Data Analysis Process for Evaluating E-government Adoption Behavior from Citizens' Perspective

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Data Analysis

Data analysis refers to the procedural steps applied to the collected data to achieve the research objectives. It aims to apply logical analysis for a better understanding of the research data. The research design, methodology, approach, and the nature of data collection all determine the appropriate and suitable data analytical methods required to be conducted Yamane [1967]; Creswell dan Creswell [2017].

In a quantitative research methodology, multivariate data analysis is commonly used to evaluate and assess the research study's hypotheses and identify the relationship between the defined constructs. Structural Equation Modelling (SEM) is a prominent and widely used method for analyzing multivariate data for a given research. It refers to a set of statistical models adopted to accurately explore the relationships among multiple variables or constructs Hair, *et al.* [2010]; Byrne [2016]. It facilitates researchers to model the relationship between constructs and their measurement items, which are the survey questions for a specific construct, and also the relationships among constructs in the proposed framework by using a series of equations Chin [1998]. Moreover, SEM evaluates whether or not the hypotheses in the proposed conceptual framework are supported by the quantitative data in the research study. If the collected quantitative data does not align with the conceptual framework, that means the related hypothesis is not supported and will be rejected. It can have a flexible interaction between the proposed conceptual framework to be examined and the quantitative data collected for a given research study Kaplan [2009]; Byrne [2016]

This research adopts the SEM method to analyze and evaluate the quantitatively collected data for exploring the significant factors affecting e-government adoption behavior. It is adopted in this research due to its ability to analyze all correlated relationships among the constructs simultaneously while taking into account the measurement errors of the research Kaplan [2009]; Hair, *et al.* [2010];

Kline [2015]. In this research, five main steps will be followed to perform the SEM analysis for evaluating the collected data obtained in this research study, as illustrated in Figure 1.1:

- **First step** refers to the data screening and conducting a preliminary analysis of the collected data. Therefore, the collected data is analyzed to eliminate missing data, and outliers. In addition, the normality, reliability, and multicollinearity tests will be applied to the data to prepare it for further analysis.

- **Second step** focuses on assessing the dimensionality of the collected data to explore whether or not the measurement items are relevant to each other to align with a corresponding construct Hair, *et al.* [2010]. The Exploratory Factor Analysis (EFA) is conducted in this step.

- **Third step** evaluates the extent to which the entire measurement model is valid and reliable. The SEM helps identify whether the proposed framework fits the collected data Hair, *et al.* [2010]. The Confirmatory Factor Analysis (CFA) is conducted in this step to examine the entire measurement model. Therefore, to guarantee that the measurement model is valid, the Goodness of Fit (GOF) indices must meet the acceptable threshold values Clark dan Watson [1995]; Hair, *et al.* [2010]. If the measurement model fails in satisfying the GOF threshold indices, the analysis of the one-factor congeneric measurement model is performed. The model is going through an iterative assessment process that refines and tests the model until confirming that the one-factor congeneric measurement models are valid, which leads to ensuring the validity of the entire measurement model. During the iterative procedure, measurement items that do not meet the acceptable threshold are dropped to ensure the validity of the indices.

- **Fourth step** refers to the assessment of the structural model validity. The structural model previews the path's value between the constructs in the conceptual framework and explores whether they are strong or not. It allows the understanding of the proposed relationships (developed hypotheses) among these constructs. It is evaluated via the magnitude of variance provided for the constructs, the path coefficient, and the P-value Kaplan [2009]; Hair, *et al.* [2010]; Byrne [2016].

- **Fifth step** is the final step in the SEM analysis that summarizes the results imported from analyzing both the measurement model and the structural model.

1 Preliminary Data Analysis

A preliminary data analysis prepares the collected quantitative data and ensures its readiness and validity for further analysis Hair, *et al.* [2010]. It confirms that the presumptions underlying the multivariate analysis are achieved prior to conducting the SEM analysis. In this research, three preliminary data analysis assessments will be performed, including missing data, outliers, and reliability.

