Journal of Travel and Tourism Research, Spring & Fall 2013

Partial Least Squares Path Modelling (PLSPM): A New Direction for Research in Tourism and Hospitality

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Received (in revised form): December 2013

Abstract

The use of partial least squares path modelling (PLSPM) has escalated in the areas of marketing, management, information systems, and organizational behaviour. Researchers in tourism and hospitality have to date been reluctant to use this approach, instead, focusing on covariance-based structural equation modelling (CBSEM) techniques conducted in Lisrel or AMOS. This article highlights the main differences between CBSEM and PLSPM and describes the advantages of PLSPM with regard to (1) testing theories and analyzing structural relationships among latent constructs; (2) dealing with sample size limitations and non-normal data; (3) analyzing complex models that have 'formative' and 'reflective' latent constructs; and (4) analyzing models with higher-order molar and molecular constructs. These advantages are put into practice using examples from a tourism context. The paper demonstrates the application of PLSPM in the case of destination competitiveness, and illustrates how this approach could enhance the theoretical and practical usefulness of tourism modelling. This paper also presents a step-by -step guide to PLSPM analysis, providing directions for future research designs in tourism. This presents valuable knowledge for researchers, editors, and reviewers with recommendations, rules of thumb, and corresponding references for appropriately applying and assessing structural models.

Keywords: Quantitative methods**,** structural equation modelling, partial least squares, tourism, rormative indicators.

Introduction

Structural equation modelling (SEM) is now widely used in business and tourism research (e.g., Babin et al., 2008; Assaker et al., 2010; Hallak et al., 2012). SEM allows for the analysis of latent variable(s) at the observation level (measurement/outer model), and to also test simultaneous relationships between latent variables at the theoretical level (structural/inner model) (Bollen, 1989). It can be used to examine research questions related to causal relationships among a set of latent factors each measured by one or more manifest [observed] variables within a single comprehensive method. There are two main approaches to SEM analysis 1) *covariance-based SEM analysis (CBSEM)(*Jöreskog, 1978, 1993), and 2) *component-based, or partial least squares SEM* (also referred as partial least squares path modelling- PLSPM) (Wold, 1982, Esposito Vinzi et al., 2010).

The two approaches serve different research purposes. CBSEM typically employs a full information maximum likelihood estimation process that yields parameter estimates that minimize the discrepancy between the implied and the observed covariance matrices. This approach examines the 'goodness-of-fit' of the computed covariance matrix from the model compared to the observed matrix from the data sample (Nunkoo and Ramkissoon, 2012). Partial Least Square Path Modelling (PLSPM) is an alternative SEM method that examines a network of relationships among latent variables (Wold, 1979). It is a partial information method that maximizes the explained variance of all dependent variables based on how they relate to their neighbouring constructs with a predictive purpose (Tenenhaus et al., 2005).

Tourism studies have mostly favoured CBSEM, using programs such as AMOS or LISREL, when dealing with structural models (e.g., Hallak et al., 2012). A review of papers published in the *Journal of Tourism Management*, *Tourism Analysis*, and *Journal of Travel Research* over the past five years yielded 196 studies that used SEM. Of those studies, only 29 used PLSPM, and this had only been in recent years (2011-2013); while the remaining 167 (85%) reviewed studies relied on CB-SEM. However, the CBSEM approach requires that the following assumptions to be met before the results can be validated: 1) multivariate normality of the data, 2) a large sample size, 3) the latent constructs are *reflective* (i.e., directional arrows progress from the constructs to the indicators), 4) the model is relatively simple with a limited number of latent variables, and 5) there is a strong theoretical basis for the model. Thus, the composition of the latent constructs, and the causal relationships among them must be theoretically derived (Diamantopoulos and Siguaw, 2006). Violations of these assumptions are problematic and may compromise the validity of any results.

Tourism researchers utilising CBSEM have adopted a 'relaxed' approach to addressing the required assumptions. For example, research on tourism competitiveness and supply-side demand models (e.g., Mazanec, 2011; Assaker et al., 2011) grouped indicators into pillars and indices on an empirical (versus theoretical) basis. CBSEM models in tourism have also overlooked the reflective versus formative specification of the constructs being examined. Construct misspecification occurs when the constructs are assumed to be reflective (the observed indicators are correlated and their scores are reflected by the latent variable) when they should have been specified as formative (the observed indicators are not correlated, but they contribute to forming the underlying latent construct). Typical examples of construct misspecifications include the operationalization of 'customer/visitor loyalty' in tourism research. Loyalty is often operationlized as a reflective, latent factor with three observed indicators: complaints to acquaintances and the public, revisit intention, and recommendations to acquaintances (Song et al., 2011). However, this assumes that loyalty indicators are correlated with each other, which might not be the case in reality. For example, a visitor to a hotel might make an official complaint to hotel managers and also spread negative word of mouth to others, but this does not necessarily imply that the guest will not return to the hotel. He/she could revisit due for convenience or financial reasons. Thus, construct misspecification can affect the veracity of the SEM results (Song et al., 2011).

CBSEM also requires a large sample size to validate the model. The more complex the model, the larger the sample needed to achieve model fit (Kline, 2004). Complex models, such as those examined in the tourism literature, become less stable without a substantially large sample; consequently, they might fail to converge. A typical example of complex models includes the operationalization of destination image in tourism research (e.g., Kim and Yoon, 2003), where image is often considered to be a second/higher-order factor that includes several first-order attribute factors, each measured by a set of directly observed items (or (see Kim and Yoon, 2003). In the operationalization of destination image as a second-order factor, authors often have to use a large datasets and impose additional constraints on the complex (higher-order) destination image model to achieve identification and ensure the convergence of results under CBSEM. In addition, the issue of model complexity and higher-order model specification is evident in the operationalization of several other constructs in tourism research, such as service quality (Howat and Assaker, 2012) and service evaluation (Huang et al., 2013). Specifically, the quality construct is often thought of as a second-order factor that includes four first-order dimensions (i.e., core services, staff, general facility, and secondary services) that influence customers' overall quality. Each dimension is measured by a set of directly observed items (Howat et al., 1996). Service evaluation is also perceived as second-order factor that includes two first-order dimensions (i.e., affective and cognitive evaluation), each measured by a set of directly observed items. In such cases, PLSPM presents a more comprehensive approach relative to CBSEM.

