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PLS-SEM: A hidden gem in tourism research methodology

Marijana Seočanac[1*]

[1] University of Kragujevac, Faculty of Hotel Management and Tourism in Vrnjačka Banja, Serbia

Abstract

Purpose – The main objective of this paper is to provide a well-organized guide for the application of partial least squares structural equation modeling (PLS-SEM) in tourism research. In this way, the paper strives to encourage future tourism studies to use PLS-SEM and contribute to methodological advances in the field. **Methodology** – This paper systematically examines the application of PLS-SEM with a particular focus on the application of hierarchical constructs in tourism research and carefully analyzes and classifies the existing literature on PLS-SEM. **Results** – Specific steps for evaluating and interpreting the hierarchical latent variables of the PLS model are presented and explained. **Implications** – This paper contributes to advancing the application of PLS-SEM in tourism research by providing researchers with a valuable tool to improve both the rigor of empirical investigation and theoretical development in the field. The insights gained from this paper can guide subsequent research to investigate specific tourism-related scenarios, potentially leading to new transformative discoveries and paradigm shifts in our understanding of tourism dynamics.

Keywords: partial least squares structural equation modeling, higher-order structural model, hierarchical component model, multidimensional construct, PLS predict, tourism
JEL classification: C38, L83

PLS-SEM: Skriveni dragulj u metodologiji naučnog istraživanja turizma

Sažetak

Svrha – Glavni cilj ovog rada je da pruži dobro organizovan vodič za primenu modeliranja strukturnim jednačinama metodom parcijalnih najmanjih kvadrata (PLS-SEM) u istraživanju turizma. Na ovaj način, rad nastoji da podstakne buduće studije iz oblasti turizma da primene PLS-SEM u svojoj metodologiji i doprinesu metodološkom napretku u ovoj oblasti. **Metodologija** – Ovaj rad sistematski istražuje primenu PLS-SEM sa posebnim fokusom na primenu hijerarhijskih latentnih varijabli u istraživanju turizma i pažljivo analizira i klasifikuje postojeću literaturu o PLS-SEM. **Rezultati** – Predstavljeni su i detaljno objašnjeni specifični koraci neophodni za evaluaciju i tumačenje hijerarhijskih latentnih varijabli PLS modela. **Implikacije** – Rad doprinosi unapređenju primene PLS-SEM u

* marijana.seocanac@kg.ac.rs

istraživanjima turizma tako što istraživačima pruža vredan alat za poboljšanje kako strogosti empirijskog istraživanja, tako i teorijskog razvoja u ovoj oblasti. Uvidi stečeni iz ovog rada mogu da usmere naredna istraživanja ka istraživanju specifičnih scenarija u oblasti turizma koja potencijalno mogu da dovedu do novih transformativnih otkrića i promena paradigme u našem razumevanju dinamike turizma.

Ključne reči: modeliranje strukturnim jednačinama metodom parcijalnih najmanjih kvadrata, strukturni model višeg reda, model hijerarhijskih latentnih varijabli, multidimenzionalni konstrukt, PLS predict, turizam
JEL klasifikacija: C38, L83

1. Introduction

Structural equation modeling (SEM), referred to as a "second-generation technique", offers researchers the ability to "simultaneously model and estimate complex relationships among multiple dependent and independent variables" (Hair et al., 2022, p. 4). SEM methods can be broadly categorized into two main types: covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM). According to Hair et al. (2019a), CB-SEM has been used in the past to analyze complex relationships between indicators and latent variables. However, the use of the CB-SEM entails the difficulty that several strict assumptions must be met (Hair et al., 2011). In response to these challenges, Wold (1982) introduced PLS-SEM as a more flexible alternative. In contrast to CB-SEM, which relies on shared variance and "models constructs as common factors that explain covariation between associated indicators" (Rigdon et al., 2017, p. 7), PLS-SEM uses total variance (Hair et al., 2017a) and focuses on "causal-predictive relations because it maximizes the amount of explained variance of dependent variables founded in well-developed explanations" (Hair et al., 2020, p. 103). This approach combines principal component analysis and regression-based path analysis to estimate the "unknown parameters of a system of simultaneous equations" (Mateos-Aparicio, 2011, p. 2311).

