CHAPTER 4

Structural equation modelling in extended TAM

In this chapter an overview on the structural equation modelling (SEM) technique is provided and the use of SEM to validate the extended TAM model is proposed. SEM is also used to test the hypothesis of the proposed model. In section 4.1 an overview and some of the history of SEM is provided. The nature and objectives of SEM are described. The advantages of SEM over other comparable techniques are discussed in section 4.2. In section 4.3 methods used to estimate the parameters associated with SEM are discussed along with measures of model fit. Many of the statistical tests associated with SEM depend on the assumption of multivariate normality in the sample data. Sample normality and multicollinearity are described in section 4.4 along with approaches to dealing with non-normal data. Sample size relative to SEM is explained in section 4.5.

A SEM model consists of two parts – a measurement component and a structural component. In section 4.6 the measurement component, namely confirmatory factor analysis (CFA), is described. The various components of a CFA are discussed along with the nomenclature associated with the technique. The mathematics that underpins CFA is briefly described while the requirements to conduct a CFA are presented. This section concludes with the CFA conducted on the proposed extended TAM model. In section 4.7 the structural part of a SEM model, path analysis, is discussed. An explanation of the various components of a

path analysis is presented and the mathematics that underpins it isdiscussed. The various aspects of the structural model including specification, identification and estimation are described. Modification and evaluation of the path analysis are presented and the outcome of the path analysis is tabled. This chapter concludes in section 4.8 with a discussion of the outcome of the SEM.

4.1. Structural Equation Modelling – an overview

SEM is a statistical technique for testing and estimating causal relations between variables using a combination of statistical data and qualitative causal assumptions. This definition of SEM was articulated by Wright (1921), Simon (1953) and formally defined by Pearl (2000). SEM models allow both confirmatory and exploratory modelling and are suited to both theory confirmation and theory development. Confirmatory modelling starts out with a hypothesis that is represented in the form of a causal model. The concepts used in the model are then tested. The hypothesis in the model is tested against empirical data to determine how well the model fits the data. With an initial model SEM can be used inductively by specifying a corresponding model and using data to estimate the values of the parameters. The initial hypothesis may require adjustment in light of model evidence. When SEM is used purely for exploration this is normally in the context of an exploratory factor analysis.

In SEM, interest usually focuses on latent constructs. Latent constructs are abstract concepts that cannot be directly observed and measured. Examples of latent factors include intelligence and attitude. In place of direct measurement, variables that are assumed to indirectly measure the latent construct are analysed. SEM allows multiple measures, called manifest variables, to be

associated with a single latent factor. Once the model parameters have been estimated, the resulting model-implied covariance matrix can then be compared to an empirical covariance matrix. If the two matrices are consistent with one another then the SEM model can be considered a plausible explanation for the measured data. SEM is widely used because it provides a quantitative method for testing substantive theory and it explicitly accounts for measurement error (Raykov and Marcoulides, 2006). SEM models are divided into two parts, a measurement component and a structural component. The measurement component deals with the relationship between manifest variables and latent variables, whereas the structural component deals with the relationship between latent factors only.

4.2. Advantages of using SEM over other techniques

There are several aspects of SEM that set it apart from the other multivariate techniques. SEM takes a confirmatory rather than exploratory approach to data analysis. By demanding the pattern of inter-variable relations be specified apriori, SEM lends itself well to the analysis of data for inferential purposes. Many other multivariate techniques are essentially descriptive by nature and consequently hypothesis testing is difficult. SEM further provides explicit estimates of measurement error (Byrne, 2006). Alternative techniques rooted in regression analysis assume that error in the manifest variables vanishes. Applying multiple regression analysis when there is an error in the manifest variables is equivalent to ignoring an error that may lead to inaccuracies. SEM can also incorporate both latent variables (unobserved) and manifest variables in a single model. This allows SEM to be useful in understanding abstract concepts. Because SEM has the capability to model multivariate relationships, it allows

comparison between groups such as gender, age and education level within a single model (Byrne, 2006). SEM has further been found to be superior to other techniques in testing whether a proposed model successfully accounts for the actual relationships observed in a sample (Kline, 2004).

Whilst SEM has significant advantages over alternative techniques, it does have disadvantages. SEM cannot test directionality in relationships. The direction of a relationship in a SEM model represents a researcher's hypotheses of causality within a system. The researcher's choice of variables and pathways represented will thus limit the SEM ability to recreate the sample covariance and variance patterns that have been observed. There may thus be several models that fit the data equally well and consequently SEM can provide confirmation for a proposed model, but cannot exclude other models that may explain the data equally well. In spite of this shortcoming the SEM approach remains useful in understanding relational data in multivariate systems. The abilities of SEM to distinguish between indirect and direct relationships, among variables and to analyse relationships between latent variables without random error differentiate SEM from other relational modelling techniques.

4.3. Model estimation and fit

The estimator takes the measured data as input and produces an estimate of the parameters, which can explain the observed behaviour in the data. Fitting a model is thus an iterative process that begins with an initial fit, tests how well the model fits, adjusts the model, tests the fit again and so forth, until the model fits well enough. The most common methods of estimation used in SEM are Maximum Likelihood (ML), Generalised Least Squares (GLS) and Weighted

Least Squares (WLS). When a hypothesized model is correctly specified and manifest variables are multivariate normal, it has been shown that ML, GLS and WLS produce estimates that converge to the same number (Browne, 1984a, 1984b).

Model specification involves determining apriori which parameters are fixed, which are free and what the relationships are between the variables. Under ideal conditions the choice between methods is thus arbitrary. Under the more realistic assumption of miss-specified models and data that are not always multivariate normally distributed, the different procedures may not converge to the same optimum (Olsson et.al, 2000). A comparison of the three estimation methods in the presence of mild misspecification of models showed that ML compared to GLS under conditions of misspecification provides more realistic indices of overall fit and less biased parameter values for paths that overlap with the true model. WLS under no conditions was preferable to the two other estimation procedures in terms of parameter bias and fit (Olsson et.al, 2000). It has further been found that ML is much less biased than WLS estimators for all distributions and sample sizes (Yuan and Bentler, 1997). The accuracy of alternative estimation method to ML (i.e. GLS and WLS) was investigated for different sample sizes using a Monte Carlo simulation (Rhee, 1992). As the number of non-normal variables increased, outcomes produced by WLS became worse whilst GLS was only slightly inferior to ML.

The objective of the estimation technique is to obtain estimates for each parameter of the model. These parameters include factor loadings, factor variances and covariances, manifest error variances and manifest error

covariances. The outcome of this estimation is a predicted variance–covariance matrix (Σ) that resembles the data sample variance–covariance matrix (S) as closely as possible. The ML technique entails using a fitting function to minimize the difference between Σ and S. The fitting function that is minimized in ML is:

$$F_{ML} = ln|S| - ln|\Sigma| + trace[(S)(\Sigma - I)] - p \quad [4.1]$$

where $|S|$ is the determinant of the input variance–covariance matrix, $|\Sigma|$ is the determinant of the predicted variance–covariance matrix, p is the order of the input matrix (i.e., the number of input indicators) and I is the identity matrix.

Model fit refers to the ability of a model to reproduce the observed data. The fit of a model is evaluated using a fit index. A good-fitting model is one that is reasonably consistent with the observed data and a good-fitting model is required before interpreting the causal paths of the structural model. In recent years computer software programs such as SAS, SPSS, Lisrel, EQS and others have made the fitting of SEM models to data much easier. As a consequence there has been a significant increase in the number of fit indices available to researchers. With regards to which fit indices should be reported, it is not necessary or realistic to include every index included reported in a program's output as it may burden both reader and reviewer (Hooper et.al, 2008). Given the plethora of fit indices, it becomes a temptation to choose those fit indices that indicate the best fit. This should be avoided.

Fit indices can be broadly characterized as falling into three categories: absolute fit; fit adjusting for model parsimony and comparative or incremental fit. This typology is not perfect, as some fit indices have features of more than one category. Researchers are advised to consider and report at least one index from each category when evaluating the fit of their models (Jackson et.al, 2009). It has also been recommended that the acceptability of a fitted SEM solution should be evaluated on the basis of three major aspects: (a) overall goodness-of-fit; (b) the presence or absence of localized areas of strain in the solution and (c) the interpretability, size and statistical significance of the model parameter estimates (Brown, 2006). Jackson (2009) reviewed a number of papers that reported model fit indices and found that after χ^2 values the most commonly reported measures of fit were the Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA) and the Tucker-Lewis Index (TLI). Nearly all papers reported χ^2 values. The number of fit measures reported in studies was three or four.

It has been recommended to report fit indices that have different measurement properties such as absolute fit indices, an incremental fit index such as the CFI and a residuals-based fit index, such as SRMR (Hu and Bentler, 1999). Absolute fit indices assess model fit at an absolute level. They assume the reasonability of the hypothesis that S = Σ without taking into account other aspects such as fit in relation to more restricted solutions. Absolute fit indices assess how well apriori model reproduces the sample data. Incremental fit indices evaluate the fit of a user-specified solution in relation to a more restricted, nested baseline models. Typically, the baseline model is a “null” or “independence” model in which the covariance’s among all input indicators are fixed to zero. A

comparative measure of fit is only interpretable when comparing two different models.