Thus, in this paper we discuss the use of PLSPM as an alternative approach to CBSEM in cases where covariance-based assumptions are violated. PLSPM provides greater flexibility in analysing complex models with a limited sample size, as well as models with formative and reflective constructs. Despite gaining popularity across various disciplines, including strategic management (e.g., Hulland, 1999), management information systems (e.g., Urbrach and Ahlemann, 2010) and marketing (e.g., Reinartz et al., 2004), the use of PLSPM in tourism research remains limited (Assaker et al., 2010). In addressing this gap, this paper aims to 1) illustrate the application and use of PLSPM in the context of tourism research, 2) demonstrate the main differences between CBSEM and PLSPM, and 3) identify research areas in tourism where PLSPM could be advantageous. This technical paper advances the knowledge of quantitative methodologies in tourism research. It presents valuable knowledge for researchers, editors, and reviewers with recommendations, rules of thumb, and corresponding references for appropriately applying and assessing structural models.

PLS Path Modelling: Basic Concepts and Algorithm

PLSPM uses an iterative algorithm in which the parameters are calculated with a series of least squares regressions after explicitly creating construct scores by weighting the sums of items underlying each construct (Chin et al., 2008). The term 'partial' thus emanates from the fact that the iterative procedure involves separating the parameters rather than estimating them simultaneously (Hulland, 1999). This differs from CBSEM which uses the model to explain covariations among the indicators and the measurement errors. PLSPM analysis is accomplished using a two-step process. The algorithm begins with arbitrary initial weights used to calculate an outside approximation of the latent variables. Then, the inner relations among latent variables (LVs) are considered in order to calculate the inside approximations. Here, the researcher has the option of choosing among three scenarios (called weighting schemes): (1) centroid, (2) factor, or (3) path, based, respectively, on the sign of the correlation between neighbour latent variables, on the correlations themselves and the regression coefficients. Once inside approximations are obtained, the algorithm turns to the outer relationships when new weights are calculated. It considers how the indicators are related to their constructs by Mode A (usually associated to reflective constructs by applied researchers) or by Mode B (usually associated to formative constructs by applied researchers). Mode A implies simple linear regressions between construct and reflecting indicators as the construct is assumed to affect each indicator separately. Mode B implies multiple linear regressions between the construct and the set of indicators as these are assumed to affect the construct on a collective basis. The simple or multiple regression coefficients are then used as new weights for outside approximation. The process continues iteratively until the weights converge.

After the latent variable (LV) scores are estimated, the second step of the process involves obtaining the parameters of the structural and the measurement models. The structural (path) coefficients are calculated by ordinary least squares regression between LVs according to the structural equations. There are as many regressions as there are endogenous latent variables. The parameters of the measurement model, known as the loading coefficients, are also estimated by least squares regressions. PLSPM estimates the latent variables as linear combinations of the observed measures, this avoids the indeterminacy (i.e. the arbitrariness of the component scores) and improper solution problems encountered under CBSEM (see Tenenhaus et al., 2005). Structural models examined using CBSEM also require a strong theoretical basis. Thus, misspecified models caused by unsubstantiated structural paths or measurement items can affect the results of the entire model. PLSPM offer greater flexibility in addressing these issues as the estimates are limited to the immediate 'blocks' (factors) to which a particular construct is structurally connected. The PLS estimation process separates the parameters rather than estimating them simultaneously. This has proven to be particularly beneficial for prediction-oriented models that are highly complex but lack a strong theoretical foundation (Jöreskog and Wold, 1982) as well as for models in which the stringent CBSEM constraints cannot be met (Haenlein and Kaplan, 2004).

PLS Path Modelling: Methodological Characteristics

CBSEM is a confirmatory approach that tests existing theories (Joreskog and Wold, 1982; Hulland, 1999). PLSPM is best suited when the phenomenon under investigation is relatively new with limited knowledge about construct compositions or the structural relationships (Wold, 1975). Furthermore, PLSPM enables the unrestricted computation of cause–effect relationship models that employ both reflective and formative measurement models (Diamantopoulos and Winklhofer, 2001). It is also possible to accurately estimate path models when sample sizes are small and data distribution is not normal (Chin and Newsted, 1999). Finally, it can examine complex models that consist of many latent and manifest variables, as well as analysing hierarchical models that consist of higher and lower order latent variables (Wold, 1982). Therefore, 'Heywood case' problems that are associated with CBSEM (Krijnen et al., 1998) can be overcome with the PLS approach. This approach would be of particular value to research on destination satisfaction, loyalty, quality, and competitiveness.

Exploratory/Predictive Nature of the Study

As we stated earlier, CBSEM is based on full information procedure. Thus, models that contain poorly developed constructs where the measurement items are weak or cross-load on other latent variables are problematic as they can bias other estimates in the model. PLSPM, on the other hand, is less affected by misspecifications as the weights developed for each construct take into account only neighbouring constructs to which they are structurally connected. As such, PLSPM is best suited to examine models where the phenomenon under investigation is relatively new, this is often the case in the tourism field. Furthermore, PLSPM estimates typically represent good proxies of CBSEM results and can represent a reasonable methodological alternative to test, not just predict, theory (Rindskopf, 1984). Although testing theories through PLSPM should be treated with caution as the analysis does not calculate goodness-of-fit indices for the model.

Formative Measurement Models

A default assumption for CBSEM analysis is that the indicators used to measure a latent variable are *reflective* in nature. This is based on the classic theory assumption where the latent construct causes observed variations in its measurement items (i.e., directional, causal arrows progress from the construct to the indictors) (Bollen, 1989; Nunnally, 1978). However, this is not always the case; applying reflective measurement as a default may result in model misspecification (Bollen, 2007). Some constructs are formed through a combination of the respective measures where changes in the indicators cause changes in the construct rather than vice versa (Jarvis et al., 2003). In such cases, a *formative* rather than a *reflective* scheme for latent constructs is required.

