A Predictive Study on Instructional Design Quality, Learner Satisfaction and Continuance Learning Intention with E-learning Courses: Data Screening and Preliminary Analysis

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Abstract

As E-learning initiatives are increasingly being deployed in educational and corporate training settings to revamp work-place productivity through life-long learning, concerns related to instructional design quality among stakeholders are equally growing. Thus, the overriding objective of the study was to carry out initial screening and preliminary analysis of the data related to the causal influence of instructional design quality on learner satisfaction and continuance learning intention. Based on the survey design, the quantitative data were collected from 837 students across ten CISCO Networking academies in Uganda. Descriptive statistics, multiple regression and factor analysis techniques were employed to address the purpose of the study. Primary attention was paid to the assumptions of response rate, missing data, outliers, data normality, multicollinearity, homoscedasticity and common method bias. The results of the initial screening and preliminary data analysis revealed non violation of prerequisite multivariate assumptions. The findings have provided empirical evidence on the psychometric study of which the instrument can be further used for future research. The steps taken for the analysis have provided a benchmark of audit trail in the methodology and statistical analysis for the replication of the study.

Keywords: instructional design quality, CISCO E-learning in Uganda, learner satisfaction, continuance learning intention, data screening and preliminary analysis

Data screening and the subsequent preliminary analysis procedures are of essence in order to avert any violations of the fundamental assumptions of multivariate data analysis (Won, Wan, & Sharif, 2017; Hair, Hult, Ringle, & Sarstedt, 2013; Ibrahim & Mohd Noor, 2014). In other words, failure to meet the prerequisite assumptions or to detect and correct errors in the data will result into distorted results from the analysis (Hair et. al, 2010; Pallant, 2007). If well conducted therefore, preliminary data analysis will ensure that the relationships between the constructs are able to guarantee good data output, and above all satisfy the assumptions of multivariate data analysis (Aliyu, Rosmain, & Takala, 2014; Hair et al, 2010). Alanazi (2016) has noted that if valid inferences are to be drawn from statistical test results with a fair degree of accuracy, the essential assumptions of multivariate data analysis must not be violated. Thus, initial data screening and preliminary data analysis are vital to identify and mend or at least minimise the methodological errors and their associated effect on the study results. It is worth noting therefore, in the process of carrying out inferential statistical analysis for hypothesis testing, satisfactory conclusions can only be made when the assumptions guiding a particular statistical analysis approach are met and sound (Maiyaki, 2012; Cruz, 2008). To that end, issues related to the assessment and treatment of (i) response rates, (ii) missing values, (iii) univariate and multivariate outliers, (iv) data normality, (v) multicollinearity, (vi) homoscedasticity, (vii) common method bias, and (viii) underlying factor structure are central to data screening (Hair, Black, Babin, & Anderson, 2016; Podsakoff, MacKenzie, Lee, & Podsakoff, 2003; Tabachnick & Fidell, 2001).

Statement of the Problem

Quantitative data screening, cleaning as well as its preparation for preliminary analysis is an essential raw material for conducting further multivariate analysis in a quantitative study that employs inferential statistics (Ibrahim & Mohd Noor, 2014). Particularly, the data screening and preliminary analysis procedures are useful to detect and address likely violations of the established assumptions associated with various multivariate statistical techniques. Besides, the research is able to have a clear understating of the quantitative data and achieve accuracy and consistency in the process of analysis (Kura, Faridahwati, & Chauhan, 2014). However, this important step has so far received less attention in the domain of E-learning Instructional design and end-user satisfaction literature. The issue is even more pronounced among novice researchers, perhaps because of the burden related to it (Abdulwahab, Dahalin, & Galadima, 2011; Hair, et al, 2010; Pallant, 2007). As Alanazi (2016) and Ibrahim and Mohd Noor (2014) have warned, ignoring this step no doubt affects the quality of the analysis results and consequently the inferences that are drawn. This is basically because the standard error estimates will tend to be inflated (Chernick, 2008 as cited in Kura et al., 2014), which inevitably will affect the statistical significance of the regression path coefficients and the predictive power of the outcomes in the analysis (Muazu & Siti, 2014; Hair et al., 2013). Thus, there is an urgent need to evaluate the quantitative data using diverse statistical tools so that established assumptions are not violated. Specifically, issues relating to response rates, missing values, outliers, data normality, multicollinearity, homoscedasticity, and common method bias are addressed.