1.1 Missing Data Assessment

Missing data refers to the questions (measurement items) in the questionnaire that were dropped and left unanswered by a respondent. They affect the reliability of the data analysis, which negatively impacts the research findings Kaplan [2009]; Hair, *et al.* [2010]. Therefore, it is essential to handle the issue of missing data in the research to enhance the data analysis process and ensure the efficiency and accuracy of the research findings. Preventive actions should be considered to confirm that the data are complete and free from any missing values. In this research, we will be using a web-based questionnaire, which helps prevent missing data. Hence, we will make answering all questions mandatory; so, participants are reminded if any items are left unanswered. Also, the survey cannot be submitted unless participants answer all measurement items.

1.2 Reliability Assessment

Construct reliability is also known as internal consistency, as mentioned in **??**. The reliability of the quantitative collected data should be examined using Cronbachs alpha, the same as the pilot study step. A Cronbachs alpha value that is greater than or equal to 0.70 indicates the reliability of the construct ($\alpha >= 0.70$) Bryman, *et al.* [2012]; Hair, *et al.* [2010]. In case Cronbachs alpha value is lower than 0.70, it is recommended to drop measurement items with a low-reliability value within the particular corresponding construct to increase Cronbachs alpha value for that construct.

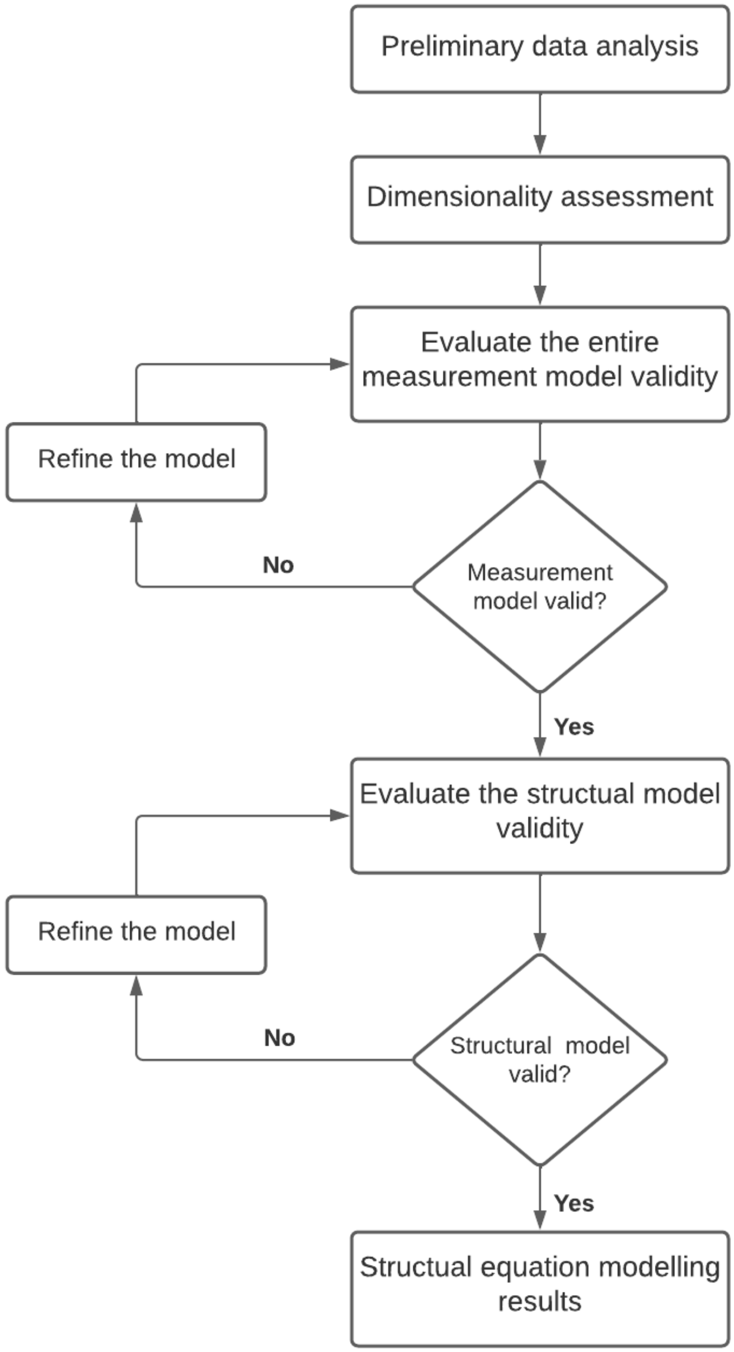

Figure 1.1: An overview of the data analysis steps

However, if the construct still has no acceptable reliability value, it should be excluded from further analysis Hair, *et al.* [2010].