PLS-SEM has gained increasing attention in the academic community, especially among researchers in the social sciences. Research by Richter et al. (2016a), Hair et al. (2022) and Sarstedt et al. (2022a) has shown that PLS-SEM is widely used in various fields, including psychology, medicine, information systems, business and marketing. Despite its widespread use, PLS-SEM has been the subject of ongoing academic discourse for several years (Rigdon et al., 2017). Criticism of its use and claims by some authors that PLS-SEM "is of no use" (Antonakis et al., 2010, p. 1103) have led to methodological advances and an increase in scholarly efforts aimed at producing comprehensive guidelines for its use (Henseler et al., 2016). The efforts of numerous authors (e.g., Hair et al., 2011; Hair et al., 2017b; Hair et al., 2019a; Hair et al., 2019b; Hair et al., 2022; Richter et al., 2016b; Sarstedt et al., 2022b) to continuously improve methods and provide clear guidelines for researchers have led to the recent recognition of the value of PLS as an SEM technique by several prominent researchers (Petter, 2018).

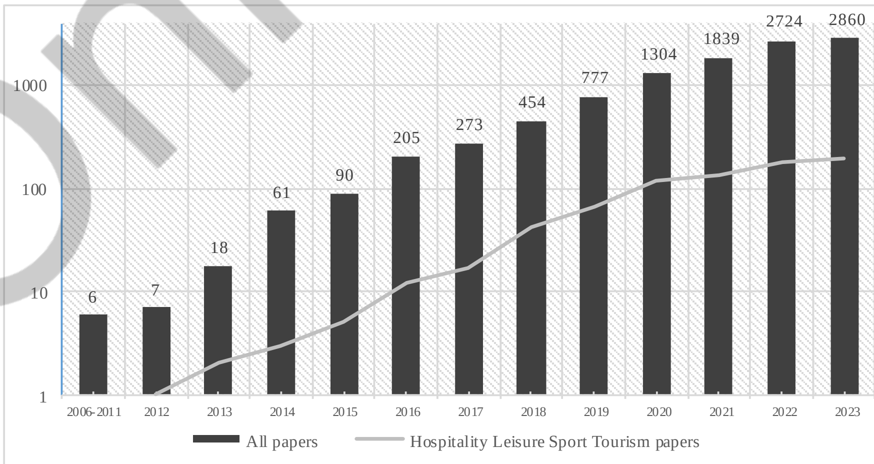
However, a search of papers indexed in the Web of Science scientific database revealed that of the total number of papers that have used PLS-SEM in their methodology (10,618) published by the end of 2023, only a modest 7.3% or 775 articles belong to the Hospitality Leisure Sport Tourism category. The low prevalence of PLS-SEM applications in the methodology of tourism-related articles highlights the significant untapped potential for novel applications of PLS-SEM in tourism. Therefore, the main goal of this paper is to provide a well-organized guide for the application of PLS-SEM by thoroughly analyzing and classifying the body of existing literature on this topic. The author seeks to illustrate the usefulness of PLS-SEM through a comprehensive literature review to provide a solid foundation for tourism researchers to build upon when incorporating this statistical modeling technique into their research. In this way, the study aims to improve the methodological rigor and empirical breadth of tourism-related research.