For example, let's consider the latent construct of 'Customer Complaints' as it applies in tourism research (Jarvis et al., 2003). Measuring complaints includes 1) the frequency of complaining to a store manager; 2) incidence of telling friends and relatives about a bad service experience; 3) likelihood of reporting the supplier to a consumer complaint agency; 4) likelihood of pursuing legal action against the supplier. In such cases, the Customer Complaints latent variable should be specified as a formative rather than a reflective construct. It is formative since a high score on one measurement item would affect the latent construct, but would not necessarily affect the other items. Thus, customer complaints should be modelled as a (typically linear) combination of its indicators plus a disturbance term (Diamantopoulos and Siguaw, 2006). This is where the correct specification of a construct (i.e. formative or reflective) becomes crucial. Misspecifications can bias estimations of inner model parameters and lead to inaccurate assessment of relationships (Jarvis et al., 2003). A latent variable/construct (LV) should be specified as formative when:

- The indicators are viewed as defining characteristics of the LV;

- Changes in the indicators are expected to cause changes in the LV;
- Changes in the LV are not expected to cause changes in the indicators;
- A change in the value of one of the indicators is not necessarily expected to be associated with a change in all of the other indicators (i.e. measurement items are not necessary correlated to each other); and,
- Eliminating an indicator may alter the conceptual domain of the LV (Jarvis et al., 2003).

A possible explanation as to why many models in tourism are misspecified as reflective is because of the limitations associated with SEM softwares including AMOS and LISREL (MacCallum and Browne, 1993). Formative constructs cause identification issues and computation problems in CBSEM softwares. PLSPM, however, can accurately analyse structural models that incorporate both formative and reflective latent constructs.

Small Sample Size and Non-Normal (Skewed) Data

CBSEM is recognised as a large sample size method. Some suggest that a minimum of 200 cases is required, however the greater the complexity of the model the larger the sample size is required for the model to converge (Boomsma and Hoogland, 2001). Sample size is less of a problem in PLSPM. A rule of thumb for robust PLSPM estimations suggests that the sample size should be at least (1) 10 times the number of indicators of the scale with the largest number of formative indicators, or (2) 10 times the largest number of structural paths directed at a particular construct in the inner path model (Barclay et al. 1995). Because this represents the largest regression performed during the PLSPM iterative process, this would be the logical starting point for choosing an adequate sample to ensure the accuracy and statistical power of the model. PLSPM can also overcome the problems associated with analysing non-normal data. Specifically, in cases where the data is skewed, evidence suggests that PLS estimates are better than maximum likelihood (ML) estimates in terms of both bias and precision. The ML estimators seem to be more sensitive to the potential deficiencies in the data and model specification (see Babakus et al., 1987; Reinartz et al., 2009; Vilares et al., 2009).

Complex Models and Higher Order Molar and Molecular Constructs

Structural models analysed using CBSEM are limited with regard to their complexity and hierarchical structures. The more complex the model with regard to the number of observed variables included, the greater the likelihood that it will fail to converge or fail to achieve *good fit* using CBSEM (Boomsma and Hoogland, 2001). PLSPM is not subjected to such constraints, thus, complex models capturing many factors related to attitudes, opinions, and behaviours over time could be examined. PLSPM is also more robust when dealing with hierarchical model comprising higher-order constructs. The algorithm explicitly weights measurement indicators to create construct scores which enables the analysis of both molar and molecular higher-order models (Chin and Gopal, 1995).

Molecular constructs represent a higher (second-order) level of abstraction with arrows pointing to its respective first-order constructs. A second-order molar model would have the arrow in the opposite direction, going from the first-order constructs to the higher second-order construct. PLSPM can analyse both molar and molecular models. CBSEM, on the other hand, is limited to molecular models, but even these models are subjected to a number of constraints. For example, uncorrelated higher-order factors need at least three lower-order factors, correlated higher order factors require at least two lower-order factors, and at least two manifest variables (indicators) are desired for each lower order factor (Rindskopf and Rose, 1988). (see Table 1)

Table 1: Guidelines for the appropriate use of PLSPM

Criterion	Description / Recommendation	Suggested References
Objective: Prediction oriented	PLSPM is appropriate when theory is weak regarding the composition of the constructs and how constructs are related. Scores on latent constructs/variables need to be calculated.	Henseler et al., 2009 Albers, 2010
Sample Size and Data Characteristics		Chin et al., 2008 Hulland, 1999
Small samples	PLSPM is robust when minimal sample size ranges from 30 to 100 cases; also use "ten times" rule as a rough guideline for minimum sample size.	
Distribution of the Sample data	PLSPM is robust when applied to highly skewed data or when data is severely non-normal.	
Formative Relationship between LVs and its Measures	PLSPM is appropriate to model formative constructs when the following conditions are not met: 1. Formative construct emits paths to at least two unrelated latent constructs with reflective indicators, or 2. Formative construct emits paths to at least two (theoretically appropriate) reflective indicators, or 3. Formative construct emits paths to at least one reflective indicator and at least one latent construct with reflective indicators.	Diamantopoulos and Siguaw, 2006 Jarvis et al., 2003
Model Complexity	PLSPM is appropriate to model models with significant complexity (i.e., 100 constructs and/or 1,000 indicators). Molar hierarchical models are being assessed. Models where sample size is small compared to the number of indicators.	Chin et al., 2008 Hair et al., 2011

Applications of PLSPM in Tourism

A typical example from the tourism literature highlighting how PLSPM was found to be superior to traditional CBSEM can be found in Assaker et al. (2011) and Assaker and Hallak (2012). Assaker et al. (2011) examined a theoretical structure model for destination competitiveness using CBSEM. They looked at how supply-side tourism factors (including economic, social, and environmental factors) affect tourism demand at the country level. In order to examine these structural relationships in CBSEM, each of the latent constructs had to be specified as reflective in nature. However, the measurement items for the 'economy' latent factor were not highly correlated to each other; therefore, they could potentially represent different relevant dimensions of latent variables (see Fig. 1a). Furthermore, Assaker et al. (2011) relied on the competitiveness indicators proposed by the World Travel and Tourism Council (WTTC) to build their measurement models. Strictly speaking, this represents an exploratory, rather than confirmatory approach to structural modelling. In a subsequent paper, Assaker and Hallak (2012) tested a structural model of destination competitiveness through PLSPM. The examined that predictive relationships between tourism supply factors and tourism demand. In this model, the latent construct of 'economy' was operatinalosed as a formative, as opposed to reflective, construct (see Figure 1b).