1.3 Outlier Assessment

Outliers refer to the different data values that lie at an abnormal distance from the other data values. They exist in the data due to data entry errors, observational errors, and instrument errors. It is essential to identify outliers and mitigate them since they have a significant impact on the data analysis process and influence the SEM model fitness Hair, *et al.* [2010]; Byrne [2016]. Therefore, outliers should be managed and controlled using available statistical procedures Byrne [2016]. The Mahalanobis distance (D_2) is measured to effectively detect outliers Hair, *et al.* [2010]. It evaluates the distance between two points (an individual observation, and the average of other observations) Kline [2015]. In this research, we will evaluate D_2 of each data value by applying the chi-square distribution (X^2) and degrees of freedom equal to the number of independent constructs in the conceptual framework. A specific data value is considered an outlier if the D_2 is higher than the X^2 value, with p value ($p < 0.001$) Kaplan [2009]; Hair, *et al.* [2010]. Table 1.1 summarizes the required assessments to prepare the data for further analysis.

Table 1.1: Required assessments for the preliminary data analysis.

Assessment	Definition	Threshold value
Missing data	Refers to any questionnaire items that are missing and not completed by a participant.	Drop incomplete responses.
Reliabillity	Refers to the internal consistency used to confirm the high consistency of the survey items.	Cronbachs alpha ($\alpha >= .70$) Byrne [2016]; Hair, *et al.* [2010].
Outliers	Refer to the different data values that lie at an abnormal distance from the other data values.	$D_2 < X^2$ Kaplan [2009]; Hair, *et al.* [2010].

2 Dimensionality Assessment

Dimensionality assessment refers to exploring whether a set of measurement items are relevant to each other to align with a corresponding construct. This assessment is essential for further SEM analysis due to its ability in encompassing the entire structure of measurement items Clark dan

Watson [1995]. The EFA test will be employed in this step to assess and ensure the construct validity of the conceptual framework Straub, *et al.* [2004]; Hair, *et al.* [2010]. EFA refers to the significant test for investigating and confirming the distinction between the constructs of the proposed conceptual framework. It allows exploring the structure of measurement items corresponding to their representations of a particular construct Hair, *et al.* [2010]. It focuses on reducing and combining measurement items into a relevant set of constructs. The EFA assessment is usually used when the association between measurement items (observed variables) and independent constructs (unobserved variables) are uncertain Byrne [2016].

However, a set of assessments should be considered before performing the EFA test: data adequacy, communality, and eigenvalue Hair, *et al.* [2010]; Tabachnick dan Fidell [2013].

2.1 Data Adequacy Assessment

It assesses whether the collected data are adequate and of anticipated quality Hair, *et al.* [2010]. The Kaiser-Meyer-Olkin (KMO) measure and Bartletts test of sphericity are usually used to check data adequacy. They are used to determine the samples suitability for running the factor analysis. The value of the KMO measure diverges between 0 and 1. Kaiser [1974] stated that KMO values greater than 0.9 are marvelous and evidence of excellent sampling adequacy, while values below 0.5 are unacceptable (KMO ¿ 0.5). Therefore, the KMO value should range between these two values to consider the significant sampling adequacy. In addition, Bartletts test of sphericity is used to compare an observed correlation matrix to the identity matrix. It checks to see if there is any specific redundancy between the variables that can be summarized with some factors. It is employed to ensure that the sampling adequacy is significant with a p-value below 0.05 ($p < 0.05$). Hair, *et al.* [2010].