Objectives of the Study

In light of the foregoing concerns, this paper set to examine the data screening and preliminary analysis procedures applied to ascertain E-learning instructional design quality, learner satisfaction and continuance learning intention constructs. The specific objectives were as to:

i. examine the extent to which the E-learning instructional design quality, learner satisfaction and continuance learning intention data meets the essential assumptions multivariate analysis.
ii. establish the underlying factor structure of the E-learning instructional design quality, learner satisfaction and continuance learning intention constructs.

Literature Review

Given the increasing need to support work-place productivity through life-long learning, E-learning has increasingly become a household brand in both educational and corporate training. It is no doubt that such increased deployment of E-learning initiatives is equally raising concerns related to instructional design quality among stakeholders. Issues are even complicated further by the absence of a consensual understanding on what actually constitutes E-learning instructional design quality. As a consequence, different stakeholders have understood and hence conceptualised E-learning instructional design quality based on their philosophical thoughts regarding human learning. A case in point, Karla (2016) has conceptualised E-learning instructional design quality on the basis effectiveness and efficiency. To Karla (2016), the effectiveness of E-learning pays attention to the extent to which the instruction enables learners realise the intended learning goals. On the other hand, efficiency focuses on the time and energy that learners invest to accomplish the instructional session. According to Quality Matters Program (2013), E-learning quality is all about issues of alignment. That is to say, the congruence of learning objectives, learning content, measurement and assessment, interactivity, course technology and engagement to enable the realisation of learning outcomes is what denotes E-learning quality. ASTD (2001) on the other hand has argued that the ability of E-learning to provide right learning content at the right time, foster mastery of knowledge and skills necessary for improved personal and organizational productivity are what constitutes quality E-learning.

From the foregoing conceptualisations of E-learning quality, it can be argued therefore that E-learning quality is a multidimensional concept. For example, the iNACOL National Standards for Quality Online Courses has classified E-learning quality in terms of instructional design, content, assessment, course evaluation and support and technology (INACOL, 2011). Yet according to Quality Matters Program (2013) eight component indicators constitute E-learning quality, namely: overview and introduction, learning objectives, instructional materials, assessment and measurement, learner interaction and engagement, learner support, accessibility and course technology. In the current study however, attention was paid to three key E-learning instructional design quality sub dimensions of interface design quality, content quality and instructional strategies from a synthesis of the classifications by INACOL (2011) and Quality Matters Program (2013). An evaluation of E-learning instructional design quality is vital because as learners and instructors tend to be separated in digital learning spaces, the instructional design attributes inherent in the E-learning course will be significant predictors of learning effectiveness, persistence and satisfaction rather than the delivery medium (Ally, 2004). Thus, the instructional design qualities of E-learning courses have been hypothesized to have a statistically significant influence on learner satisfaction and continuance learning intention.

Methodology

Participants and Procedures

This cross-sectional survey was based on a stratified random sampling of 900 E-learners who were selected from a population of 5239 across ten CISCO academies in Uganda. According to Krejcie and Morgan (1970)'s Table for sample size determination, a sample of 361 would be sufficient from the population of 5239 respondents. However, given the fact that the larger the sample size, the more confidence the researcher has with regard to generalisability of results, a sample size of 900 respondents was taken. Thus, a self-administered questionnaire was employed to collect data regarding the respondents' background variables, as well as their perceptions on E-learning instructional design quality, satisfaction and continuance learning intention.