As evident from the results of the two models (Figure 1a using CBSEM, and Figure 1b using PLSPM), the composition of the economy construct changed across the two estimation processes. In particular, when the economy construct was correctly specified as a formative construct and tested using PLSPM, the measurement items of purchasing power parity (PPP), industry value added (IVA), and foreign direct investment (FDI) were found to be strong predictors of the economy. In addition, the standardized regression coefficient of the path between economy and infrastructure was lower when the economy was specified as formative. The overall predictive power of the model improved under PLSPM as the R-square for the tourism demand construct was greater.

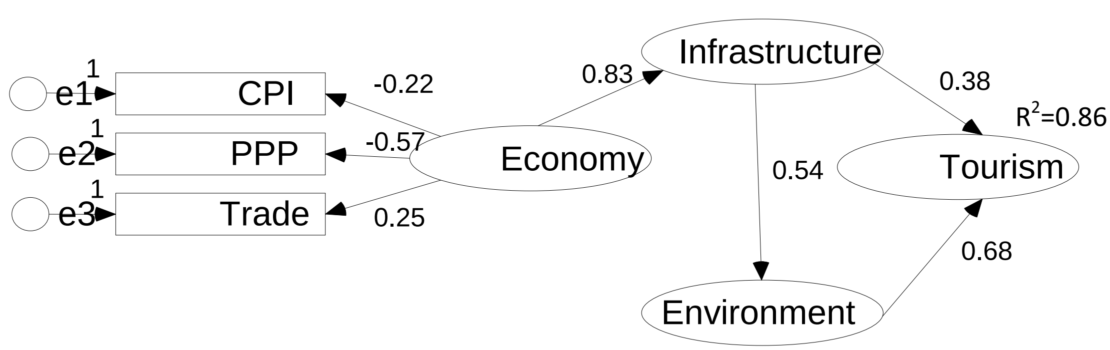

Figure 1a: Destination competitiveness model: Reflective economy indicators using CBSEM

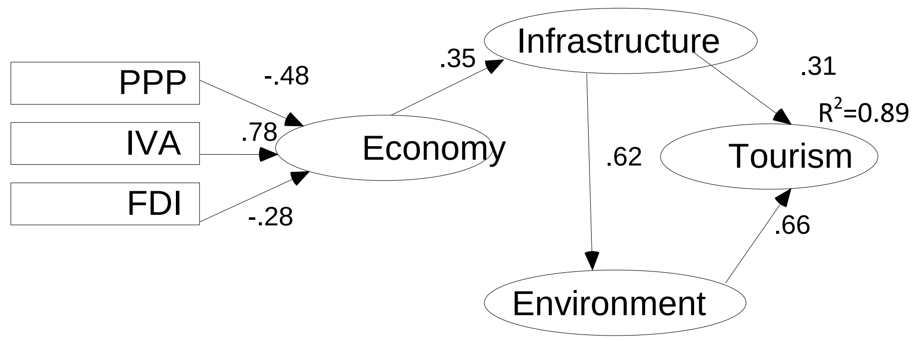

Figure 1b: Destination competitiveness model: Formative economy indicators using PLSPM

PLS Path Modelling: Model Assessment and Evaluation of Results

The previous sections of this paper have explained the differences between CBSEM and PLSPM and illustrated how the two modelling approaches can be used to achieve different purposes. The following section presents a series of guidelines on how to conduct PLSPM. In particular we discuss the process of examining reflective measurement models, formative measurement models, as well as determining the validity of the structural model in the absence of goodness-of-fit indicators.

Assessing the Reflective Measurement (Outer) Models

Validation of PLSPM models involves a two-step process: 1) assessing the outer (measurement) model and (2) assessing the inner (path) model. The reliability and validity of the outer-model need to be established before the inner-model is examined (Chin, 1998; Henseler et al., 2009). As discussed earlier, measurement models can be either reflective or formative in their specification. Different approaches are used to validate these measurement models in PLSPM. Reflective measurement models are examined for their unidimensionality, internal consistency, reliability, convergent validity, and discriminant validity (Straub et al. 2004; Lewis et al. 2005).

Unidimensionality refers to how well the indicators of the same latent variable relate to each other (Gerbing and Anderson, 1993). This can be assessed using exploratory factor analysis (EFA) to establish whether the measurement items load with a high coefficient on only one factor; and whether this factor is the same for all items that are supposed to measure it. The number of selected factors is determined by the number of factors with an eigenvalue > 1.0 (when EFA is applied to standardized data). An item loading is usually considered high if the loading coefficient is above .600 and considered low if the coefficient is below .400 (Gefen and Straub, 2005).

The reliability (internal consistency) of the measurement models is determined through a number of indices. This includes the *Cronbach's alpha* and the *composite reliability* tests. The composite reliability is preferred as it draws on the standardized loadings and measurement error for each item to measure reliability (Werts et al., 1974;

Chin 1998). As a rule of thumb, values below .60 suggest poor reliability (Nunnally and Bernstein, 1994).

Convergent validity is the degree to which individual items reflecting a construct converge (or explain that construct well), compared to items measuring different constructs. This is examined by using the average variance extracted (AVE) index (Fornell and Larcker, 1981). The AVE should exceed .50 for a valid construct (Fornell and Larcker, 1981). This indicates that a latent construct is, on average, able to explain more than half of the variance of its indicators (Chin, 1998). Higher AVE occurs when indicators are truly representative of the latent construct. Moreover, the significance of the indicator loadings can also be used to test convergent validity. Significance can be tested using resampling methods, such as bootstrapping (Efron and Tibshirani, 1993) or jackknifing (Miller, 1974).

Discriminant validity represents the extent to which measures of a given construct differ from measures of other constructs in the same model. This is determined by calculating the shared variance between two constructs and verifying that the result is lower than the AVE for each individual construct (Fornell and Larcker, 1981). Each latent construct should share greater variance with its assigned indicators than with any other latent constructs. Discriminant validity can be determined by examining cross-loadings of each latent construct's indicators with all the other constructs (Chin, 1998). If each indicator's loading is higher for its designated construct than it is for any of the other constructs, and each construct loads highest with its assigned items, the discriminant validity of the model is supported (see Table 2).