2.2 Communality Assessment

For each measurement item, the communality indicates the common variance found in that item. It calculates the sum of the squared loadings for each measurement item. The measurement item gets a better fit to explain the corresponding construct when the communality value gets greater Tabachnick dan Fidell [2013]. It usually ranges from 0 to 1 where a value close to 1 shows more variance.

However, the minimum acceptable communality value for each measurement item is set to be 0.5 to confirm that each measurement item shares a common variance with other items for the corresponding construct ($communality >= 0.5$). With a low communality value, the measurement item will be removed as it cannot be loaded on any construct Hair, *et al.* [2010]; Tabachnick dan Fidell [2013].

2.3 Eigenvalues Assessment

It is also known as characteristic roots. The eigenvalue is a condition that is employed to retain the number of constructs according to their measurement items loading Straub, *et al.* [2004]. It computes the amount of variation in the total measurement items accounted for by each construct. If the eigenvalue of a construct is low, then the contribution of that construct to supporting the dependent construct in the proposed framework is not significant Hair, *et al.* [2010]; Tabachnick dan Fidell [2013]. Therefore, constructs with low eigenvalues might be ignored and removed from the framework. According to kaisers rule Kaiser [1960], to define the number of factors with which their measurement items are supposed to be loaded, the eigenvalue should be equal to or greater than 1 ($eigenvalue >= 1$) Hair, *et al.* [2010].

2.4 EFA Assessment

It is a reduction technique that aims to identify the covariance structure of the observed measurement items by reducing the number of measurement items that represent each construct. It explores the actual number of factors that the measurement items are supposed to load. Hence, these items increase the demonstrated variance in the corresponding construct. Therefore, the factor loading will be verified for each measurement item. A load of items above 0.5 meets the minimum acceptable threshold value in the IS research to consider that item as a representative of the corresponding construct ($factorloading > 0.5$) Hair, *et al.* [2010]. With factor loading above 0.5, no cross-loading can be detected between the measurement items. The EFA test will be applied with the varimax rotation method to evaluate constructs validity Hair, *et al.* [2010]; Byrne [2016]. Table 1.2 summarizes the required assessments for evaluating the EFA for the given data.

Table 1.2: Required assessments for the exploratory factor analysis.

Assessment	**Definition**	**Threshold value**
Data adequacy	It assesses whether the collected data are adequate and of anticipated quality.	($KMO > 0.5$) Kaiser [1974], Bartletts test ($p < 0.05$) Hair, *et al.* [2010].
Communality	It represents the shared and common variance that exists in a measurement item.	($communality >= 0.5$) Hair, *et al.* [2010]; Tabachnick dan Fidell [2013].
Eigenvalue	It is a condition that is employed to retain the number of constructs according to their measurement items loading.	($eigenvalue >= 1$) Kaiser [1960]; Hair, *et al.* [2010].
EFA	It explores the actual number of factors that the measurement items are supposed to load.	($factor\ loading > 0.5$) Hair, *et al.* [2010].

3 Measurement Model Analysis

Measurement model analysis examines the relationship structure between the latent variables (the independent constructs) and their measurement items in the proposed framework. In the quantitative study, observed variables are usually computed numerically by obtaining participants' response values to a particular question in the developed questionnaire. We cannot measure the latent construct directly. Otherwise, it is usually evaluated through its corresponding observed variables (measurement items) Byrne [2016]; Hair, *et al.* [2010]. To guarantee the reliability and validity of the measurement model, every observed variable (measurement item) must be appropriately attached to only one individual latent variable (independent construct). The CFA measures are usually conducted to evaluate the GOF indices to assess the full measurement model Hair, *et al.* [2010].

CFA is a statistical technique employed to assure the fit of the measurement model to the collected data in a given context. It examines whether the measures of independent constructs (latent variables) and their corresponding measurement items (observed variables) are consistent with the proposed conceptual framework. CFA refers to a better understanding of the shared variance among the measurement items Byrne [2016]; Hair, *et al.* [2010]. This shared variance reflects the measurement items assembled to represent a corresponding construct. Therefore, in the measurement model, the CFA presents how every measurement item is contributed to its corresponding independent construct.