Measures

In order to accomplish the study objectives, a 41-item questionnaire was used for data collection to assess instructional design quality, learner satisfaction and continuance learning intention with E-learning courses. The measurement items used were drawn and adapted from literature review of empirical studies on E-learning instructional design, learner satisfaction and continuance use intention. Specifically, the measurement items were adapted from Clawson, (2007), Georgiadou, Economides, Michailidou, and Mosha, (2001), Wang, Wang, and Shee, (2007), Bhattacherjee, (2001), and Bhattacherjee, Perols, and Sanford, (2008). The measurement items were then content-validated by six Experts in Instructional Technology and Research Methodology, and thereafter subjected to a pilot study before being used in the final study.

Instructional design quality. Three sub dimensions of content quality, interface design quality and instructional strategies were used to assess the instructional design quality construct. Learners rated the interface design quality of the E-learning courses using 8 items; while 9 items were used to measure content quality; both of which were based on a five response category Likert scale, i.e. "Strongly agree", "Agree", "Neutral", "Disagree" and "Strongly disagree". On the other hand, 12 items were used to examine instructional strategies in the E-learning courses based on the response category of "Never", "Rarely", "Sometimes", "Often", and "Always". The reliability indices for interface design quality, content quality, instructional strategies were Cronbach's alpha= .849, .869, and .902 respectively.

Learner satisfaction. Learner satisfaction with E-learning courses was measured using 8 items based on the five-point category of “Strongly agree”, “Agree”, “Neutral”, “Disagree” and “Strongly disagree”; with the reliability index for the dimension being Cronbach alpha=.814.

Continuance learning intention. E-learners reported their intentions to continue learning with E-learning courses using 5 items with a reliability index of alpha=.854. The five measurement items were based on a five response category Likert scale, of “Strongly agree”, “Agree”, “Neutral”, “Disagree” and “Strongly disagree”.

Data Analysis Procedures

This study applied both univariate and multivariate data analysis techniques in fulfilment of the study purpose based on SPSS version 22.0. Specifically, descriptive statistics via frequency counts and percentages were used to examine the response rate, missing data and normality. From the multivariate data analysis perspective, multiple regression analysis was applied to detect and understand outliers, homoscedasticity and multicollinearity. Lastly, Exploratory Factor Analysis was used to establish the underlying structure of both the exogenous constructs and endogenous constructs; and eventually establish the existence of any common method bias.

Results

Sample Characteristics

As summarised in Table 1, male learners who took part in the study constituted over 60% (506/837) as compared to the females who trailed with almost 40% (331/837). In addition, learners who rated their ICT use experience as being at beginner and advanced levels made up around 22% respectively. Yet the largest portion of students constituting 56% (468/837) rated their ICT knowledge level as intermediate. In terms of levels of ICT self-efficacy, almost 40% of the learners reported their ICT self-efficacy level as being good. This is trailed by those who perceived their ICT self-efficacy as being very good (28%), satisfactory (22%) and those who rated themselves as having excellent levels of ICT self-efficacy were merely at 10%. Lastly, 78% (651/837) of the E-learners were taking the CCNA course, while 22% (186/837) were offering other E-learning courses of CCNP, IT Essentials and Cyber Security.

Table 1
Analysis of Learner Demographic Attributes

Characteristic	Category	Frequency	%
Gender			
	Male	506	60.5
	Female	331	39.5
CISCO course enrolled			
	IT Essentials	83	10.3
	CCNA	621	77.1
	CCNP	67	8.3
	Cyber Security	30	3.7
	Other	4	0.5
ICT use experience			
	Beginner	185	22.1
	Intermediate	468	55.9
	Advanced	184	22.0
Level of ICT Self-efficacy			
	Excellent	86	10.3
	V. Good	234	28.0
	Good	336	40.1
	Satisfactory	181	21.6

Response Rate

A clear breakdown of data from a survey is vital so as to assess if the questionnaires gathered the information that is critical to the analysis process (Hair et al. 2010). Hamilton (2009) as cited in Won, Wan and Sharif (2017), has defined response rate as being the segment of the participants who actually responded to the items in a study in relation to the sample size.