Table 2: Guidelines for assessing reflective measurement models

Validity Type	Criterion	Description	Suggested Literature
Unidimensionality	Exploratory Factor Analysis (EFA)	Measurement items should load with a high coefficient on only one factor, and this factor is the same for all items that are supposed to measure it. The number of selected factors is determined by the numbers of factors with an Eigenvalue exceeding 1.0. Loading is usually considered high if the loading coefficient is above 0.600.	Gefen and Straub, 2005 Gerbing and Anderson, 1988
Internal consistency reliability	Cronbach's alpha	Measures the degree to which the indicators belong together. Alpha values ranges from 0 (completely unreliable internal consistency) to 1 (perfectly reliable consistency). For confirmative research: CA > 0.700.	Cronbach, 1951 Nunnally and Bernstein, 1994 Werts et al., 1974
	Composite reliability (CR)	Alternative to Cronbach's alpha, allows indicators to be unequally weighted. Proposed threshold value for confirmative research: CR > 0.700.	
Convergent Validity	Indicator Loadings	Measures how well the indicators explain their corresponding LV. Values should be significant at the .050 level and higher than .0.70. The significance can be tested using bootstrapping or jackknifing.	Chin, 1998 Gerbing and Anderson, 1988
	Average variance extracted (AVE)	Attempts to measure the amount of variance that an LV component captures from its indicators relative to the amount due to measurement error. Proposed threshold value: AVE > 0.500.	
Discriminant Validity	Cross-loadings	Cross-loadings are obtained by correlating the loadings of each item with all latent variables. If the loading of each indicator is higher for its designated construct than for any of the other constructs, it can be inferred that the models' constructs differ sufficiently from one another.	Chin, 1998 Chin et al., 2008 Fornell and Larcker, 1981
	Fornell-Larcker criterion	Requires an LV to share more variance with its assigned indicators than with any other LV. Accordingly, the AVE of each LV should be greater than the LV's highest squared correlation with any other LV.	

Assessing Formative Measurement Models

The procedure for establishing the validity and reliability of formative measurement models is slightly different. Formative indicators are not necessary correlated with one another. Thus, the traditional approaches to examining internal consistency and validity for reflective models are redundant (Bollen, 1989; 2011). Alternatively, formative constructs are assessed in terms of content validity at the indicator and construct levels (Henseler et al., 2009).

Indicator level. The estimated weights of formative measurement models should be significant at $p < .05$. These can be computed in PLSPM by using bootstrapping (Efron and Tibshirani, 1993) or jackknifing (Miller, 1974). The recommended standardized path coefficients should be greater than .100 (Lohmöller, 1989) or .200 (Chin, 1998). In addition, the degree of multicollinearity among the formative indicators is assessed through the variance inflation factor (VIF) (Cassel and Hackl, 2000; Fornell and Bookstein, 1982). This indicates how much of an indicator's variance is explained by the other indicators of the same construct. VIF values should be below the accepted threshold of 10 (Diamantopoulos and Siguaw, 2006)

Construct level. The content validity of the formative construct is established through nomological validity. This determines whether the formative construct behaves as it should (as initially hypothesized) within a system of related constructs. The hypothesized relationships between the formative construct and other constructs in the path model should be strong and significant (Henseler et al., 2009; Straub et al., 2004). The achieved explained variance (R^2) of the endogenous constructs is primarily used to determine whether a theoretically sound formative factor was appropriately operationalized (Diamantopoulos and Winkholfer, 2001) (see Table 3).

Table 3: Guidelines for assessing formative measurement model validity

Validty Type	Criterion	Description	Suggested Literature
Indicators content validity	Indicator weights	Significance at the .050 level suggests that an indicator is relevant for constructing the formative index and, thus demonstrates a sufficient level of validity. Some authors also recommend path coefficients greater than .100 or .200.	Chin, 1998 Lohmöller, 1989
Constructs content validity	Nomological validity	Means that relationships between the formative construct and other models' constructs, which are well known through prior literature, should be strong and significant.	Henseler et al., 2009 Straub et al., 2004
	Multicollinearity / Variance inflation factor (VIF)	Variance inflation factor can be used to test for multicollinearity among manifest variables in a formative block. As a rule of thumb, VIF < 10 indicates the absence of harmful collinearity among indicators, suggesting that each indicator contribute significantly to its formative block.	Mackenzie et al., 2005

***Assessing the* Structural (Inner) Model**

Once the validity of the measurement (outer) models are established, the structural (inner) model can be analyzed. The primary criterion for inner model assessment is the coefficient of determination (R^2), which represents the amount of an LV's explained variance to its total variance, for each endogenous latent variable. Chin (1998) describes R^2 values of 0.670, 0.333, and 0.190 in PLSPM as substantial, moderate, and weak, respectively. In cases where the path model is relatively simple and includes a limited number (i.e one or two) exogenous latent variables then a 'moderate' R^2 may be acceptable. However, more complex models require the R^2 value to be substantial (i.e. .670) in order to establish validity.

A second approach to testing model validity concerns the standardized path coefficients between the latent constructs. For each path coefficient, the algebraic sign, magnitude, and significance need to be scrutinised. Paths between latent constructs should be both statistically significant ($p<.05$) and theoretically sound. Standardized path coefficients should also exceed .100 to account for a certain impact within the model (e.g., Huber et al., 2007). The significance of the path coefficients may be calculated using resampling techniques such as bootstrapping or jackknifing,

The *effect size* of each path in the inner model can be calculated through the Cohen's *f2* (Cohen, 1988). the *effect size* is the increase in R^2 of the latent construct to which the path is connected, relative to the latent construct's proportion of unexplained variance (that is, relative to the proportion of variance of the endogenous latent variable that remains unconsidered) (Chin, 1998). Cohen's *f2* values of 0.02, 0.15, and 0.35 signify small, medium, and large effects, respectively, on endogenous latent constructs (Chin, 1998; Cohen, 1988).

The Goodness-of –Fit (GOF) Index (Tenenhaus et al. 2004) can also be used to establish model validity. However, this is applicable to PLSPM models with reflective constructs only. Nonetheless, the GOF can be used to compare different models in terms of their predictive performance as it presents the percentage of explained variance in the model as a whole. Finally, validity of the inner model can be determined through the cross-validated redundancy measure (Wold, 1982) – the model's ability to predict the endogenous latent variable's indicators. To this end, the Stone Geisser's Q2 (Stone, 1974; Geisser, 1975) can be computed using blindfolding procedures (Tenenhaus et al., 2005) to create estimates of residual variances. Positive Q2 values confirm the model's strength in predicting the endogenous constructs.