Two major steps should be taken into consideration while performing the CFA assessment:

The first step focuses on the specifications of the measurement model and how well it developed. At first, the entire measurement model is assessed based on the GOF indices that meet the satisfactory threshold values. In case the GOF indices fail to meet the satisfactory threshold values, the entire measurement model should be divided into separate one-factor congeneric measurement models, each of which assesses one latent variable along with its measurement items individually. This step provides an iterative modification process of the individual model for obtaining a group of measurement items that best fit a corresponding construct. After reaching satisfactory fitness values from all these individual one-factor congeneric measurement models, they will be aggregated in an entire updated measurement model. Then, the GOF indices will be examined to ensure they meet the satisfactory threshold values in the updated measurement model. The measurement model will go through iterative processing and reassessment until all GOF indices meet the satisfactory threshold values. During this iterative procedure, the measurement items that fail to statistically fit with other items will be dropped.

The second step examines the extent to which the entire measurement model is reliable and valid by evaluating the convergent and discriminant validity Byrne [2016]; Hair, *et al.* [2010].

3.1 The Measurement Model Assessment

As mentioned above, the measurement model is considered valid when it meets the satisfactory GOF indices values Byrne [2016]; Hair, *et al.* [2010]. The satisfactory GOF values show that the sample data is properly represented by the proposed framework. They are used as a guideline rather than a confirmation of the model fitness Hair, *et al.* [2010]; Byrne [2016]; Kline [2015]. Table 1.3 illustrates the list of common GOF assessments alongside their definitions, sensitivity to the sample size (N), measures the type of fit index, and acceptable cutoff values Chen [2007]; Hoyle [2012]; Niemand dan Mai [2018]; Hair, *et al.* [2010].

Table 1.3: The GOF assessments of the full measurement model.

Assessment	**Definition**	**Sensitive to N?**	**Measure type**	**Cutoff value**
Ration of X^2 to degrees of freedom (X^2/df)	It evaluates the overall fit and the discrepancy between the sample data and fitted covariance matrices. It signifies the difference which is the ratio of X^2 to the df.	Yes	Badness	<= 5.0
Goodness of Fit Index (GFI)	It refers to the proportion of variance accounted for by the estimated population covariance. It is similar to X^2.	Yes	Goddness	>= 0.90
Adjusted Goodness of Fit Index (AGFI)	AGFI is the extended version of GFI measure. It corrects GFI based on the df. It favors more restrictions and parsimony.	Yes	Goddness	>= 0.80
Comparative Fit Index (CFI)	It is a frequently reported fit index. It is a replacement of fit indices that are affected by (N). It compares the fit of a target model to the fit of an independence or null model by measuring the extent to which it is superior to the independence model.	No	Goddness	>= 0.90
Tucker-Lewis Index (TLI)	It is an incremental fit index that indicates the model of interest improves the fit by 90% relative to the null model. It can detect model mis-specifications.	No	Goddness	>= 0.90
Root Mean Square Error of Approximation (RMSEA)	It is an index of the difference between the observed covariance matrix per the df and the hypothesized covariance matrix which denotes the model. It is a parsimony-adjusted index.	Yes to small N	Badness	<= 0.05
Standardized Root Mean Residual (SRMR)	It represents the square root of the difference of the average of standardized residuals between the sampled (observed) and the posited (hypothesized) covariance matrices.	Yes	Badness	<= 0.09

The initial full measurement model should be first assessed in the study by applying the GOF assessments. The results of GOF values should be acceptable and meet the acceptable threshold value mentioned in Table 1.3. In case any GOF value is not satisfactory and below the recommended threshold value, that means the entire measurement model fails to properly fit the data Hair, *et al.* [2010]. Consequently, refinements to the measurement model are necessary by separately analyzing every independent construct alongside its corresponding measurement items, by creating one-factor congeneric measurement models.

One-Factor Congeneric Measurement Model is a subset model of the entire measurement model. A measurement model is considered congeneric if a measurement item loads only on one individual underlying construct and there are no correlations between error terms Byrne [2016]; Hair, *et al.* [2010]. This practice will be adopted in this research study to detect the fit indices measures separately for every construct alongside its measurement items. The refinement process of the entire measurement model begins with constructing six one-factor congeneric measurement models according to the proposed conceptual framework, namely, Perceived Ease Of Use (PEOU), Perceived Usefulness (PU), Social Influence (SI), Facilitating Conditions (FC), Trust of Government (TOG), and Adoption Behavior (ADOPT). These models are evaluated by applying the GOF indices provided in Table 1.3.