2. PLS-SEM in tourism studies

PLS-SEM has been used in studies on various aspects of the travel and tourism industry. For example, it has been used to understand the factors that influence destination management (e.g., Molinillo et al., 2018) and marketing effectiveness (e.g., Assaker, 2014). Researchers have investigated the relationships between different variables such as destination image, tourist satisfaction and loyalty. It has also been used to investigate the relationship between tourism activities and individual well-being (e.g., Sie et al., 2021; Tan et al., 2020) and to develop a scale to measure the transformation process through travel experiences (e.g., Tasci & Godovykh, 2021). Researchers have used PLS-SEM to investigate the adoption of technological innovations by tourists and tourism businesses. This includes examining factors that influence the adoption of online booking systems (e.g., Hateftabar, 2022), mobile applications (e.g., Nathan et al., 2020), and other technological advances (e.g., Pillai & Sivathanu, 2020). PLS-SEM has also been used to model and analyze the complex decision-making processes of tourists. This includes examining the factors that influence travel decisions (e.g., Alhemimah, 2022) and information-seeking behavior (e.g., Chopra et al., 2022). The relationships between job satisfaction, organizational support and employee engagement (e.g., Sun & Yoon, 2022) and the impact of work-life balance and social support on employee well-being (e.g., Medina-Garrido et al., 2023) have also been examined using this statistical modeling technique.

Although PLS-SEM is present in academic discourse on various topics in the field of tourism, its dissemination remains relatively limited. A detailed analysis of research articles found in the Web of Science database shows a significant increase in the use of PLS-SEM in tourism studies since Assaker et al. first included it in 2012. However, the peak recorded in 2023 represents only a small proportion of the total corpus of studies that have used PLS-SEM in their methodology (Figure 1).

Figure 1: Number of papers that applied PLS-SEM



Source: Author, based on the results of the Web of Science database

When reviewing the abstracts of the identified papers, it also became clear that there is a lack of papers in the field of tourism that deal with advanced modeling or modeling at a higher level of abstraction. To investigate this apparent gap, the following specific query was created: TS=(PLS-SEM) AND TS=(higher-order OR hierarchical), and only 20 articles were found (Table 1). This indicates that hierarchical variables were only included in the methodology in 2.58% of the studies in the Hospitality Leisure Sport Tourism category that used the PLS-SEM method. Therefore, this paper aims to address this noticeable gap in the existing literature regarding the specific application of hierarchical constructs within PLS-SEM in the field of tourism. The following sections of this paper have been written with the aim of contributing to the knowledge base and advancement of research methods in tourism by providing a comprehensive understanding of how hierarchical constructs can be easily established and estimated within PLS-SEM.

Table 1: Papers that applied hierarchical latent variable models in PLS-SEM

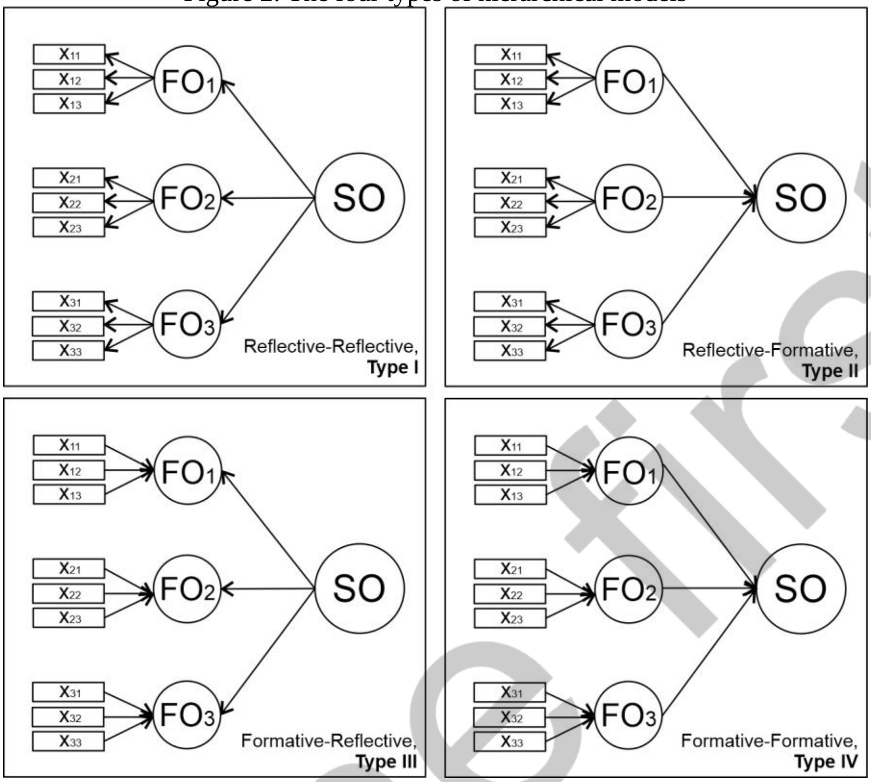
Context	Author/s
Destination image and authenticity	Assaker & Hallak (2016); Nguyen (2020)
Service quality	Assaker (2020); Hallak et al. (2017); Howat & Assaker (2013); Muskat et al. (2019); Priporas et al. (2017)
Tourist behavior and experience	Ansari et al. (2022); Aybek & Özdemır (2022); Badu-Baiden et al. (2022); Dayour (2023); Deng et al. (2020); Leung & Jiang (2018); Luo et al. (2021); Perez-Vega et al. (2018); Ritchie et al. (2019); Sie et al. (2021)
Hospitality management	Lee et al. (2016)
General tourism	Assaker et al. (2012); Becker et al. (2022)