The abovementioned tests and indices are necessary in order to establish the validity of the inner model. Once validated, the parameter estimates can be interpreted on the basis of theoretical foundations of the model. Consequently, the hypotheses expressed in a model can be confirmed or rejected based on the analysis. The criteria for assessing a PLSPM model at the structural (inner) level are summarized in Table 4.

Table 4: Guidelines for assessing inner structure/structural models

Validty Type	Criterion	Description	Suggested Literature
Structural Predictive Hypothesis	Path coefficients	Path coefficients between the LVs should be analyzed in terms of their algebraic sign, magnitude, and significance. The significance can be tested using bootstrapping or jackknifing.	Chin, 1998 Ringle, 2006
Model Validity	Coefficient of determination (R2)	R^2 Measure the explained variance of an LV relative to its total variance. Values of 0.67, 0.33,or 0.19 for endogenous latent variables in the inner path model are described as substantial ,moderate, or weak.	Cohen, 1988 Stone, 1974 Geisser, 1975 Fornell and Cha, 1994
	Effect size (f2)	Measures if an independent LV has by itself a substantial impact on a dependent LV. Values of .020, .150, .350 indicate the predictor variable's weak, medium, or large effect in the structural model.	Cohen, 1988 Stone, 1974 Geisser, 1975
	Predictive relevance (Q2)	The Q2 statistic measures the predictive relevance of the model in terms of manifest variables. A tested model has more predictive relevance the higher Q2 is. The proposed threshold value is Q2 > 0.	Cohen, 1988 Stone, 1974 Geisser, 1975

Conclusion and Future Directions

In this methodology paper, we have discussed the component-based procedure of SEM known as Partial Least Squares Path Modelling (PLSPM). Despite its popularity in mainstream business research, its application in tourism remains limited. We have compared PLSPM to the more popular CBSEM and have explained its advantages in tourism studies when the assumptions for applying traditional the CBSEM approach cannot be met. PLSPM, can open the doors to new and innovative types of causal modelling.

We have demonstrated that PLSPM works best when: (1) the aim of the study is prediction; (2) the phenomenon to be investigated is relatively new; (3) measurement models need further development; (4) the model incorporates both reflective and formative constructs (5) the model is hierarchical in nature and involves first and second order constructs; (6) the sample size is relatively small; (7) there is non-normality in the dataset; and (8) the proposed structural model is complex with several observed and latent variables.. Previous literature on tourism research modelling (Mazanec, 2011) suggests that researchers in most cases/most often tend to not explicitly discuss their justification for their method of analysis. Future studies in tourism need to be more explicit in the method of analysis that is used. In particular, the specification of measurement models within the structural model (i.e. reflective or formative) requires greater attention. This paper has presented important guidelines for tourism researchers to follow when conducting structural equation modelling. We presented examples of how PLSPM is used to model destination competitiveness. Such an approach would enable researchers to re-examine the specification of the measurement models, which, consequently could produce more effective and valid results for the structural model.

It is our objective that this paper will enhance the quality of future studies in tourism utilising structural equation modelling. In particular, the use of the PLSPM method could expand our understanding of many tourism phenomena including destination competitiveness, satisfaction, and customer loyalty. PLSPM can overcome the difficulties associated with non-normal datasets, complex models, and relatively small sample sizes. These issues are common in tourism research and we believe that this paper has identified ways to address these problems.

Although this paper has presented a detailed discussion of PLSPM and its application, it is important to note that some of the more advanced PLSPM techniques were beyond the scope of our discussion. These include response-based segmentation techniques, such as finite mixture partial least squares to deal with heterogeneous datasets (Sarstedt et al., 2011), or techniques to analyze moderating effects and conduct multi-group analysis in PLSPM (e.g., Henseler and Chin, 2010). These recent advancements are integrated in PLS-based softwares such as SmartPLS (www.smartpls.de) and XLSTAT-PLSPM (XLSTAT, 2011) and can expand PLSPM's application to tourism research. Advances in PLSPM, and structural modelling in general, have the potential to advance the quality of tourism studies as they enable researchers to examine more complex problems requiring sophisticated levels of quantitative analysis.

References

Albers, S. I. E. (2010). PLS and Success Factor Studies in Marketing. In V. Esposito Vinzi, Chin, W.W., Henseler, J. And Wang, H. (Ed.), *Handbook Of Partial Least Squares: Concepts, Methods, and Applications*. Berlin: Springer.

Assaker, G., Esposito Vinzi, V. and O'Connor, P. (2010). Structural Equation Modeling in Tourism Demand Forecasting: A Critical Review. *Journal of Travel and Tourism Research,* Spring/Fall, 1-27.

Assaker G., Esposito Vinzi V. and O'Connor, P. (2011). Modeling a Tourism Causality Network: An Empirical Analysis. *Journal of Modeling in Management,* 6(3): 258-278.

Assaker, G. and Hallak, R. (2012). Examining a Supply-Side Predictive Model in Tourism Using Partial Least Squares Path Modeling: An Empirical Analysis at the Country Aggregate Level. *Tourism Analysis*, 17(5): 587-599.

Babakus, E., Ferguson, C. E. and Joreskog, K. G. (1987). The Sensitivity of Confirmatory Maximum Likelihood Factor Analysis to Violations of Measurement Scale and Distributional Assumptions. *Journal of Marketing Research,* 37, 72-141.

Babin, B. J., Hair, J. F. and Boles, J. S. (2008). Publishing Research in Marketing Journals Using Structural Equation Modeling. *Journal of Marketing Theory & Practice,* 16(4): 279-285.

Barclay, D., Higgins, C. and Thomson, R. (1995). The Partial Least Squares Approach (Pls) to Causal Modeling, Personal Computer Adoption and Use as an Illustration. *Technology Studies,* 2(2): 285-309.

Bollen, K. A. (1989). *Structural Equations with Latent Variables*. New York: Wiley.

Bollen, K. A. (2007). Interpretational Confounding Is Due to Misspecification, Not to Type of Indicator: Comment on Howell, Breivik, and Wilcox (2007). *Psychological Methods,* 12(2): 219-228.

Bollen, K. A. (2011). Evaluating Effect, Composite, and Causal Indicators in Structural Equation Models. *MIS Quarterly*, 35(2): 359-372.