Table 2
Questionnaire Distribution and Return Rates

Item	Frequency	%
Questionnaires Distributed	900	100
Questionnaires Returned	864	96
Incomplete Questionnaires	27	3
Questionnaires captured for analysis	837	93

As summarised in Table 2, nine hundred questionnaires were sent out to students in ten CISCO Networking academies in Uganda. Returns from the survey instruments revealed that a total of 864 students had actually responded to the survey; of which, 27 were found to be incomplete and thus not captured into SPSS. The actual data analysis therefore made use of 837 questionnaires that were considered valid, accounting for 93% of response rate. In light of the recommendations by Sekaran and Bougie (2010) and Chatman (2007) that a study with a response rate of 30% or greater is considered acceptable, the current study did not violate assumptions regarding response rates.

Assessment of Missing Data

Instances of missing data arise either due to participants failing to respond to questionnaire item(s) or because of errors made during data entry, all of which may make the data unsuitable for final analysis (Won et al., 2017; Hair et al., 2010). Missing data in the current study were detected using frequency counts and percentages under descriptive analysis with SPSS version 20.0. Variables that had missing values were referenced to the respective questionnaire to establish if errors were made at data entry stage and corrected. But for questionnaire items where the participants did not supply the required responses, the SPSS Missing value analysis tool was used to do further assessment. Although there seems to be no universally agreed upon position on the cut-off percentage for missing data, Hair et al. (2010) and Bennett (2001) have suggested that missing values of 10% or less are not a big problem to final statistical analysis. In a related instance, Schafer (1999) has argued that missing values of 5% or less are not a threat to further data analysis. In the current study, missing data were less than 5% across the items. As recommended by Tabachnick and Fidell (2001), the missing values in the study's data set were handled with the help of the mean substitution approach.

Assessment of Data Normality

Data normality demonstrates the shape of data distribution for metric variables (Hair, et al, 2010). The assumption of data normality in this study was detected by examining the shape of the graphical data distribution (Tabachnick & Fidell, 2001), and skewness and kurtosis (Pallant, 2007). Specifically, data normality was detected with the help of the graphical Normal P-P plot and Histogram method using linear regression. As depicted in Figure1, the variance followed along the normal straight line, hence providing evidence that residual error terms are expected to exhibit a normal distributed. Additionally, Figure 2 shows normal distribution of standard errors. In light of the suggestions by Kim (2013), the skewness and kurtosis values were seen to be within the range of 2 and 5 respectively, the implication being that the data in the current study demonstrated an approximately normal distribution.