Source: Author, based on the results of the Web of Science database

3. Estimation and interpretation of hierarchical latent variable models in PLS-SEM

The construction of latent variables on a more abstract level is considered an advanced modeling technique (Hair et al., 2017c). Variables that span more than one dimension are referred to as higher-order or hierarchical variables (Wetzels et al., 2009). The advantage of using higher-order variables is that they simplify the path model by reducing the number of relationships between latent variables, thus improving the interpretability of the model (AlNuaimi et al., 2021; Hair et al., 2022). According to the relationships between first-order latent variables and their indicators and the relationships between second-order latent variables and first-order latent variables, Becker et al. (2012) divided hierarchical models into four categories, which are shown in Figure 2. Therefore, it is crucial to define the measurement model for lower-order latent variables and specify the relationship between the higher-order latent variable and the associated lower-order latent variables when implementing hierarchical latent variables (Sarstedt et al., 2019).

Figure 2: The four types of hierarchical models



Source: Author, based on Becker et al. (2012), p. 363

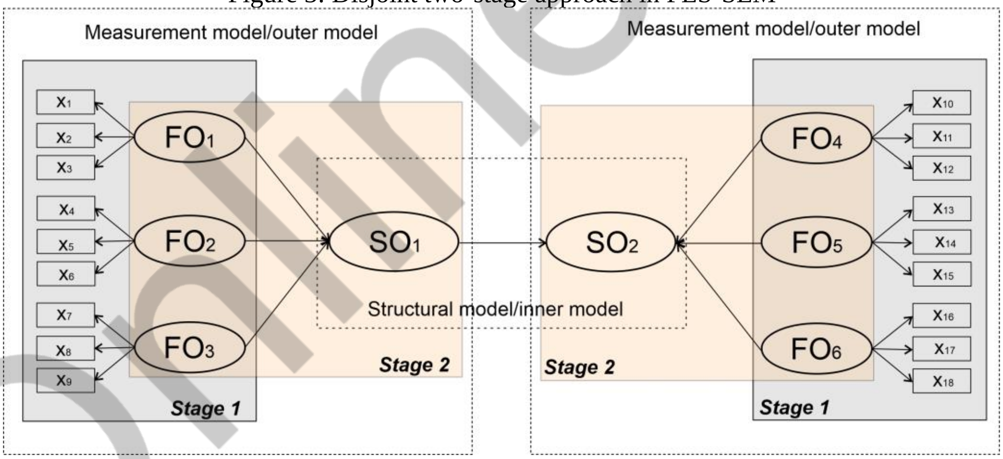
The typical evaluation and interpretation of PLS models consists of two steps: 1. the evaluation of the validity and reliability of the measurement model (outer model) and 2. the evaluation of the structural model (inner model) (Henseler et al., 2016). Latent variables and their conceptually or theoretically defined relationships form a structural model (Richter et al., 2016a), while the measurement model examines the relationships between the variables and their associated indicators (Hair et al., 2022). When it comes to the validation and estimation of higher-order variables, different approaches are used in the literature, with two methods standing out in particular: the (extended) repeated indicator approach and the two-stage approach (Becker et al., 2012). According to the studies of these authors, there is generally less bias in the estimation of the higher-order measurement model when the repeated indicators approach is used. On the other hand, the two-stage approach performs better in estimating the path parameters “from exogenous construct to the higher-order construct and from the higher-order construct to an endogenous construct” (Sarstedt et al., 2019, p. 198). Sarstedt et al. (2019) point out that both the repeated indicators approach and the two-stage approach provide quite similar results. They advise choosing the approach that best suits the aim of the study. In other words, when choosing between the two-stage approach and the repeated indicators approach for estimating and testing higher-order variables, researchers should consider their specific research objectives and context.