The CFI (Bentler, 1990) is a statistic that performs well even when sample size is small (Tabachnick and Fidell, 2007). The CFI is defined by the following formula;

$$CFI = 1 - \left[\frac{\max[(\chi_T^2 - df_T), 0]}{\max[(\chi_T^2 - df_T), (\chi_B^2 - df_B), 0]}\right] \quad [4.2]$$

where χ_T^2 is the χ^2 value of the target model, df_T is the degree of freedom (df) of the target model, χ_B^2 is the χ^2 value of the baseline (null) model and df_B is the df of the baseline model. The CFI has a range of possible values of 0.0 to 1.0, with values closer to 1.0 implying good model fit.

Another popular fit index falling under this category is the TLI (Tucker and Lewis, 1973). The TLI has features that compensate for the effect of model complexity and includes a penalty function for adding freely estimated parameters that do not markedly improve the fit of the model. The TLI is calculated using the formula:

$$TLI = \frac{\left[\left(\frac{\chi_B^2}{df_B}\right) - \left(\frac{\chi_T^2}{df_T}\right)\right]}{\left[\left(\frac{\chi_B^2}{df_B}\right) - 1\right]} \quad [4.3]$$

where as with CFI, χ_T^2 is the χ^2 value of the target model, df_T is the df of the target model, χ_B^2 is the χ^2 value of the baseline (null) model and df_B is the df of the baseline model. The TLI is interpreted in a fashion similar to the CFI in that

values approaching 1.0 are interpreted in accord with good model fit. Methodologists have noted that CFI and TLI values below 0.90 should lead the researcher to strongly suspect the solution. CFI and TLI values in the range of 0.90 – 0.95 may be indicative of acceptable model fit (Bentler, 1990).

Having a model with relatively few free parameters and high complexity means that the estimation process is dependent on the sample data. This may result in a less rigorous theoretical model that paradoxically produces better indices (Mulaik et al, 1989; Crowley and Fan, 1997). To overcome this problem Mulaik et al (1989) developed the Parsimony Goodness-of-Fit Index (PGFI). The PGFI is based upon the standard goodness-of-fit index and adjusts it for the loss of degrees of freedom (Mulaik et al 1989). The index penalizes model complexity and results in parsimony fit index values that are considerably lower than other goodness-of-fit indices. While no threshold levels have been recommended for these indices, Mulaik et al (1989) noted that it was possible to obtain parsimony fit indices within the 0.50 region while other goodness-of-fit indices achieve values over 0.90 (Mulaik et al 1989).

The RMSEA is an "error of approximation" index and assesses the extent to which a model fits reasonably well in the population (Steiger and Lind, 1980). RMSEA is a fit adjusting for the model parsimony and is a population-based index. RMSEA is calculated as

$$RMSEA = \sqrt{\max\left[\frac{(\chi_T^2 - df_T)}{(ndf_T)}, 0\right]} \qquad [4.4]$$

where χ_T^2 is the χ^2 value of the target model, df_T is the df of the target model and n is the number of samples. The RMSEA values can be classified into four categories: good fit (0.00 – 0.05), fair fit (0.05 – 0.08), mediocre fit (0.08 – 0.10) and poor fit over 0.10). RMSEA smaller than 0.05 indicates good fit and the non-central χ^2 distributions can be used to obtain confidence intervals for RMSEA (a 90 percent interval is typically used). The confidence interval indicates the precision of the RMSEA point estimate. Methodologists recommend including this confidence interval when reporting the RMSEA (MacCallum et al., 1996). Additional support for the fit of the solution would be evidenced by a 90 percent confidence interval of the RMSEA whose upper limit is below these cut-off values.

The SRMR is an absolute measure of fit and is defined as the standardized difference between the observed correlation and the predicted correlation. It is a positively biased measure and an absolute measure of fit. The bias is greater for small n or for low df . This measure tends to be smaller as sample size increases and as the number of parameters in the model increases. The SRMR has no penalty for model complexity. The SRMR is the root of the mean of the squared standardized residual and is calculated as;

$$SRMR = \sqrt{\frac{2}{n(n+1)}\sum_{i}^{n}\sum_{j}^{i}\frac{(s_{ij}-c_{ij})^2}{s_{ij}c_{ij}}} \qquad [4.5]$$

where n is the sample size, s_{ij} is the i,j^{th} element of the covariance matrix and c_{ij} is the i,j^{th} element of the predicted model matrix. The SRMR can take a range of values between 0.0 and 1.0, with 0.0 indicating a perfect fit. A value less

than 0.08 is generally considered a good fit (Hu and Bentler, 1999). From the review of recommended fit indices to report, this study will report CFI, PCFI, RMSEA, SRMR and TLI as measures of fit.

4.4. Assessment of normality and multicollinearity

Multivariate normality of the sample data is assumed for most SEM estimation methods, including ML. Research has found that the failure to meet the assumption of multivariate normality can lead to an overestimation of the χ^2 statistic and to an inflated type 1 error (Curran et.al, 1996; Powell and Schafer, 2001). It may also lead to downward biased standard errors (Bandalos, 2002; Nevitt and Hancock, 2001). Where there is a significant departure from the assumption of multivariate normality in the sample data the assumptions inherent in several ancillary fit measures may be undermined (Yuan, 2005). It should be noted that ML estimation might perform well with mild departures from multivariate normality (Chou et.al, 1991; Fan and Wang, 1998). When conducting a SEM researchers are advised to report on both univariate and multivariate normality (Jackson et.al, 2009).

Multivariate normality implies that all variables in the data set under consideration are univariate normally distributed, the distribution of any pair of variables is bivariate normal and all pairs of variables have linear and homoscedastic scatterplots (Kline, 2004). The overall distribution of the data should also be normal. To determine the multivariate and univariate normality of the sample data, IBM SPSS Statistics 20.0.0 software was used to determine the skewness and kurtosis of the data, as well as the Mardia co-efficient. Mardia's coefficient is determined by $p(p+2)$ where p is the number of observed

variables. According to Bollen (1989), if Mardia's coefficient is lower than $p(p+2)$, then the combined distribution of the variables is multivariate normal. In table 4.1 below are the values for skewness and kurtosis used to test for normality, as well as the Mardia co-efficient.

Table 4.1: Data normality assessment.

Variable	min	max	skew	c.r.	kurtosis	c.r.
Q147K	1.000	7.000	-.303	-2.287	.521	1.964
Q152C	1.000	7.000	-.334	-2.522	-.059	-.222
Q152E	1.000	7.000	.080	.600	-.139	-.525
Q152H	1.000	7.000	-.427	-3.217	.399	1.505
Q135BA	.000	1.000	1.332	10.040	-.226	-.853
Q135AS	.000	1.000	1.253	9.443	-.431	-1.625
Q135AC	.000	1.000	1.332	10.040	-.226	-.853
Q135M	.000	1.000	.803	6.051	-1.356	-5.111
Q145	1.000	10.000	-1.105	-8.328	.748	2.820
Q144	1.000	10.000	-1.216	-9.167	1.031	3.885
Q143	1.000	10.000	-1.122	-8.456	.943	3.554
Q142	1.000	10.000	-1.139	-8.588	.841	3.171
Q147L	1.000	7.000	-.308	-2.325	-.318	-1.198
Q147M	1.000	7.000	-.280	-2.114	.146	.551
Q147D	1.000	7.000	-.101	-.762	.096	.361
Q147B	1.000	7.000	-.387	-2.920	.049	.185
Q147J	1.000	7.000	-.070	-.530	-.239	-.900
Q147G	1.000	7.000	-.129	-.975	-.433	-1.632

Q147C	1.000	7.000	-.186	-1.401	.026	.100
Q152A	1.000	7.000	-.302	-2.274	-.155	-.584
Q152G	1.000	7.000	.095	.714	-.780	-2.940
Q152J	1.000	7.000	.051	.383	-.745	-2.809
Q156H	.000	1.000	3.449	26.004	9.898	37.311
Q156G	.000	1.000	3.117	23.498	7.716	29.083
Q156E	.000	1.000	1.505	11.343	.264	.994
Q156D	.000	1.000	3.757	28.320	12.112	45.656
Q152D	1.000	7.000	-.245	-1.844	.413	1.558
Q147H	1.000	7.000	-.239	-1.804	.338	1.275
Q147E	1.000	7.000	-.351	-2.649	.469	1.769
Mardia					256.439	55.838

A Mardia value of 256.439 was obtained which is lower than the Mardia coefficient cut-off of 449.50 obtained with p = 29 observed variables. To test for univariate normality, the skewness and kurtosis for each variable in the data set was determined. There is no consensus regarding an acceptable degree of non-normality, but cut-off values of 3.00 for univariate skewness and 7.00 for univariate kurtosis have been proposed (Finney and DiStefano, 2006). Inspection of the assessment of normality table shows that there are 3 variables (Q156H, Q156G and Q156D) which displays skewness > 3.00 and kurtosis > 7.00. From the total of 29 variables, 89.7 percent of the variables are thus normally distributed. It is concluded that the sample data is not multivariate normal but instead displays mild non-normality, whilst the overall data distribution meets the criteria for normality.