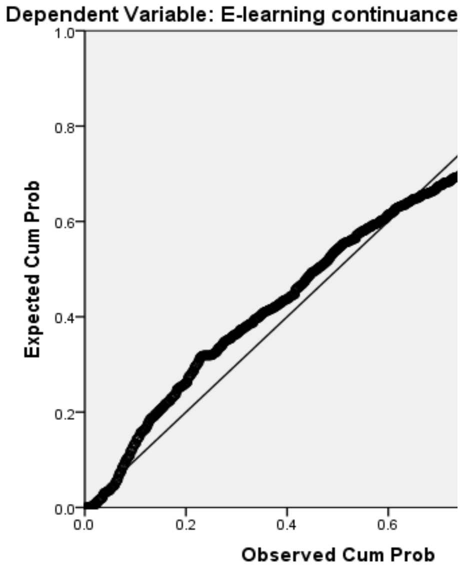

Figure 1. Normal P-P plot of Regression Standardized Residual

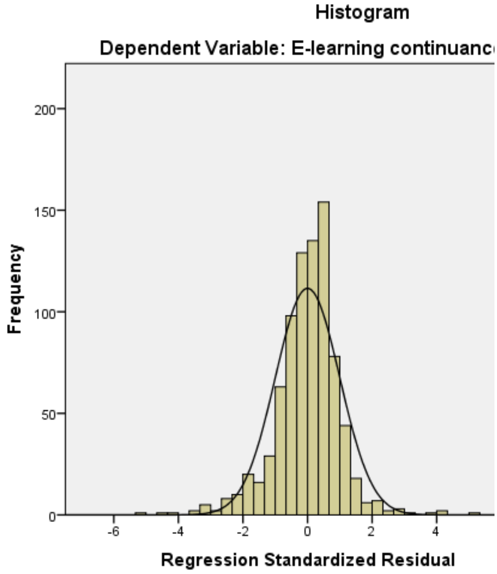

Figure 2. Histogram for normal distribution of the Standardized Residuals

Detection of Outliers

According to Hair, Black and Anderson (2010), outliers are scores that are not consistent with the rest of the data and are likely to affect the efficacy of multivariate analysis. Detecting and managing outliers is an essential activity as they tend to affect regression co-efficient estimates, hence leading to unreliable results (Verardi and Croux, 2009). Mahalanobis Distance (D^2) was used to detect multivariate outliers in the current study and then elimination was based on the critical values and significance levels. Data assessment identified that 32 cases exhibited outliers with Mahalanobis Distance values that were greater 18.47. Moreover, the 32 cases with outliers were accompanied with significance level of $p<.001$. The 32 cases with outliers had to be eliminated given the fact that outliers could easily compromise the results multivariate analysis. In the final analysis, the final dataset that could be applied in future for analysis now had 805 participants.

Examination of Homoscedasticity

Homoscedasticity is concerned with the variance of residuals on the predicted endogenous variable scores, which ideally are expected to indicate a similar pattern across all variables to be predicted (Pallant, 2007; Hair et al., 2010). In this study, the Koenker heteroscedasticity test was applied to check for the assumption of homogeneity of the residuals (Pryce, 2002). Accordingly, the result of the Koenker test was non-significant (p=.111,>.05). Thus, the null hypothesis that the data are not heteroscedastic was accepted, implying non-violation of the assumption of homoscedasticity.

Evaluation of Multicollinearity and Linearity

Multicollinearity is an indication of the extent to which a variable is explained by other variables in a given study (Kline, 2016). Two common diagnostic tools of Variance Inflation Factor (VIF) and Tolerance are essential for checking for multicollinearity (Hair et al., 2010; Kline, 2016). The Tolerance value gives an indicator of how much of the variability an exogenous variable is not explained by other exogenous variables in the analysis. Yet VIF is simply the inverse of Tolerance. According to Table 3, VIF values range between 1.923 and 2.342 (<10); and the Tolerance values were between 0.427 and 0.468 (>0.10), and indeed all are within the acceptance limits.

Table 3

Linearity and Multicollinearity Diagnostics for the Constructs

		CLI	ContQ	IntfQ	Instr	Sat	Collinearity Statistics	
							Tolerance	VIF
Pearson Correlation	CLI							
	ContQ	.443					.468	2.137
	IntfQ	.441	.651				.457	2.187
	Instr	.492	.645	.669			.427	2.342
	Sat	.641	.598	.579	.637		.520	1.923
Sig. (1-tailed)	CLI							
	ContQ	.000						
	IntfQ	.000	.000					
	Instr	.000	.000	.000				
	Sat	.000	.000	.000	.000	.		

To that effect, the results in the current study have demonstrated non-violation of Multicollinearity assumptions among the exogenous and endogenous variables. Additionally, the linearity statistics in Table 3 have further indicated positive and statistically significant relations among the constructs.

Exploratory Factor Analysis for Exogenous Variable

In pursuit of the data screening process, Exploratory Factor Analysis (EFA) in SPSS Version 20.0 was conducted on the 29 items used to measure the instructional design quality constructs. Moreover, Promax was chosen as the rotation method given that the expected components were assumed to be theoretically related (Matsunaga, 2011). To ensure that the data met the minimum requirements for Factor Analysis, the Kaiser-Meyer-Olkin Measure of Sampling Adequacy, Bartlett's Test of Sphericity, correlation matrix and the item communalities were first examined. Preliminary results revealed that the KMO index of 0.957 which was within the threshold of at least 0.7 (Yong and Pearce, 2013), indicating that the sample was adequate for Factor Analysis. Additionally, the Bartlett's Test of Sphericity was significant x^2 (1176) =19166.158, p=.000, hence supporting the factorability of the correlation matrix. Table 4 gives the details of the corresponding factor loadings and communalities. Exploratory Factor Analysis revealed three components with Eigenvalues greater than 1, and they explained 36.6%, 5.7% and 4.0% of the variance respectively. The three components were named as content quality, instructional strategies and interface design quality. Lastly, the quality of the extracted factors in terms of their factor loadings was assessed to ensure that items with loadings ≥ 0.5 and with no cross loadings were retained (Matsunaga, 2010; Karuthan, 2016).