This paper uses the two-stage approach, in particular the disjoint two-stage approach (Becker et al., 2012; Sarstedt et al., 2019), and explains how it can be used to validate and estimate the reflective-formative (Type II) model. This choice is based on the fact that it offers the possibility to explain the model estimation procedure in a stepwise and comprehensive manner, covering both reflective and formative measurement models. Reflective measurement models "represent composite latent constructs whose indicators (measured variables) are assumed to be influenced, affected, or caused by the underlying latent variable" (Hair et al., 2020, p. 104). In reflective models, the indicators that measure a latent variable "reflect the meaning and concept of same attribute, are highly correlated and interchangeable" (Rasoolimanesh & Ali, 2018, p. 239). This interchangeability means that any indicator can be removed without changing the meaning of the latent variable (Hair et al., 2022). On the other hand, formative measurement models are defined as "linear combinations of a set of indicators that form the construct" (Hair et al., 2020, p. 105). The indicators in formative models are seen as causes of the underlying latent variable and not as its effects (Stadler et al., 2021). The definition of the latent concept could change if one or more indicators were added or removed (Hair et al., 2022). In contrast to reflective indicators, formative indicators provide precise suggestions for improving a particular target construct, which makes them useful for drawing practical conclusions (Sarstedt et al., 2022a).

3.1. Measurement model assessment

For models containing higher-order variables, the measurement model must be estimated for both the lower-order variables and the higher-order variables. The disjoint two-stage approach involves two different stages of the model estimation process (Sarstedt et al., 2019). As shown in Figure 3, stage I involves the estimation of the measurement model of the lower-order variables, while stage II involves the estimation of the measurement model of the higher-order variables.

Figure 3: Disjoint two-stage approach in PLS-SEM



Abbreviations: FO: first-order (lower-order variables); SO: second-order (higher-order variables)
Source: Author

Confirmatory composite analysis (CCA) is a new approach developed as an alternative to Confirmatory factor analysis (CFA) to assess the validity and reliability of PLS measurement models. Both analyses are used to develop, adjust and validate measurement scales, but compared to CFA, CCA offers certain advantages that are directly related to the characteristics of the chosen SEM method. First, PLS-SEM produces higher variable loadings because it accounts for total variance. This increases content coverage and variable validity because more items are retained to measure the variables than with CFA. The scores of the latent variables are then available and it is possible to apply CCA to formative measurement models (Hair et al., 2020).

CCA involves a series of steps that differ depending on whether it is applied to reflective or formative measurement models. The steps are illustrated in Figure 4, and each step is explained in detail in the following section.