One means of addressing multivariate non-normal data is through the use of a procedure known as the bootstrapping. While Mardia's statistic shows that the data is normally distributed and consequently it should be possible to use estimation techniques that are suited for data that are normally distributed, the presence of 3 variables in the sample data set that are non-normal is cause for caution. The sample data set does not meet the strict criteria for multivariate normality that all variables in the data set being normally distributed. With non-normal data, the χ^2 statistics may be inflated when using ML. Bootstrapping is best described as a resampling procedure in which the original sample is considered to represent the population. Multiple sub-samples of the same size as the parent sample are drawn randomly with replacement from the population. The subsamples provide the data for an empirical investigation of parameter estimates and indices of fit.

Bootstrapping is based on the notion that when the assumptions of normality in a distribution are violated, a sampling distribution can be relied upon to describe the actual distribution of the population (Varian, 2005). Cases from the original data set are randomly selected with replacement to generate other data sets, usually with the same number of cases as the original. Because of sampling with replacement, (1) the same case can appear in more than one generated data set and (2) the compositionof cases will vary slightly across the generated samples. When repeated many timesbootstrapping simulates the drawing of numerous random samples from apopulation (Kline, 2011). The bootstrapped averaged estimates and their standard errors can be compared against the results from the original sample to evaluate the stability of model parameters. Nevitt and

Hancock (2001) suggested that using bootstrapping standard errors from complete data sets may be unwise with a sample size of 100 and recommended sample sizes of 200 or above. The sample size in the study was 341. Inspection of the sample data found that there were no missing values in any of the 341 cases and no adjustment for missing data was needed.

When using bootstrapping the Bollen-Stine p value can provide corrected values for the χ^2 goodness-of-fit statistic (Bollen and Stine, 1992). The Bollen-Stine p value adjusts the standard error of the path estimates to help adjust for the non-normality of the estimation. Using a conventional significance level of 0.05, the model would be rejected if the p -value was smaller than 0.05. If p-value were larger then 0.05, the model would not be rejected. When conducting a bootstrap exercise, it is recommended that at least 2000 bootstraps be utilised (Nevitt and Hancock, 2001). A potential limitation of the bootstrap confidence intervals is that two researchers analysing the same set of data may obtain different confidence intervals because the bootstrap samples generated by each researcher may be different (Gleser, 1996; MacKinnon et al., 2004). The differences should be negligible when the number of bootstrap samples is large.

In order that the results of the analysis were valid, it was important to check the data for multicollinearity. Multicollinearity refers to a situation in which two or more explanatory variables in a model are highly and linearly related. In perfect multicollinearity the correlation between two independent variables is equal to 1 or -1. Multicollinearity increases the standard errors of the coefficients that in turn mean that coefficients for some independent variables may be found not to be significantly different from 0. Without the presence of multicollinearity these

same coefficients might have been found to be significant and the researcher may not have come to null findings. Multicollinearity may thus inflate standard errors and make some variables statistically insignificant where they should be otherwise significant Very high multicollinearity can result in matrix entries that approach 0. Given that SEM uses covariance matrices as input, very high multicollinearity may cause the model-fitting program to be empirically under identified and thus to generate estimates which are not reliable (Kline, 2004).

If a data set has variables that are multi-collinear, the researcher should possibly consider combining them into a single variable or drop one or more of the affected variables from the data set. Multicollinearity can be detected the correlations between independent variables are larger than 0.80 or 0.90. In general if the correlation value between two items is higher than 0.90, multicollinearity is a problem in data analysis (Hair et. al., 1998). Kline (2004) suggested the cut-off of 0.85 as the border of "extreme". In appendix 8.11 the matrix of implied correlations between the independent variables in the data is shown. The highest value is 0.831, which is below the cut-off proposed by Kline (2004). It was concluded that there was no multicollinearity in the sample data set and consideration of dropping any variables from the data set need not be given.

4.5. SEM sample size

Where structural equation modelling (SEM) is proposed as the basis for testing a research hypothesis it is further necessary to determine the optimal sample size for an SEM. Ad hoc rules of thumb requiring the choosing of 10 observations per indicator in setting a lower bound for the adequacy of sample sizes have been widely used since their original articulation (Nunnally, 1967). Justifications for

this rule of 10 appear in several publications (Barclay et al. 1995, Chin, 1998, Kahai and Cooper, 2003). The rule of 10 couches the sample size question in terms of the ratio of observations (sample points) to free parameters. Bollen (1989) stated that "though I know of no hard and fast rule, a useful suggestion is to have at least several cases per free parameter" and Bentler (1989) suggested a 5:1 ratio of sample size to number of free parameters. Sample size in SEM can be computed through two methods: the first as a function of the ratio of indicator variables to latent variables and the second as a function of minimum effect, power and significance. Software and methods for computing both have been developed (Westland, 2010).

A meta-study into lower bounds on sample sizes in structural equation modelling found that there was a systematic bias towards choosing sample sizes that were significantly too small (Westland, 2010). Actual sample sizes averaged only 50 percent of the minimum needed to draw the conclusions the studies claimed. Overall, 80 percent of the research articles in the meta-study drew conclusions from insufficient sample sizes. An algorithm for computing the lower bound on sample size required to confirm or reject the existence of a minimum effect in an SEM at given significance and power levels has been developed (Westland, 2010). Whereas the sample size for hypothesis testing is typically determined from a critical value ($\mathbf{z}$) that defines the boundary between the rejection (set by α) and non-rejection (set by β) regions the minimum sample size that can differentiate between $\mathbf{H_0}$ (null hypothesis) and $\mathbf{H_A}$ (alternative hypothesis) occurs where the critical value is exactly the same under the null and alternative hypotheses. To just detect the minimum effect size δ

$$H_0: d - d_0 = 0 \quad [4.6]$$

$$H_A: d - d_0 = \delta \quad [4.7]$$

The minimum sample size n is given by

$$n = \frac{1}{2H}\left(A\left(\frac{\pi}{6} - B + D\right) + H + \sqrt{\left[A\left(\frac{\pi}{6} - B + D\right) + H\right]^2 + 4AH\left(\frac{\pi}{6} + \sqrt{A} + 2B - C - \right.}\right. \quad [4.8]$$

and where

$$A = 1 - d^2 \quad [4.9]$$

$$B = d\ arcsin\left(\frac{d}{2}\right) \quad [4.10]$$

$$C = d\ \arcsin(d) \quad [4.11]$$

$$D = \frac{A}{\sqrt{3 - A}} \quad [4.12]$$

$$H = \left(\frac{\delta}{z_{1-\frac{\alpha}{2}} - z_{1-\beta}}\right)^2 \quad [4.13]$$

where d is the effect size. Specifically an apriori solution is sought viz. a sample size that will be sufficient given the prior requirement on what the minimum effect is that the tests will need to detect. Minimum effect, in the context of SEM, is the smallest correlation between latent variables that should be detectable with the sample size and model parameters.

Using the above methodology software has been developed that can compute the sample size required for a study that uses a SEM model given the number of

observed and latent variables in the model, the anticipated effect size and the desired probability and statistical power levels (Soper, 2012). The software also determines the minimum sample size required to detect the specified effect and the minimum sample size required given the structural complexity of the model. The proposed SEM to validate the extended TAM model has 9 latent constructs and 29 observed variables. Using the software developed by Soper (2012) with an anticipated size effect of d = 0.2, a desired statistical power level of 0.8 and a p = 0.05 the minimum sample size to detect effect is 157. The minimum sample size for model structure is 170. These findings yields a recommended minimum sample size of 170 at the p=0.05 level. For a probability level of 0.01 the minimum sample size to detect effect rises to 222 while the minimum sample size for model structure remains 170. With the data set having 341 observations it is concluded that the data set is large enough to detect effect and determine model structure at both the p=0.05 and p=0.01 levels. From the analysis it was found that the sample of 341 was large enough to conduct an SEM analysis.

4.6. Measurement model - Confirmatory factor analysis

The first component of an SEM is the measurement model, conducted using CFA. CFA tests hypothesized relationships between the manifest variables and latent constructs or factors. When a CFA is conducted, the researcher uses a hypothesized model to estimate a population covariance matrix that is then compared with the observed covariance matrix. Latent factors are theoretical in nature and they cannot be observed directly. Consequently latent factors cannot be measured directly either. To measure a latent factor, researchers capture indicators that are assumed to represent the underlying construct. The indicators are directly observable and believed by the researcher to accurately represent the

construct that cannot be observed. An example of a latent factor is happiness. Happiness cannot be measured directly as it is a state of mind. A researcher can identify manifest variables that together would define the factor happiness - such as being healthy; being in love, being financially secure etc. All of these manifest variables are assumed to be indicators of happiness.