Table 4
Factor Loadings and Communalities for the Exogenous Variables

	Items	Content quality	Instructional strategies	Interface design quality	Communalities
cp3	Text content	.711			.461
cp4	Lessons notes that are clear	.786			.508
cp5	Pictures to illustrate the learning content	.716			.510
cp7	Content uses vocabulary suitable to my learning level	.550			.385
css1	Provides me with learning activities to support the course objectives	.559			.386
css2	Clearly states the grading method to be used	.549			.404
css3	Provides me with content that is well-organized	.677			.540
css4	Breaks down practice activities appropriately for ease of my understanding	.699			.524
css5	provides me with learning activities that follow each other	.599			.508
ts3	Discuss my ideas with my peers		.585		.418
ts4	Study real-world problems in classroom activities		.570		.439
ts5	Work on assignments that deal with real-world information		.554		.460
ts8	Seek my own answers while learning		.543		.426
ts9	Solve learning problems I encounter		.575		.428

esd1	Elements for gaining attention during learning	.779		.559
esd2	Lesson activities that increase my learning success	.772		.548
esd3	Strategies for stimulating recall of my prior information	.783		.517
esd4	Strategies for maintaining attention on content being learnt	.747		.527
esd5	Strategies for enhancing learning retention	.716		.490
esd6	Elements that maintain my motivation during learning.	.736		.522
esd7	Opportunities for practice of difficult concepts I learn	.650		.488
nav1	Has navigational tools on all pages		.603	.487
nav2	Enables me to control my learning progress.		.624	.541
nav3	Has well organized pages		.534	.467
nav4	Has predictable screen changes		.746	.507
nav5	Presents me with a logical sequence on how to complete tasks		.636	.520
nav6	Gives me clear page directions.		.665	.553
nav7	Allows a new page to open in a new browser window		.711	.518
nav8	Requires less scrolling no matter the screen size used		.718	.436

Note. Extraction Method: Principal Component Analysis. Rotation Method: Promax with Kaiser Normalization.

Exploratory Factor Analysis for Endogenous Variables

Table 5 reveals the results of the Factor Analysis for the endogenous variables that were measured using 7 and 5 items respectively. Inspection of the correlation matrix revealed the presence of many coefficients scoring above 0.3 but less than 0.9, hence indicating absence of issues related to multicollinearity. The result of KMO measure of sampling adequacy was 0.920; while the Bartlett's Test of Sphericity was found to be statistically significant which supported the correlation matrix (p=0.000).

Table 5
Factor Loadings and Communalities for the Endogenous Variables

	Items	Learner satisfaction	Continued learning intention	Communalities
sat2	Relevance of learning content	.532		.489
sat3	Knowledge gained from the course	.672		.549
sat4	E-learning course functions	.747		.550
sat5	Learning content quality	.749		.539
sat6	Meeting my learning expectations	.797		.600
sat7	My learning interest in the course	.755		.561
sat8	Overall learning experience with this E-learning course	.811		.551
cui1	I would like to take another E-learning course after this		.730	.530
cui2	I will recommend this E-learning course to my friends		.804	.635
cui3	I intend to continue using the E-learning course for sharing knowledge		.843	.667
cui4	I will use the E-learning system on a regular basis in the future		.741	.515
cui5	I intend to continue using a related E-learning course for life-long learning		.725	.540

Note. Extraction Method: Principal Component Analysis. Rotation Method: Promax with Kaiser Normalization.

PCA indicated the presence of two components with Eigenvalues exceeding 1, which were named learner satisfaction and continuance learning intention, and accounted for 45.5% % and 10.2% of the variance in the factor solution.