Boomsma, A., and Hoogland, J.J. (2001). The Robustness of LISREL Modeling Revisited. In R. Cudeck, S. du Toit and D. Sörbom (Eds.), *Structural Equation Models: Present and Future. A Festschrift in Honor of Karl Jöreskog* (pp. 139–168). Lincolnwood, IL: Scientific Software International.

Cassel, C. M. and Hackl, P. (2000). On Measurement of Intangible Assets: A Study of Robustness of Partial Least Squares. *Total Quality Management,* 11(7): 897–907.

Chin, W. W. and Gopal, A (1995). Adoption Intention in GSS: Relative Importance of Beliefs. *Database*, 26(2-3): 42-64.

Chin, W. W. (1998). The Partial Least Squares Approach to Structural Equation Modeling. In G. A. Marcoulides (Ed.), *Modern Methods for Business Research* (pp. 295–336). Mahwah: Lawrence Erlbaum Associates.

Chin, W. W. and Newsted, P. R. (1999). Structural Equation Modeling Analysis with Small Samples Using Partial Least Squares. In R. H. Hoyle (Ed.), *Statistical Strategies for Small Sample Research* (pp. 307–341). Thousand Oaks: Sage.

Chin, W. W., Peterson, R. A. And Brown, S. P. (2008). Structural Equation Modeling in Marketing: Some Practical Reminders. *Journal Marketing Theory and Practice*, 16(4): 287-298.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences*. New Jersey: Lawrence Erlbaum Associates.

Cronbach, L. J. (1951). Coefficient Alpha and the Internal Structure Of Tests. *Psychometrika*, 16(3): 297–334.

Diamantopoulos, A., and Winklhofer, H. M. (2001). Index Construction with Formative Indicators: An Alternative to Scale Development. *Journal of Marketing Research*, 38(2): 269-277.

Diamantopoulos, A. and Siguaw, J. A. (2006). Formative vs. Reflective Indicators in Organizational Measure Development: A Comparison and Empirical Illustration. *British Journal of Management*, 17(4): 263–282.

Efron, B. and Tibshirani, R. J. (1993). *An Introduction to the Bootstrap*. New York: Chapman Hall.

Esposito Vinzi, V., Trinchera, L. and Amato, S. (2010). *Handbook of Partial Least Square*. Berlin-Heidelberg: Springer.

Fornell, C. and Larcker, D.F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18, 39-50.

Fornell, C. G. and Bookstein, F. L. (1982). Two Structural Equation Models: LISREL and PLS Applied to Consumer Exit-Voice Theory. *Journal of Marketing Research*, 19(4): 440–452.

Fornell, C. and Cha, J. (1994). Partial Least Squares. In R. P. Bagozzi (Ed), *Advanced Methods of Marketing Research*, 152–78, 1994.

Gefen, D. and Straub, D. (2005). A Practical Guide to Factorial Validity Using PLS-Graph: Tutorial and Annotated Example. *Communications of the AIS*, 16, 91–109.

Geisser, S. (1975). The Predictive Sample Reuse Method with Applications. *Journal of the American Statistical Association*, 70, 320-328.

Gerbing, D. W. and Anderson, J. C. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, *103*, 411–423.

Gerbing, D. W. and Anderson, J. C. (1993). Monte Carlo Evaluations of Goodness-Of-Fit Indices for Structural Equation Models. In K. A. Bollen and Long. J.S. (Ed.), *Testing Structural Equation Models* (pp. 40-65). Newbury Park, CA: Sage.

Haenlein, M. and Kaplan, A. M. (2004). A Beginner's Guide To Partial Least Squares Analysis. *Understanding Statistics*, 3(4): 283–297.

Hair, J. F., Sarstedt, M., Ringle, C. M. and Mena, J. A. (2011). An Assessment of the Use of Partial Least Squares Structural Equation Modeling in Marketing Research. *Academy of Marketing Science*, 22, 1-20.

Hallak, R., Brown, G. and Lindsay, N. J. (2012). The Place Identity - Performance Relationship among Tourism Entrepreneurs: A Structural Equation Modelling Analysis. *Tourism Management*, 33(1): 143-154.

Henseler, J., Ringle, C. M. and Sinkovics, R. R. (2009). The Use of Partial Least Squares Path Modeling in International Marketing. *New Challenges to International Marketing: Advances in International Marketing*, 20, 277-319.

Henseler, J. and Chin, W. W. (2010). A Comparison of Approaches for the Analysis of Interaction Effects Between Latent Variables Using Partial Least Squares Path Modeling. *Structural Equation Modeling*, 17(1): 82-109.

Howat, G., Absher, J., Crilley, G. and Milne, I. (1996). Measuring Customer Service Quality in Sports and Leisure Centres. *Managing Leisure*, 1(1): 77-89.

Howat, G. and Assaker, G. (2012). The Hierarchical Effects of Perceived Quality on Perceived Value, Satisfaction, and Loyalty: Empirical Results from Public, Outdoor Aquatic Centres in Australia. *Sport Management Review*, http://dx.doi.org/10.1016/j.smr.2012.10. 001

Huber, F., Herrmann, A., Frederik, M., Vogel, J. and Vollhardt, K. (2007). *Kausalmodellierung mit Partial Least Squares—Eine Anwendungsorientierte Einführung*. Wiesbaden: Gabler.

Hulland, J. (1999). Use of Partial Least Squares (PLS) in Strategic Management Research: A Review of Four Recent Studies. *Strategic Management Journal*, 20(2): 195-204.

Huang, SS, Wiler, B. and Assaker, G. (In Press). Effects of Interpretive Guiding Outcomes on Tourist Satisfaction and Behavioural Intention, *Journal of Travel Research.*

Jarvis, C. B., Mackenzie, S. B. and Podsakoff, P. M. (2003). A Critical Review of Construct Indicators and Measurement Model Misspecification in Marketing and Consumer Research. *Journal of Consumer Research*, 30(2): 199-218.

Jöreskog, K. G. (1978). Structural Analysis of Covariance and Correlation Matrices. *Psychometrika*, 43(4): 443–477.

Jöreskog, K. G. and Wold, H. (1982). The ML and PLS Techniques for Modeling with Latent Variables: Historical and Comparative Aspects. In K. G. Jöreskog and Wold, H. (Ed.), *Systems under Indirect Observation: Part I* (pp. 263–270). Amsterdam: North-Holland.