CFA explicitly tests the priori hypotheses about relationships between manifest variables and latent factors. CFA is often the analytic tool of choice for developing and refining measurement instruments, assessing construct validity, identifying method effects and evaluating factor invariance across time and groups (Brown, 2006). A key aspect of CFA evaluation is the ability of the parameters from the measurement model to reproduce the observed relationships among the indicators. The results of CFA can provide evidence of the convergent and discriminant validity of theoretical constructs.

Convergent validity refers to the degree to which scores on a test correlate with scores on other tests that are designed to assess the same construct. Convergent validity is indicated by evidence that different indicators of theoretically similar or overlapping constructs are strongly interrelated. Discriminant validity is the degree to which scores on a test do not correlated with scores from other tests that are not designed to assess the same construct. A fundamental strength of CFA is that the resulting estimates of convergent and discriminant validity is adjusted for measurement error. CFA provides a stronger analytic framework than traditional methods such as ordinary least squares approaches or multiple regressions, which assume variables in the analysis are free of measurement error. Brown (2006) states that the fundamental intent of CFA is to determine

the number and nature of latent constructs that account for the variation and co-variation among a set of manifest variables. The observed measures are inter-correlated because they share a common underlying construct. If the latent construct were removed the correlations among the manifest measures would be zero.

In CFA the researcher must specify all aspects of the model. The number of factors, pattern of indicators–factor loadings and so forth. In figure 4.1 below the structure of typical CFA along with its notation and components is shown. Latent factors are drawn as circles or ellipses (F_i), manifest variables are drawn as squares (X_i) with the error associated with the manifest variables drawn as a circle (ε_i). Single headed arrows indicate the causal paths between latent factors with the factor loading denoted as λ_{ij}. Double-headed arrows denote either correlation between the error terms of manifest variables or latent factors.

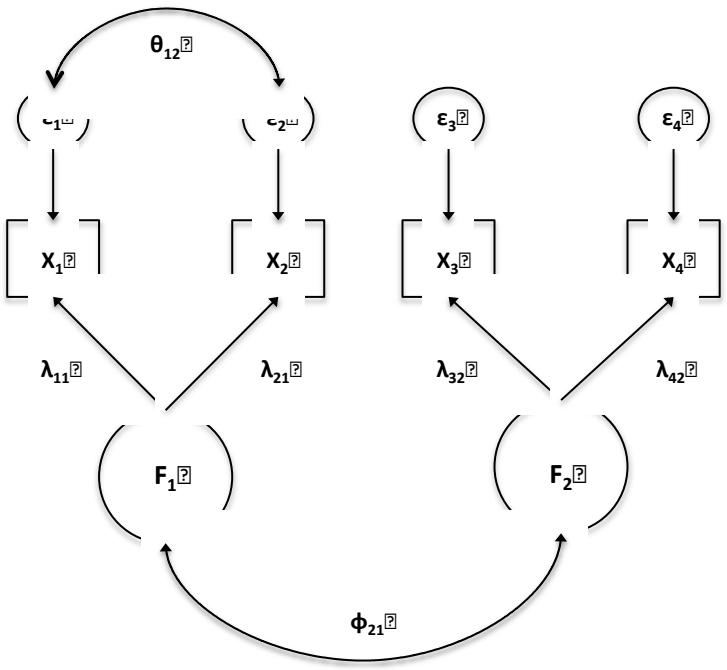

Figure 4.1: Typical CFA model

Correlations between manifest variables are denoted by Θ_{ij} while that between latent factors is denoted by ϕ_{ij}. The fundamental equation of the common factor model is the variable X explained in terms of the latent factor is,

$$X_i = \lambda_{ij} F_j + \varepsilon_i \qquad [4.14]$$

where X_i is the i th manifest variable, F_j represents the j th latent factor and λ_{ij} the factor loading relating the i th variable to the j th factor. ε_i represents the variance that is unique to the variable X_i. A series of equations will result, one for each variable associated with a latent factor. This set of equations can be summarized into a single equation that expresses the relationships among observed variables y, latent factors η and unique variances ε :

$$X = \Lambda_x F + \varepsilon \qquad [4.15]$$

or in expanded matrix form:

$$\Sigma = \Lambda_x \Psi \Lambda_x' + \Theta_\varepsilon \qquad [4.16]$$

where Σ is the $p \times p$ symmetric correlation matrix of p indicators, Λ_y is the $p \times m$ matrix of factor loadings λ, Ψ is the $m \times m$ symmetric correlation matrix of the factor correlations and Θ_ε is the $p \times p$ diagonal matrix of unique variances ε. Matrices are represented in SEM by uppercase Greek letters (e.g.,

Λ , Ψ and Θ) and specific elements of these matrices are denoted by lowercase Greek letters (e.g., λ , ψ and ε)

In order to estimate the parameters in CFA the model must be identified. A model is identified if, on the basis of known information it is possible to obtain a unique set of parameter estimates for each parameter in the model whose values are unknown (e.g., factor loadings, factor correlations, etc.). Model identification pertains in part to the difference between the number of freely estimated model parameters and the number of pieces of information in the input variance–covariance matrix. In order to conduct a CFA every latent factor must have its scale identified. By definition latent factors are unobserved and thus have no defined units of measurement. The researcher must set these units of measurement and two methods exist to establish scales for latent factors. In the first method the researcher fixes the metric of the latent factor to be the same as one of its indicators. The indicator selected to pass its metric onto the latent factor is referred to as a marker or reference indicator. In the second method the variance of the latent variable is fixed to a specific value, usually 1.0 (Brown, 2006).

This approach produces both a standardized and an unstandardized solution. Although the latent factors would have been standardized (i.e., their variances are fixed to 1.0) the fit of this model is identical to the unstandardized model (i.e., models estimated using marker indicators). Besides scaling the latent variable, the parameters of a CFA model can be estimated only if the number of freely estimated parameters does not exceed the number of pieces of information in the input variance/covariance matrix. For these and other reasons such as increased

statistical power and precision of parameter estimates researchers recommend that latent factors be defined by a minimum of three indicators (Marsh et.al, 1998).

4.6.1. CFA specification and estimation

The CFA for the extended TAM model is shown in figure 4.2. The model comprises of the nine latent factors hypothesized in the extended TAM model along with the 29 manifest variables that are loaded onto the respective latent constructs. For each of the manifest variables an error term is included. The manifest variables each loaded onto a single latent factor and no cross loadings were permitted. Whilst CFA does allow for the covariance of error terms across manifest variables that load onto a single factor, the researcher excluded any covariance between error terms. The covariance of error terms would need empirical justification and none was readily identified in then literature to support any cross loading. Figure 4.2 shows covariance between latent factors, but for simplicity in drawing figure4.2 not all covariances between latent facts were shown. It should be noted that all latent factors were covaried with each other in the model. To conduct the CFA, the researcher used SPSS AMOS. A ML minimization function using 3,000 bootstrap samples was used to evaluate the CFA.