Common Method Bias

Common method bias is the kind of bias in a study's dataset that result from some influences that are external to the measures used. For example data collection that employs a single common method, such as online survey (Gaskin, 2017). In this study, Harman's single factor test and common latent factor (CLF) were used to check for common method bias (CMB). In the case of the Harman's single factor test, all the 41 items measuring instructional design qualities, learner satisfaction and continued learning intention where loaded into SPSS and fixed to one factor. According to Podsakoff, MacKenzie, Lee, and Podsakoff (2003), CMB is evident if one general factor accounts for over 50% of the variance.

In this study, the variance was 35.4%, which indicated absence of issues related to Common method bias. Additionally, results of the CLF method for the one factor measurement model in Figure 1 demonstrated poor fit to the data:

χ^2/df=5.853, CFI=.745, TLI=.731, RMSEA=.078, suggesting that the measurement model was inconsistent with the data (Nordin et al., 2016).

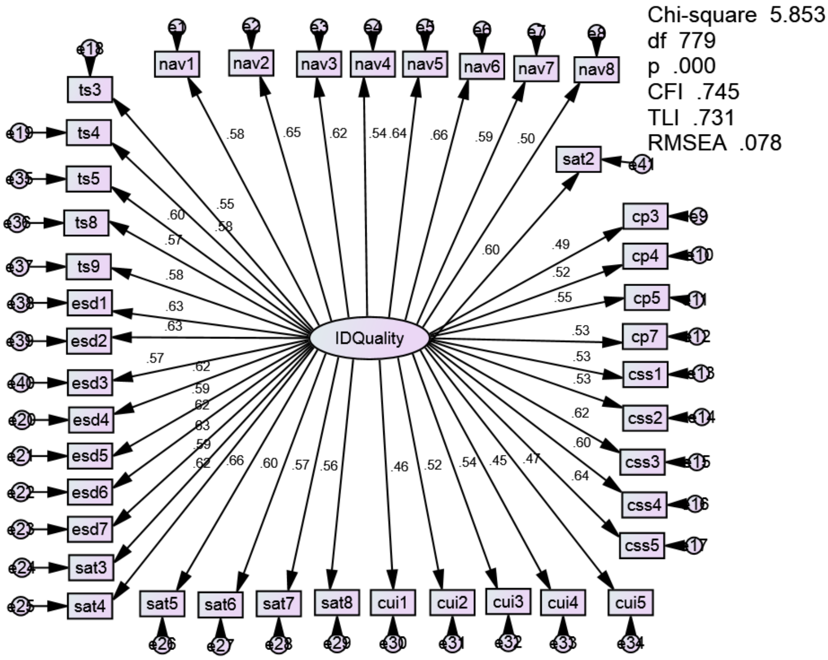

Figure 1. One-Factor measurement model for testing common method bias

Thus, the absence of model fit for the one-factor measurement model and 35% variance for a single factor all provide evidence that the Common method bias was not a threat to the measurement of instructional design qualities, learner satisfaction and continuance use intention.

Conclusion

This paper has presented the quality of the data on instructional design quality, learner satisfaction and continuance learning intention with E-learning courses. Many quantitative studies which were based on instructional design quality have been found to pay limited attention to data screening, perhaps because of the burden associated with procedures involved. However, turning a blind eye to the prerequisite initial data screening poses a threat to the results of multivariate analysis as the standard error tends to be inflated. The current study was therefore timely to shed light on this vital part of multivariate analysis that eventually impacts on the quality of inferences drawn from the data. Besides, initial data screening has been reported to enhance the researchers' understanding of their data characteristics. Upon successful assessment, detection and treatment of missing data, outliers, data normality, multicollinearity homoscedasticity, and common method bias, the current study has provided evidence that the essential assumptions of multivariate analysis have not been violated. The conclusions on the violations of the assumptions were guided by the recommendations offered by Hair et. al, (2010); Tabachnick & Fidell (2001); Podsakoff, MacKenzie, Lee, and Podsakoff (2003); and Pallant (2007). The quantitative data is therefore fit and recommended for further multivariate analysis, including but not limited to Confirmatory Factor Analysis, Structural Equation Modeling, Multivariate Analysis of Variance, Multiple Regression Analysis techniques.

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