Stage 1

The CCA must first be carried out for the measurement model presented in the first stage. Since all variables in the first stage are reflective, the criteria for reflective measurement models must be checked. First, the reliability of the indicator must be assessed by checking the loadings of the indicators (outer loadings). For an indicator to be considered reliable, its standardized loadings must have a minimum value of 0.708, which means that "the variable explains more than half of its indicators' variance" (Hair et al., 2011, p. 146). According to Hair et al. (2017b), 0.70 is generally considered sufficiently close to 0.708 to be considered acceptable. Hair et al. (2011) state that values above 0.4 may also be acceptable if the internal consistency of the measurement model is between the acceptable limit and the model meets the requirements for convergent validity. The reliability coefficient *(rho_A – ρA), the composite reliability (ρC) and Cronbach's alpha (α)* must be tested in the second step to ensure internal consistency. Cronbach's alpha and the composite reliability values must be less than 0.95 (the recommended upper limit is 0.9) and greater than 0.7. If the value is 0.95 or higher, this indicates that the indicators measure the same concept, which does not provide the necessary diversity that is a prerequisite for a multi-item variable and reduces the validity of the variable (Diamantopoulos et al., 2012; Hair et al., 2019a). As Cronbach's alpha often underestimates the actual reliability of the variables, Sijtsma (2009) suggests that it should rather be regarded as a lower limit. Hair et al. (2019a) claim that ρC is a more reliable measure than Cronbach's alpha because it takes into account the individual loadings of the indicators. However, Sarstedt et al. (2022a) are of the opinion that the composite reliability is too liberal, and that the true reliability of the variable lies within these two extreme values. They advise the use of ρA, a measure whose value is normally between Cronbach's alpha and the composite reliability. According to Benitez et al. (2020), a lower limit of 0.707 is recommended for ρA.

In the third step, it is important to assess the convergent validity based on the average variance extracted (*AVE*). Based on this metric, the average variance shared between the variable and its individual indicators is measured. According to Hair et al. (2019a) and Sarstedt et al. (2022b), the *AVE* must be at least 0.5, which means that 50% or more of the variation in the indicators is explained by the variable and that no other variable is more significant. The fourth step in evaluating a measurement model is discriminant validity, which indicates how unique a variable is compared to other variables in the model (Sarstedt et al., 2022b). If the variance shared within a variable (*AVE*) is greater than the variance that it shares with other variables in the model, then it is possible to establish discriminant validity. The Fornell-Larcker criterion, which states that the correlation value between latent variables in the reflective model must not be greater than the square root of the *AVE* in each latent variable, and cross-loadings, which state that the loading indicator in the associated variables must be higher than in the other variables in the model, are the most commonly used methods for determining discriminant validity (Hair et al., 2017b). However, various studies have come to the conclusion that these two criteria are not suitable for assessing discriminant validity in PLS-SEM (Franke & Sarstedt, 2019; Sarstedt et al., 2022a), which is why the use of heterotrait-monotrait (*HTMT*) criteria is recommended. Hair et al. (2019a) explain *HTMT* as "the mean value of the item correlations across constructs relative to the (geometric) mean of the average correlations for the items measuring the same construct" (p. 9). A problem with discriminant validity is considered to exist if the *HTMT* values are high, i.e., above 0.85 for conceptually dissimilar variables or 0.90 for conceptually similar variables (Henseler et al., 2015). Henseler et al. (2015) also recommend determining the confidence interval using the bootstrapping method to "test whether the *HTMT* statistic is significantly different from 1" (Hair et al., 2017b, p. 141).

Hair et al. (2020) suggest measuring the nomological validity of the variables as the final step of CCA for a reflective measurement model, bearing in mind that PLS-SEM is based on causal-predictive relationships. When measuring nomological validity, the correlation of variables in a nomological network is examined. According to Cronbach and Meehl (1955), the nomological network represents concepts or constructs, their indicators and mutual relationships. In this way, it is determined whether the latent variables are related to each other in accordance "with the theoretical direction as well as the size and significance of the correlations" (Hair et al., 2020, p. 105). This analysis must be performed using the bootstrapping method. It is recommended to use the bias-corrected bootstrapping method (without sign change) with 10,000 repeated samples (Sarsted et al., 2022a).