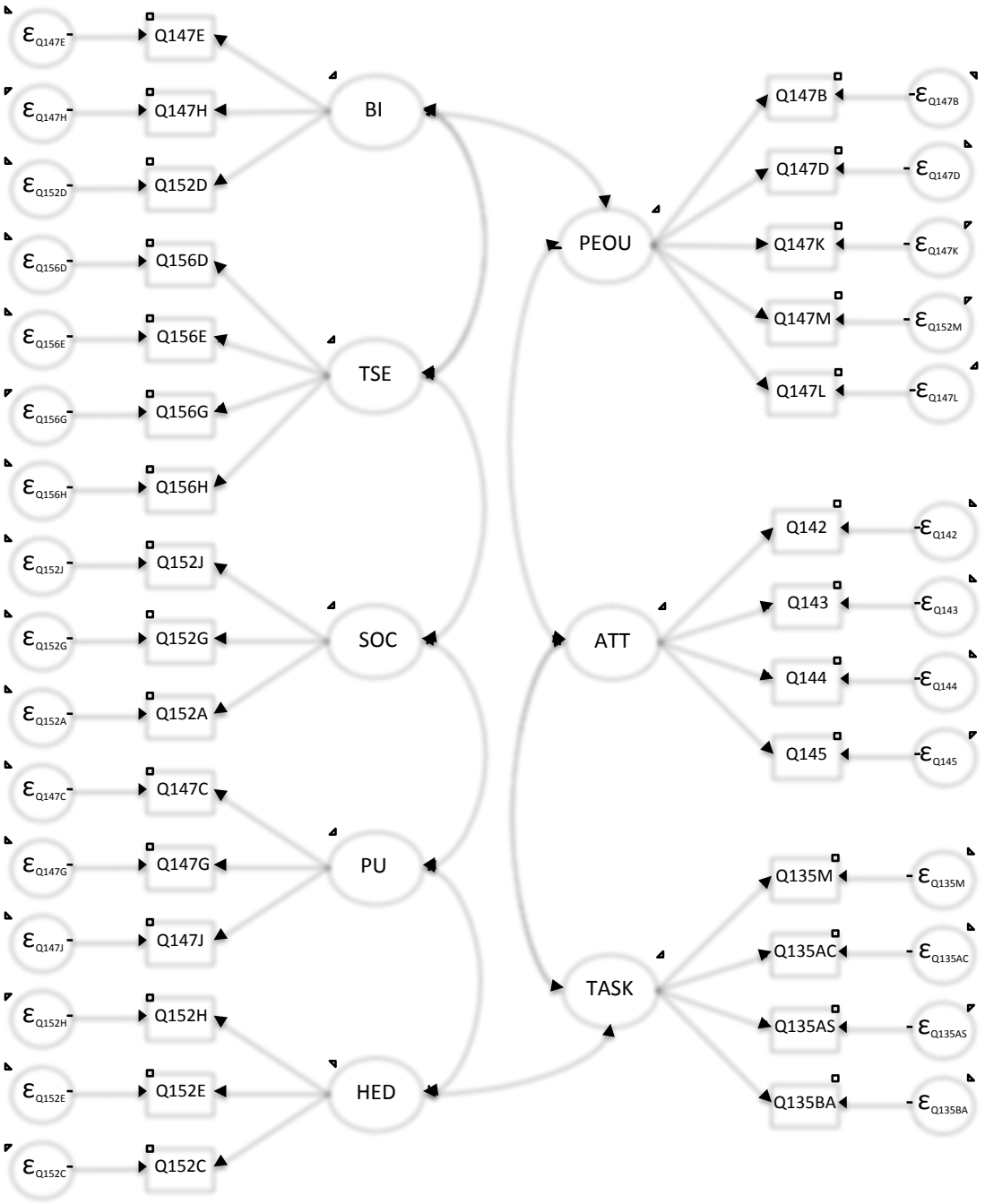

Figure 4.2: CFA for the extended TAM model

Before conducting the CFA it is essential to ensure that the proposed model is properly identified. CFA models must be identified to enable the estimation of parameters. When a model is identified, it is possible to fit unique estimates for each parameter with unknown values in the model. It further implies that there is one best value for each parameter in the model whose value is not known. To

be properly identified CFA models must consequently have degrees of freedom (d_f) greater than 0 for models (Kline, 2004). The proposed model had 434 distinct sample moments and 112 parameters, producing 322 d_f. The measurement model was thus identified. The researcher utilized IBM SPSS AMOS version 20.0.0 to conduct the model fit. The indices reported on (CFI, TLI, PCFI and RMSEA) are shown in the table 4.2 below. The complete set of fit indices generated by the software is included in appendix 8.12

Table 4.2: CFA model fit values

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	0.891	0.874	0.960	0.953	0.959
Saturated model	1.000		1.000		1.000
Independence model	0.000	0.000	0.000	0.000	0.000

Model	PRATIO	PNFI	PCFI
Default model	0.860	0.766	0.825
Saturated model	0.000	0.000	0.000
Independence model	1.000	0.000	0.000

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	0.039	0.032	0.046	0.997
Independence model	0.180	0.176	0.185	0.000

The Bollen-Stine p -value = 0.083 which was above the 0.05 cut-off for rejecting the null hypothesis that the model does not describe the sample data. The CFI for the model was 0.964, which is above 0.95 indicating a good fit. The TLI for the analysis was 0.957, which is above 0.95 also indicating a good fit. The RMSEA for the model is 0.038, which is below 0.05 indicating a good fit. Furthermore the 90 percent confidence interval for RMSEA is (0.030 - 0.045) which is below 0.05

indicating a good fit at the 90 percent confidence interval. The Standardized Root Mean Square Residual (SRMR) = 0.0427 which is less than 0.08 indicating a good fit. The PCFI is 0.825, which was also acceptable.

Goodness-of-fit indices provide a global descriptive summary of the ability of the model to reproduce the input covariance matrix, but the other two aspects of fit evaluation, localized strain and parameter estimates, provide more specific information about the acceptability and utility of the solution. There are three matrices associated with the typical CFA model: the sample variance–covariance matrix (S), the model-implied or predicted variance–covariance matrix (Σ) and the residual variance–covariance matrix which reflects the difference between the sample and model-implied matrices. In some instances, overall goodness-of-fit indices suggest acceptable fit despite the fact that some relationships among indicators in the sample data have not been reproduced adequately. Large, positive standardized values in the residual variance–covariance matrix may indicate that additional parameters are needed in the model to better account for the covariance between the indicators. Negative standardized residual suggests that the model's parameters overestimate the relationship between two indicators to some extent.

Standardized residuals that greater than |1.96| are regarded as significant because this value corresponds to a statistically significant z score at $p < 0.05$. In general, larger sample sizes are associated with larger standardized residuals because the size of the standard errors of the fitted residuals is often inversely related to sample size. For this reason, some methodologists recommend the use of larger cut-off values of |2.58| which corresponds to the 0.01 α level (Byrne,

1998). The standardized CFA residual matrix is included in appendix 8.13. The sample size of 341 was characterized as a large sample. The values in the matrix ranged from -1.743 to +2.654. There was only a single value (+2.654), which was outside the acceptable range and consequently it was concluded that the solution does not have areas of localized strain.

Another aspect of model evaluation that focuses on specific relationships in the solution is the modification index (Sorbom, 1989). Modification indices can be computed for each fixed and constrained parameter in the model. The modification index reflects an approximation of how much the overall model fit index would improve if the fixed or constrained parameter were freely estimated. Researchers undertaking modifications may capitalize on chance variations in the obtained sample and any such modifications should be viewed as tentative until cross-validated on an independent sample. The researcher did not undertake any modification to the CFA. As part of its standard output AMOS provides modification indices and these have included this in appendix 8.14. Inspection of the table indicated that the implied parameter change for the proposed modification indices were small, indicating that minimal improvement in fit would be obtained if modification indices had been used to improve the fit of the model.

4.6.2. Outcome of the measurement model

The measurement model contained no double-loading indicators and all measurement error was presumed to be uncorrelated. The model was over identified with 322 df . As noted in the introduction section, the data was gathered from 341 respondents. All 341 cases had complete data and there were

no missing values. Prior to the CFA analysis, the data was evaluated for univariate and multivariate normality by examining inter-item and item to total correlations for each variable loading onto latent factors. Normality of the data was examined using SPSS AMOS 20.0.0 and the joint test of non-normality in terms of skewness and kurtosis, Mardia's co-efficient, was not significant.

The CFA was analysed using SPSS AMOS 20.0.0 and a maximum likelihood minimization function using 3,000 bootstrap samples was used. Goodness-of-fit was evaluated using PCFI, RMSEA and its 90 percent confidence interval, CFI and the TLI. Multiple indices were used because they provided different information about model fit. When used together these indices provided a more conservative and reliable evaluation of the solution. Each of the overall goodness-of-fit indices suggested that the nine-factor model fits the data well. Bollen-Stine p -value = 0.083, SRMR = 0.046, RMSEA = 0.038 (90 percent CI = 0.030; 0.045; CFit = 0.99), TLI = 0.957 and CFI = 0.964. Inspection of standardized residuals and modification indices indicated no significant localized points of ill fit in the solution. It can thus be concluded that the latent factors and associated variables are a good measurement fit for the data.

4.7. Structural model – Path Analysis

The second component of a SEM is the structural model. The structural model in SEM is essentially a path analysis. Path analysis is a statistical technique used to examine causal relationships between two or more variables. It is based upon a linear equation system and was first developed by Sewall Wright in the 1930s for use in phylogenetic studies. Path analysis is different from other linear equation models in that in path analysis mediated pathways viz. those acting

through a mediating variable can be examined. Pathways in path models represent hypotheses of the researcher. The introduction of a measurement model in SEM has the effect that the estimated parameters in the structural model are free from the influence of measurement errors. As a result of this the errors in the structural model are separated from the errors in the measurement model.

The parameters of a structural model are the variances, regression coefficients and covariances among variables. In figure 4.3 below a typical structural model is shown along with its key components. The nomenclature for structural models used in SEM is similar to that used for CFA. Latent factors are drawn as circles or ellipses (F_i), observed variables are drawn as squares (X_i) with the error associated with the observed variables drawn as a circle (ε_i). Endogenous latent variables are in a sense dependent and consequently have a residual error associated with them. This residual is drawn as a circle and denoted (δ_i) and measures the portion of the variance in the latent variable unexplained by the exogenous latent variables. Single headed arrows indicate the causal paths between latent variables with the factor loading denoted as β_{ij}.