If any one-factor congeneric measurement model fails to meet the acceptable GOF indices, it needs to be reassessed and refined to ensure its validity and to meet the cutoff GOF indices values. The model can be reassessed to improve its fitness to the full measurement model by using diagnostic measures, including standardized factor loadings (SFL), standardized residuals (SR), and the GOF indices threshold Byrne [2016]; Hair, *et al.* [2010]:

1. **Standardized Factor Loadings (SFL)**, also known as "standardized regression weights," refers to the level to which each measurement item converges with the corresponding construct. It indicates the convergent validity of the construct. It is indicated that the measurement item fails in explaining the corresponding construct when the SFL value is below 0.5. As a result, measurement items with ($SFL < 0.5$) should be dropped from the model Hair, *et al.* [2010]. This measure helps eliminate measurement items that are not relevant.

2. **Standardized Residuals (SR)** indicates the difference between both the observed and the estimated covariance. A good SR value, which shows that a particular relationship is well considered, should fall in the range from -2.58 to +2.58 ($SR = \pm 2.58$). The SR values that do

not fall in this range indicate an unsatisfactory level; therefore, the corresponding measurement item should be eliminated Hair, *et al.* [2010]; Schumacker dan Lomax [2004]. A summary of the above three diagnostic measures is represented in Table 1.4.

Table 1.4: The diagnostic measurements to improve model fitness.

Measure	Definition	Threshold
SFL	It indicates the level to which each measurement item converges with the corresponding construct.	($SFL >= 0.5$) Hair, *et al.* [2010].
SR	indicates the difference between both the observed and the estimated covariance.	($+2.58 > SR > -2.58$) Hair, *et al.* [2010]; Schumacker dan Lomax [2004].

It is highly recommended that each construct should have at least three measurement items to provide an acceptable coverage of that construct Hair, *et al.* [2010]. Therefore, it is important to maintain the number of measurement items for each construct throughout the iterative processing and refinement measures mentioned above.

3.2 The Measurement Model Validation

The Convergent Validity refers to the convergent degree between several measurement items to measure an individual underlying construct. It is evidenced when measurement items corresponding to a particular construct show significant correlations with each other, compared to the other measurement items convergent to other constructs Hair, *et al.* [2010]. Convergent validity can be assessed by examining the value of the SFL of all valid measurement items, applying the composite reliability to measure the internal consistency in scale items for each construct, and measuring the Average Variance Extracted (AVE) Hair, *et al.* [2010]; Straub, *et al.* [2004]:

1. **The SFL** is evaluated for each individual measurement item that existed in the valid one-factor congeneric measurement model to assure the validity of the respective construct. The cutoff value should be equal to or greater than 0.5 ($SFL >= 0.50$) as mentioned in Table 1.4 Hair, *et al.* [2010].

2. **Composite Reliability (CR)** estimates the internal consistency of a set of measurement

items to the corresponding factor. It represents the extent to which the measurement items for a given factor are measuring the same underlying factor Fornell dan Larcker [1981]. Composite reliability is calculated by using the formula explained by Wynne W [1998]:

$$CR = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum_i \epsilon_i} \tag{1.1}$$

Where λ is the standardized factor loading of each measurement item to the given factor, and ϵ is the respective error variance for each item. ϵ is calculated for each measurement item as:

$$\epsilon_i = 1 - \lambda_i^2 \tag{1.2}$$

The acceptable CR value should be 0.70 or greater to support the construct reliability ($CR >= 0.70$) Aguirre-Urreta, *et al.* [2013]; Wynne W [1998].