Jöreskog, K. G. (1993). Testing Structural Equation Models. In K. A. Bollen, & Long. J.S. (Ed.), *Testing Structural Equation Models* (pp. 294–316). Newbury Park: Sage.

Kim, S. and Yoon, Y. (2003). The Hierarchical Effects of Affective and Cognitive Components on Tourism Destination Image. *Journal of Travel & Tourism Marketing*, 14(2): 1-22.

Kline, R. B. (2004). *Principles and Practice of Structural Equation Modeling* (Second ed.): The Guilford Press.

Krijnen, W. P., Dijkstra, T. K. and Gill, R. D. (1998). Conditions for Factor (In)Determinacy in Factor Analysis. *Psychometrika*, 63(4): 359–367.

Lewis, B. R., Templeton, G. F. and Byrd, T. A. (2005). A Methodology for Construct Development in MIS Research. *European Journal of Information Systems*, 14(4): 388–400.

Lohmöller, J.-B. (1989). *Latent Variable Path Modeling with Partial Least Squares*. Heidelberg: Physica.

MacCallum, R. C. and Browne, M. W. (1993). The Use of Causal Indicators in Covariance Structure Models: Some Practical Issues. *Psychological Bulletin*, 114(3): 533-541.

MacKenzie, S. B., Podsakoff, P. M. and Jarvis, C. B. (2005). The Problem of Measurement Model Misspecification in Behavioural and Organizational Research and Some Recommended Solutions. *Journal of Applied Psychology,* 90(4): 710-730.

Mazanec, J. (2011). Tourism Destination Competitiveness: Second Thoughts on the World Economic Forum Reports. *Tourism Economics*, 17(4): 725-751.

Miller, R. G. (1974). The Jackknife – A Review. *Biometrika*, 61, 1-15.

Nunkoo, R. and Ramkissoon, H. (2012). Structural Equation Modeling and Regression Analysis in Tourism Research. *Current Issues in Tourism*, 15(8): 777-802.

Nunnally, J. (1978). *Psychometric theory* (1st ed.). New York: McGraw-Hill.

Nunnally, J. C. & Bernstein, I. H. (1994). *Psychometric Theory*. New York: McGraw-Hill.

Reinartz, W., Krafft, M. and Hoyer, W. D. (2004). The CRM Process: Its Measurement and Impact on Performance. *Journal of Marketing Research*, 41, 293-305.

Reinartz, W. J., Haenlein, M. and Henseler, J. (2009). An Empirical Comparison of the Efficacy of Covariance-Based and Variancebased SEM. *International Journal of Market Research*, 26(4): 332–344.

Rindskopf, D. (1984). Structural Equation Models: Empirical Identification Heywood Cases and Related Problems. *Sociological Methods and Research*, 13(August): 109-119.

Rindskopf, D. and Rose, T. (1988). Some Theory and Applications of Confirmatory Second-Order Factor Analysis. *Multivariate Behavioral Research*, 23(January): 51-67.

Ringle, C. M. (2006). *Segmentation for Path Models and Unobserved Heterogeneity: The Finite Mixture Partial Least Squares Approach*. Hamburg: University of Hamburg.

Sarstedt, M., Becker, J.-M., Ringle, C. M. and Schwaiger, M. (2011). Uncovering and Treating Unobserved Heterogeneity with FIMIXPLS: Which Model Selection Criterion Provides An Appropriate Number of Segments. *Unobserved Heterogeneity*, 63(January): 34-62.

SmartPLS. (2013). *SmartPLS Software version 2.0 (Beta)*. TUHH - Hamburg University of Technology, Institute for Human Resource Management Organizations.

Song, H., Li, G., Van der Veen, R. and Chen, J. R (2011). Assessing Mainland Chinese Tourists' Satisfaction with Hong Kong Using Tourist Satisfaction Index. *International Journal of Tourism Research*, 13, 82–96.

Stone, M. (1974). Cross-Validatory Choice and Assessment of Statistical Predictions. *Journal of the Royal Statistical Society*, 36(2): 111–133.

Straub, D., Boudreau, M. and Gefen, D. (2004). Validation Guidelines for IS Positivist Research. *Communications of the AIS*, 13, 380–427.

Tenenhaus, M., Amato, S. and Esposito Vinzi, V. (2004). A Global Goodness-of-Fit Index for PLS Structural Equation Modelling. *Proceedings of the XLII SIS Scientific Meeting, pp. 739-742*. Padova.

Tenenhaus, M., Esposito, Vinzi V., Chatelin, Y. M. and Lauro, C. (2005). PLS Path Modeling. *Computational Statistics and Data Analysis*, 48, 159-205.

Urbrach, N. and Ahlemann, F. (2010). Structural Equation Modeling in Information Systems Research Using Partial Least Squares. *Journal of Information Technology Theory and Application*, 11(2): 5-40.

Vilares, M. J., Almeida, M. H. and Coelho, P. S. (2010). Comparison of Likelihood and PLS Estimators for Structural Equation Modeling: A Simulation with Customer Satisfaction Data. In V. Esposito Vinzi, Chin, W. W., Henseler, J., and Wang, H. (Ed.), *Handbook of Partial Least Squares: Concepts, Methods, and Applications*. Berlin: Springer.

Werts, C. E., Linn, R. L. and Joreskog, K. G. (1974). Intraclass Reliability Estimates: Testing Structural Assumptions. *Educational and Psychological Measurement,* 34(1): 25-33.

Wold, H. (1975). Soft Modeling By Latent Variables: The Nonlinear Iterative Partial Least Squares Approach. In J. Gani (Ed.), *Perspectives in Probability and Statistics, Papers In Honor of M. S. Bartlett* (pp. 117-142). London: Academic Press.

Wold, H. (1979). Model Construction and Evaluation when Theoretical Knowledge Is Scarce: An Example of the Use of Partial Least Squares. Genève, Switzerland: Faculté des Sciences a Économiques et Sociales, Université De Genève.

Wold, H. (1982). Soft Modeling: The Basic Design and Some Extensions. In K. G. Jöreskog and Wold, H. (Ed.), *Systems under Indirect Observations: Part II* (pp. 1–54). Amsterdam: North-Holland.

XLSTAT. (2011). *XLSTAT-PLSPM Module*. Paris: XLSTAT Software, Addinsoft.

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