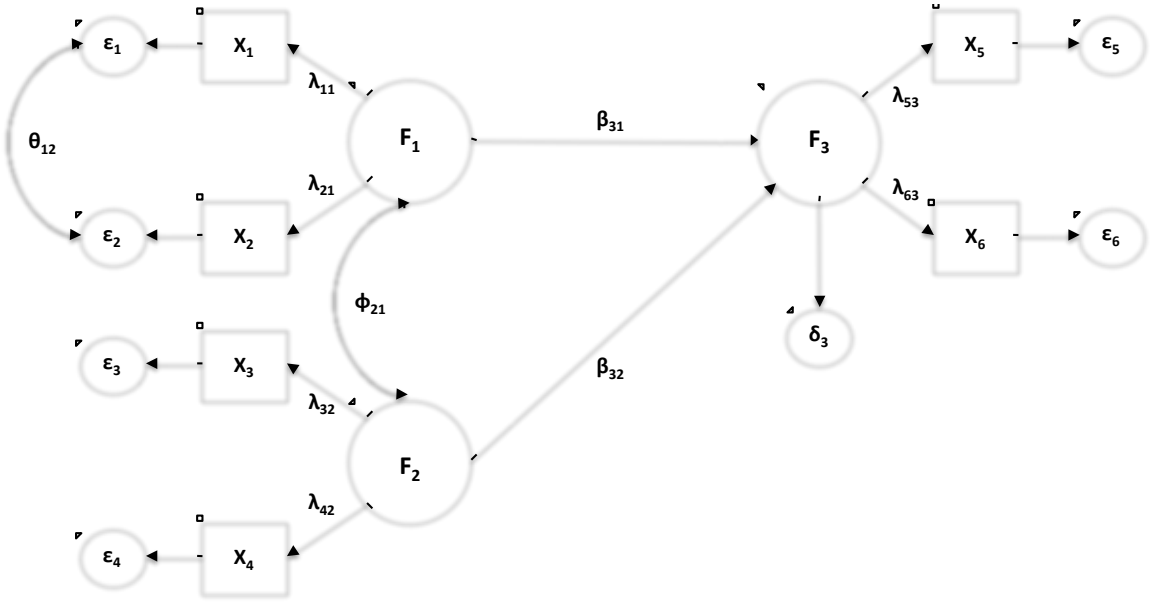

Figure 4.3: Typical SEM structural model

As with CFA the factor loadings between the observed variables and the exogenous latent factors are denoted (λ_{ij}). Double-headed arrows denote either correlation between the error terms of observed variable (denoted by Θ_{ij}) or between exogenous latent factors (denoted by (ϕ_{ij}). The causal model illustrated in fig 4.2 can be written as a series of equations:

$$F_3 = \alpha_{31}F_1 + \beta_{32}F_2 + \delta_3 \qquad [4.17]$$

and;

$$X_1 = \lambda_{11}F_1 + \varepsilon_1 \qquad X_2 = \lambda_{21}F_2 + \varepsilon_2 \qquad X_3 = \lambda_{32}F_2 + \varepsilon_3$$
$$X_4 = \lambda_{42}F_2 + \varepsilon_4 \qquad X_5 = \lambda_{53}F_3 + \varepsilon_5 \qquad X_6 = \lambda_{63}F_3 + \varepsilon_6 \qquad [4.18]$$

in order to estimate the regression coefficient β_{ij} between two latent factors i and j a simple regression model is used. This is described by

$$Y = \beta X + \delta \qquad [4.19]$$

where both X and Y are observed variables and it is assumed that both variables are measured as deviations from their average. Under this assumption the following expected values E arise

$$E(Y) = E(X) = E(\delta) = 0 \quad [4.20]$$

and further:

$$Var(Y) = E(Y^2) \quad [4.21]$$

$$Var(X) = E(X^2) \quad [4.22]$$

$$Cov(Y, X) = E(YX) \quad [4.23]$$

now:

$$Var(Y) = Var(\beta X + \delta) = \beta^2 \sigma_X^2 + \sigma_\delta^2 \quad [4.24]$$

because $E(X\delta) = 0$ following the usual assumption of regression analysis and from the above;

$$Cov(Y, X) = E(YX) = E[(\beta X + \delta)X] \quad [4.25]$$

$$Cov(Y, X) = \beta E(X^2) + E(X\delta) \quad [4.26]$$

$$Cov(Y, X) = \beta \sigma_X^2 \quad [4.27]$$

which can then be written as two covariance matrices:

$$\begin{bmatrix} \sigma_X^2 & \\ \sigma_{YX} & \sigma_Y^2 \end{bmatrix} = \begin{bmatrix} \sigma_X^2 & \\ \beta\sigma_X^2 & \beta^2\sigma_X^2 + \sigma_\delta^2 \end{bmatrix} \quad [4.28]$$

the simple regression model implies a functional connection between the theoretical covariance matrix and the parameters of the model namely β and σ_δ^2. If the empirical values are substituted for the theoretical ones, the above becomes

$$\begin{bmatrix} s_X^2 & \\ s_{YX} & s_Y^2 \end{bmatrix} \cong \begin{bmatrix} s_X^2 & \\ bs_X^2 & b^2s_X^2 + s_\delta^2 \end{bmatrix} \quad [4.29]$$

It cannot be expected that the two matrices to be exactly equal, but the better the model describes the data the more equal the matrices will be. If there is a one to one correspondence between the sample covariance matrix and the parameters of a model assumed to have generated the sample then the model can be estimated, its fit tested and measures of fit can be calculated based on the difference between the two matrices which is the residual matrix given by:

$$\begin{bmatrix} s_X^2 & \\ s_{YX} & s_Y^2 \end{bmatrix} - \begin{bmatrix} s_X^2 & \\ bs_X^2 & b^2s_X^2 + s_\delta^2 \end{bmatrix} = \begin{bmatrix} 0 & \\ s_{YX} - bs_X^2 & s_Y^2 - b^2s_X^2 + s_\delta^2 \end{bmatrix} \quad [4.30]$$

minimising the elements of the residual matrix leads to the traditional estimates of β and σ_δ^2

$$\beta \approx b = \frac{s_{Y,X}}{s_X^2} \quad [4.31]$$

$$\sigma_\delta^2 \approx s_y^2 - s_{y,x}^2 \quad [4.32]$$

The above is the basis in which estimation is built. The model formulation implies a certain form of the covariance matrix of the manifest variables and the parameters are estimated as the values that minimise the difference between the sample covariance matrix and the implied covariance matrix or residual matrix.

4.7.1. Path analysis specification and identification

In order to conduct the path analysis the model must be specified. Model specification involves determining every relationship and parameter in the model that is of interest to the researcher. In this step theparameters, which are set to be fixed or free, are determined. Fixed parameters are not estimated from the sample data and are typically fixed at zero indicating no relationship between variables. Free parameters are estimated from the observed data and are hypothesized by the researcher to be non-zero. Determining which parameters are fixed and which are free in a SEM is important because it determines which parameters will be used to compare the hypothesized model with the sample population variance and covariance matrix in testing the fit of the model. The choice of which parameters are free and which are fixed in a model is up to the researcher. This choice represents the researcher's apriori hypothesis about which pathways in a system are important in the generation of the observed system's relational structure.

In figure 4.4 the proposed structural model for the data is illustrated.In chapter 2 the proposed model to explain financial services adoption through an intermediary was derived and in figure 4.4 this is expressed as a path diagram in SEM.