3. **Average Variance Extracted (AVE)** focuses on evaluating the amount of variance captured by a particular construct to the amount of variance due to random measurement error. It is calculated by using the following formula Fornell dan Larcker [1981]; Wynne W [1998]:

$$AVE = \frac{\sum \lambda_i^2}{\sum \lambda_i^2 + \sum_i \epsilon_i} \tag{1.3}$$

Where λ is the standardized factor loading of each measurement item to the given factor, and ϵ is the respective error variance for each item. ϵ is calculated using the Equation 1.2. An AVE value of 0.5 or greater is considered a good rule of thumb for supporting the convergent validity for each construct ($AVE >= 0.5$) Hair, *et al.* [2010].

Table 1.5 summarizes the above three measurements used to confirm the convergent validity of the refined one-factor congeneric measurement models.

Table 1.5: The convergent validity assessments.

Measure	**Definition**	**Threshold**
SFL	It evaluates the extent to which the collected data are sufficient and has the expected quality.	($SFL >= 0.5$) Hair, *et al.* [2010].

Table 1.5: The convergent validity assessments (continued).

Measure	Definition	Threshold
CR	It estimates the reliability of a construct based on its corresponding measurement items.	($CR >= 0.70$) Wynne W [1998].
AVE	It is the average of the amount of variance captured by a particular construct to the amount of variance due to random measurement error.	($AVE >= 0.5$) Fornell dan Larcker [1981].

The Discriminant Validity indicates the extent to which a construct is distinct from other constructs in the proposed framework Hair, *et al.* [2010]. It seeks to confirm that two underlying constructs that existed in the framework that are not supposed to be related are unrelated; it seeks to discriminate among different independent constructs. The discriminant validity can be assessed by comparing the value of $\sqrt{AVE}$ for each construct with its relationship to other constructs Hair, *et al.* [2010]; Fornell dan Larcker [1981]. The $\sqrt{AVE}$ for each construct should exceed the values of its correlation to all other constructs to confirm the discriminant validity of the measurement model.

After finalizing this step, the CFA measurement analysis helps confirm that the updated entire measurement model properly fits the sample data for the given research. Therefore, we can move forward and examine the structural model using further SEM analysis.

4 Structural Model Analysis

The last step of the analysis procedure is assessing the structural model's validity. It examines how constructs are related to each other by measuring the path among them in the proposed conceptual framework. The path coefficient assesses the strength, nature, and importance of each relationship among the constructs Hair, *et al.* [2010]; Schumacker dan Lomax [2004]. The developed hypotheses would be either accepted or rejected based on the significance of the relationship among constructs Byrne [2016]; Schumacker dan Lomax [2004]. Before measuring the path coefficient, it is important to guarantee the fit of the structural model by measuring the GOF indices values and obtaining the acceptable threshold values as shown in Table 1.3. If the structural model does not meet satisfactory GOF values, it requires further refinement to ensure its validity Hair, *et al.* [2010].

Once the structural model has confirmed an acceptable fit, the SEM analysis can continue to compute the path coefficient to decide whether the developed hypotheses are accepted or rejected. Individual estimates of parameters for every developed relationship (hypothesis) between two theoretical constructs will be assessed. The Maximum Likelihood Estimation (MLE) method is commonly used to estimate these parameters in the SEM analysis. It determines the values for the parameters in the model that best describe the observed relationships by maximizing the likelihood function to find the probability distribution Hoyle [2012]; Ullman dan Bentler [2013]. In hypothesis testing, the z value and the p value are considered statistically significant tests of the estimated parameters. Therefore, the z value is defined by calculating the ratio of each parameter estimate to its standard error. The z value is statistically significant if it exceeds the range of ± 1.96, with a significant p value less than 0.05 ($p <= 0.05$). Hence, the relationship will be considered significant, and the developed hypothesis will be supported. Otherwise, the developed hypothesis will be rejected Hoyle [2012]; Ullman dan Bentler [2013]. These structural model assessments are shown in Table 1.6.

Table 1.6: The assessments of the structural model.

Measure	**Definition**	**Significant value**
Z **value**	It is the ratio of each parameter estimate to its standard error.	($-1.96 > Z > +1.96$) Hoyle [2012]; Ullman dan Bentler [2013].
P **value**	It represents the probability value of obtaining the results of the z value.	($P <= 0.05$) Hoyle [2012]; Ullman dan Bentler [2013].

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