysis in this study.

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