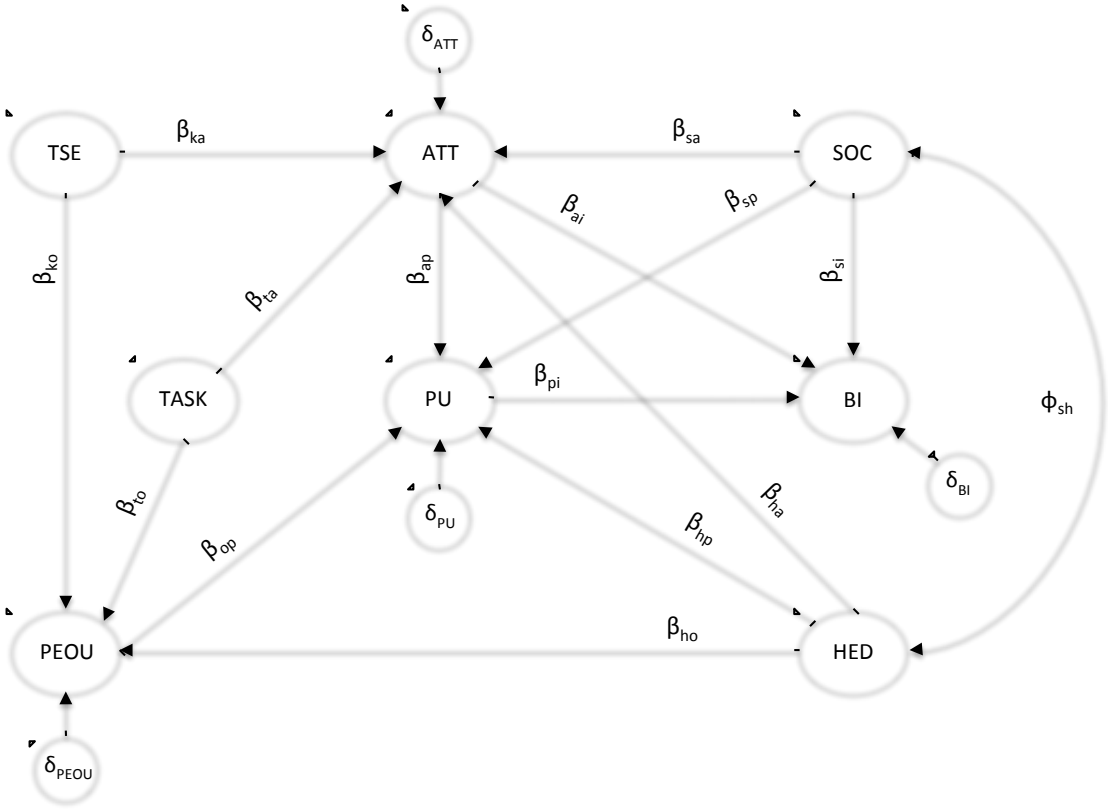

Figure 4.4: Proposed SEM model

The proposed model can be reduced to a set of simultaneous equations that the estimation will optimize and obtain parameter estimates for. As for a CFA, a path analysis uses two different kinds of variables, namely exogenous and endogenous variables. The distinction between these two types of variables is whether the variable regresses on another variable or not. An exogenous variable is influenced by other variables in the path diagram. An endogenous variable is free from the influence of other variables in the model. The set of equation describing the model is shown below;

$$BI = \beta_{pi}PU + \beta_{ai}ATT + \beta_{si}SOC + \delta_{BI} \quad [4.33]$$

$$PU = \beta_{hp}HED + \beta_{op}PEOU + \beta_{ap}ATT + \beta_{sp}SOC + \delta_{PU} \quad [4.34]$$

$$PEOU = \beta_{ho}HED + \beta_{to}TASK + \beta_{ko}TSE + \delta_{PEOU} \quad [4.35]$$

$$ATT = \beta_{ha} HED + \beta_{ta} TASK + \beta_{ka} TSE + \beta_{sa} SOC + \delta_{ATT} \quad [4.36]$$

where β_{xy} represents the path co-efficient between the latent factors x and y and δ_x represents the error associated with the latent exogenous factor x . The latent factors behavioural intent (BI), perceived usefulness (PU), perceived ease of use (PEOU) and attitude (ATT) are exogenous factors. Each of these factors consequently has an error term associated with them that explains the portion of the variance that is unexplained by the dependent latent factors in our model. The remaining factors hedonistic (HED), task (TASK), technology self-efficacy (TSE) and social (SOC) are endogenous variables, which are independent and do not have error terms associated with them.

The proposed model is also recursive in that there are no feedback loops in the proposed relationship between the latent factors. Recursive models can pose a problem when trying to estimate parameters in a model.Once a structural equation model has been specified the next step is to determine whether the model is identified. An identified model is a model where a specific parameter value uniquely identifies the model and no other equivalent formulation can be given by a different parameter value. Model identification was determined by first checking the order condition. The order condition requires that the number of free parameters to be estimated must be less than or equal to the number of distinct values in the matrix S. In the model there are 97 free parameters that need to be estimated. There are a total of 29 observed variables. The number of distinct values in the matrix S is equal to $\frac{p(p+1)}{2}$ where p is the number of observed variables. Consequently the number of distinct values in the S matrix is 406, which is larger than the number of free parameters and consequently the

model order condition is acceptable. The model has 464 distinct sample moments and 102 parameters that need to be estimated. The model consequently had 362 degrees of freedom and is identified. With the model meeting the order condition and being identified it was possible to obtain unique estimates for the model parameters.

4.7.2. Path analysis estimation

In path analysis estimation start values of the free parameters are chosen in order to generate an estimated population covariance matrix, Σ, from the model. Start values can be chosen by the researcher from prior information or by computer programs used to build SEMs. For the SEM the software estimated start values. For the analysis bootstrapping using the ML estimator and 3,000 samples was used to deal with the mild non-normality. SPSS AMOS version 20.0.0 software was used to conduct the analysis. Using this technique a Bollen-Stine p = 0.079 was obtained. As this is greater than 0.05 the null hypothesis is rejected and it was concluded that the model fits the data well. The indices reported on (CFI, TLI, PCFI and RMSEA) are shown in the table 4.3 below. The complete set of fit indices generated by the software is included in appendix 8.15

Table 4.3: SEM Model fit values.

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	0.889	0.875	0.960	0.954	0.959
Saturated model	1.000		1.000		1.000
Independence model	0.000	0.000	0.000	0.000	0.000

Model	PRATIO	PNFI	PCFI
Default model	0.892	0.792	0.855

Saturated model	0.000	0.000	0.000
Independence model	1.000	0.000	0.000

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	0.038	0.032	0.045	0.999
Independence model	0.180	0.176	0.185	0.000

All the values indicate that the model is a good fit to the data. The RMSEA for the hypothesized model had a value of 0.38. The confidence interval at the 90 percent level was 0.31 to 0.45. Both RMSEA and the confidence interval are within the values that indicate good fit. In addition, the researcher noted that the PGFI indicated good parsimony fit for the model. For the hypothesized model a PGFI of 0.777 was obtained that indicated a good fit. The CFI for the hypothesized model was 0.963 that is above the cut-off of 0.95 indicating a good fit.

4.7.3. Path analysis modification and evaluation

If the covariance matrix estimated by the model does not adequately reproduce the sample covariance matrix, the initial hypotheses can be adjusted and the model retested. To adjust a model, new pathways are added or original ones removed. In modification parameters are changed from fixed to free or from free to fixed. It should be noted that adjusting a model after initial testing increases the chance of making a Type I error. There are benefits and disadvantages to using model modification. Any re-specification of the model implicitly changes its meaning in some way. In many instances a change in model specification results in a trivial or unimportant corresponding alteration of the model's substantive meaning, but in other cases model modification can foreshadow a strong shift in the model's meaning from a theoretical standpoint. A second consideration to

take into account when modifying a model is that there is a reliance on empirical data rather than theory to help specify the model.

The more empirically based modifications that are incorporated into the final model, the less likely the model is to be replicated in new samples of data. For these reasons modification of models should be based upon theory as well as the empirical results provided by the modification indices. Appendix 4.6 shows the modification indices for the SEM analysis. The threshold for modification Indices allows one to specify what level of change is required for a path to be included in the modification index output. The default value is 4.00 because it slightly exceeds the tabled critical value of a chi-square distribution with one degree of freedom that is 3.84. Inspection of the modification indices shows that despite several large modification indices identified, the impact on model fit improvement would be relatively small and none of the suggested modifications could be readily supported by the theory or derivation of the model. Consequently the researched decided against modifying the model using modification indices.

With the model having an acceptable fit to the data, the researcher analysed the parameter estimates to identify the significance of specific model paths. The values associated with each path are standardized regression coefficients. These values represent the amount of change in y given astandard deviation unit change in x . Because standardized residuals can be roughly interpreted as z scores, the z score values that correspond to conventional statistical significance levels are employed as practical cut-offs. The size of standardized residuals is influenced by sample size. In general larger samples sizes are associated with larger standardized residuals because the size of the standard errors of the fitted

residuals is often inversely related to sample size. For this reason, some methodologists recommend the use of larger cut-off values such as |2.58| which corresponds to the .01 α level (Byrne, 1998). Confidence intervals can be created for parameters estimated with SEM by the bootstrap method. In table 4.4 the unstandardized regression weights for the paths in the proposed model are shown

Table 4.4: Bootstrap unstandardized regression weights with 95 percent confidence intervals

Regression path			Estimate	S.E.	Lower	Upper	C.R.
PEOU	<---	TASKm	-.153	.091	-.180	.005	-1.689
PEOU	<---	HED	.585	.075	.611	.854	**7.769**
PEOU	<---	TSEm	.034	.299	-.088	.098	.115
ATT	<---	TASKm	1.437	.287	.209	.388	**5.000**
ATT	<---	SOC	.072	.098	-.110	.221	.732
ATT	<---	TSEm	-1.022	.934	-.181	.042	-1.095
ATT	<---	HED	.360	.169	-.018	.335	**2.135**
PU	<---	PEOU	.973	.138	.572	1.035	**7.045**
PU	<---	SOC	-.073	.035	-.283	.002	**-2.056**
PU	<---	ATT	.033	.020	-.034	.207	1.648
PU	<---	HED	.261	.091	-.007	.552	**2.857**
BI	<---	PU	.903	.092	.718	.934	**9.762**
BI	<---	SOC	.149	.039	.108	.415	**3.853**
BI	<---	ATT	-.011	.025	-.146	.096	-.429

The critical ratio (CR) and 95 percent confidence interval values for the parameter estimates, indicated as Lower and Upper in the table, are also displayed. If the critical ratio associated with a path in the hypothetical model exceeds the critical value of |1.96|, (at α =0.05) and the critical value of |2.58| (at α =0.01) the null hypothesis that the parameter was equal to 0 is rejected and the hypothesized relationship is supported (Mueller, 1996). From the critical ratio six paths were identified that were significant at the p = 0.01 levels and two paths that were significant at the p = 0.05 level. The significant critical ratios are highlighted in the table. Unstandardized regression weights are indicated in the Estimate column. TASK has a significant effect on ATT (CR = 4.998, Std. = 0.298) at the p=0.01 level. HED has a significant effect on ATT (CR = 2.130, Std. = 0.174) but only at the p=0.05 level. HED as a significant effect on PEOU (CR = 6.768, Std. = 0.781) at the p = 0.01 level whilst PEOU has a significant effect on PU (CR = 6.534, Std. = 0.908) at the p = 0.01 level. Finally PU has a significant effect on BI (CR = 5.288, Std. = 0.669) at the p=0.01 level as does SOC on BI (CR = 2.606, Std. = 0.192). None of the other paths in the hypothesized model have significance at either the p = 0.05 or the p =0.01 level.

Cheiung and Lau (2008) have highlighted the importance of mediation effects in SEM and advised researchers to include these in any complete analysis of an SEM model. Mediation effect is frequently referred to as an indirect effect, where the effect of the independent variable X_1 on the dependent variable Y goes through a mediator X_2. The mediation effect is commonly defined as the reduction in the regression coefficient of X_2 on Y, when the effects of X_2 are controlled for (Baron and Kenny, 1986; Judd and Kenny, 1981). When the suppression effect is not controlled for, the relationship between X_1 and Y would

appear to be smaller (Cohen and Cohen, 1983). MacKinnon et. al. (2002; 2004) suggest using the bootstrap method to define the confidence intervals for mediation effects estimated with SEM by the bootstrap method. To determine the significance of the indirect effects a critical ratio was calculated by dividing the standard estimate generated from the 3,000 bootstrap examples by its associated standard error. In table 4.5 below the critical ratios for the indirect effects is shown.

Table 4.5: Indirect effects

	TASKm	SOC	TSEm	HED	ATT	PEOU	PU	BI
ATT	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
PEOU	-0,308	-0,200	0,177	-0,235	0,000	0,000	0,000	0,000
PU	-1,496	-0,365	-0,408	**3,732**	-0,300	0,000	0,000	0,000
BI	-0,897	-0,939	0,160	**2,014**	0,606	**2,198**	0,000	0,000

One indirect effects was significant at the p =0.01 level and an additional two were significant at the p=0.05 level. The statistically significant indirect effects are highlighted in the table. HED has a significant indirect effect on BI (CR = 2.014) at the p=0.05 level. PEOU has a significant indirect effect on BI (CR = 2.198) at the p=0.05 level. HED will also have a significant indirect effect on PU. This is confirmed in the table at the p = 0.01 level (CR = 3.732). None of the other indirect paths in the hypothesized model have significance at either the p = 0.05 or the p =0.01 level.

The SEM standardized residual covariance matrix is included in appendix 8.17. Standardized residuals that are equal to or greater than +2.58 or less than -2.58

are used to identify localized areas of weakness. The values in the matrix ranged from +2.626 to -3.125. There was only a single value (+2.626) above the range and a single value (-3.125) below the range. It was concluded that the solution did not have significant areas of localized strain. Modification indices were computed for each fixed and constrained parameter in the model. The table of SEM modification indices is included in appendix 8.16. Inspection of the table indicated that the implied parameter change for the proposed modification indices were small, indicating that minimal improvement in fit would be obtained if these had been used to improve the fit of the model. Consequently no post hoc modification to the initial fit was undertaken.

4.7.4. Outcome of the structural model

The structural model was analysed with a maximum likelihood minimization function using 3,000 bootstrap samples. Goodness-of-fit was evaluated using the SRMR, RMSEA and its 90 percent confidence interval (90 percent CI), CFI and the PCFI. Each of the overall goodness-of-fit indices suggested that the nine-factor structural model fit the data well. The Bollen-Stine p -value = 0.079, SRMR = .046, RMSEA = 0.038 (90 percent CI = 0.030 – .045) and PCFI = 0.863. Inspection of standardized residuals and modification indices indicated no localized points of ill fit in the solution. The final SEM model with significant paths is shown in figure 4.5 below. Path analysis identified five causal paths that had statistical significance at the p = 0.01 level (CR > 2.58) and one path that had statistical significance at the p = 0.05 level. Two latent factors were identified that had a direct causal effect on behavioural intent (BI) to utilize financial services through an intermediary (SOC, PU) and one latent factor was

identified that had a statistically significant indirect effect on behavioural intent through an intermediary (HED).

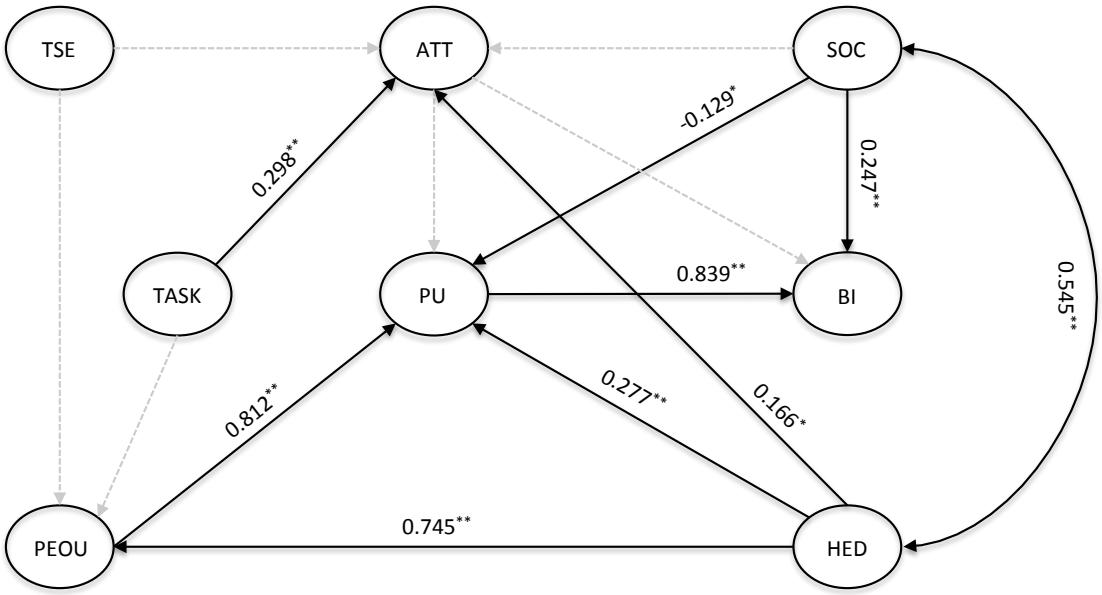

Figure 4.5: Final SEM model with significant causal paths highlighted

4.8. Conclusion

This chapter provided an overview of the structural equation modelling (SEM) technique. The researcher has shown that SEM is well suited to test hypothesized causal models against measured data. The advantages of SEM over similar techniques are that it allows the researcher to take a confirmatory rather than an exploratory approach to the data analysis, obtain explicit estimates of measurement error variance and allow the incorporation of latent and observed variables into a single model. SEM is shown to consist of two parts, a measurement part and a structural part. The measurement part used for the analysis is confirmatory factor analysis (CFA), a special form of factor analysis. CFA is used to confirm that a set of latent factors constructed from a group of observed variables is able to account for the variance seen in the associated data.

The objective of CFA is to obtain estimates for each parameter in the measurement model and to identify measurement error explicitly before attempting the structural component of the model.

The structural component of the model is derived using path analysis and allows researchers to confirm or reject the proposed causal relationships in a proposed model. A variety of model fit indices was described that are used equally for CFA as well as SEM model fits and the values associated with acceptable fits in the indices was also discussed. The analysis of the hypothesis extended TAM model for financial services adoption through an intermediary was conducted using structural equation modelling. The sample size of 341 was found to have the appropriate power to detect type II errors and was large enough to carry out a SEM analysis. The combined distribution of the data is assumed to be normal, however three of the 29 variables used were not univariate normal and the combined data was characterized as mildly non-normal.

With the data distribution being mildly non-normal a bootstrap maximum likelihood estimation approach was used with 3,000 bootstrap samples. The observed variables that described the nine latent factors were tested and found to be valid and reliable indicators of the latent constructs. The SEM model comprised two components, the measurement component and the structural component. The measurement component of the model was tested using confirmatory factor analysis and showed good fit across all reported indices and no post hoc modification was deemed necessary. It was concluded that the eight latent factors were a good fit to the data. The structural equation component of the SEM was over identified, allowing estimation of the model parameters. The

structural model showed good fit across all reported indices. The hypothesized model was thus confirmed as a good fit to the data. The critical ratios of the path analysis identified six statistically significant relationships in the model. Two latent factors were found to directly affect behavioural intent and two latent factors were found to indirectly affect behavioural intent to adopt financial services through an intermediary.