Stage 2

Considering that the model contains formative variables in the second stage, CCA must be performed for the formative measurement model. One of the most common problems here is multicollinearity, which results from high correlations between the variables. Therefore, it is necessary to first determine the collinearity for all formatively specified items by examining the *VIF*. If the *VIF* is 3 or less, it is assumed that multicollinearity between the formative variables is not a problem (Hair et al., 2020). This step is followed by the determination of the relative contribution of the formative indicator to the formation of the variable (Hair et al., 2021). The contribution is measured using the outer weights corresponding to the beta coefficient, with a higher weight indicating a higher contribution. The weight value must also be statistically significant at the ≤ 0.05 level (Hair et al., 2020). As PLS-SEM is a non-parametric method, statistical significance is determined using the bootstrapping method (Hair et al., 2019a). The final step in evaluating the formative measurement model is to assess the absolute contribution of the formative indicator (outer loadings). According to Hair et al. (2020), it can be explained as "the amount of information contributed by the indicator in forming the construct, if no other indicators are considered in the calculation" (p. 106). Furthermore, it is considered absolutely important for the formation of the formative latent variable if it is ≥ 0.50 and statistically significant. If the outer weight of the formative indicator is not significant and the outer loading is less than 0.50, consideration should be given to removing the formative indicator from the model (Hair et al., 2019a).

The CCA for formative measurement models usually includes a further step – the redundancy analysis or the determination of convergent validity. This analysis involves determining the path coefficient between a formatively measured variable and a reflectively measured indicator that reflects the essence of the same concept (Sarstedt et al., 2022b). In this example, it was not possible to assess the convergent validity of the formative variables because, as Ringle (2017) explains, the analysis is not applicable to second-order variables, as these are usually multidimensional, i.e., consisting of lower-order variables.

3.2. Structural model assesment

Once the measurement model has been found suitable, the structural model must be estimated. In the disjoint two-stage approach, the results of the second stage serve as the basis for the evaluation of the structural model (Sarstedt et al., 2019). Checking the multicollinearity between the variables is the first step of the evaluation procedure. High multicollinearity between the variables in the structural model can subsequently lead to a change in sign or to a reduction/increase in the weights (beta coefficients) (Hair et al., 2020). In the structural model, multicollinearity is considered less problematic if the VIF value is below 3 (Hair et al., 2021). In the second step, the path coefficient, i.e. its size and significance, is examined using a bias-corrected bootstrapping method (without changing the sign to avoid type I errors) with 10,000 resamples, as recommended by Sarstedt et al. (2022a). The path coefficient represents standardized values that can range from +1 (indicating that a strong positive relationship exists) to –1 (indicating that a strong negative relationship exists) (Sarstedt et al., 2022b). On the other hand, values closer to 0 indicate that the independent variables are weaker in predicting dependent variables, while values closer to 1 indicate that the independent variables are stronger in predicting dependent variables. In complex models with multiple independent variables, path coefficient values rarely approach +1 or –1. In addition to interpreting the direct effect between variables, this analysis also provides insights into the indirect effect that a particular variable has on the endogenous (dependent) target variable via one or more (mediating) variables (Hair et al., 2019a; Hair et al., 2020).

After this step, the effect size (f^2) and the coefficient of determination (R^2) of the endogenous variables must be used to evaluate the predictive power of the structural model. The f^2 value indicates the predictive power of each independent variable in the model, while the R^2 value indicates the percentage by which the exogenous (independent) variables explain the endogenous variable. According to Hair et al. (2011), "R^2 values of 0.75, 0.50, or 0.25 for endogenous latent variables in the structural model can, as a rule of thumb, be described as substantial, moderate, or weak, respectively" (p. 147). The effect size indicates whether the independent variable is a reliable predictor of the dependent variable (Hair et al., 2017b). According to Cohen (1988), f^2 values between 0.02 and 0.15 indicate a small effect, 0.15 to 0.35 indicate a medium effect and values above 0.35 indicate that the exogenous variable has a large effect on the endogenous variable.

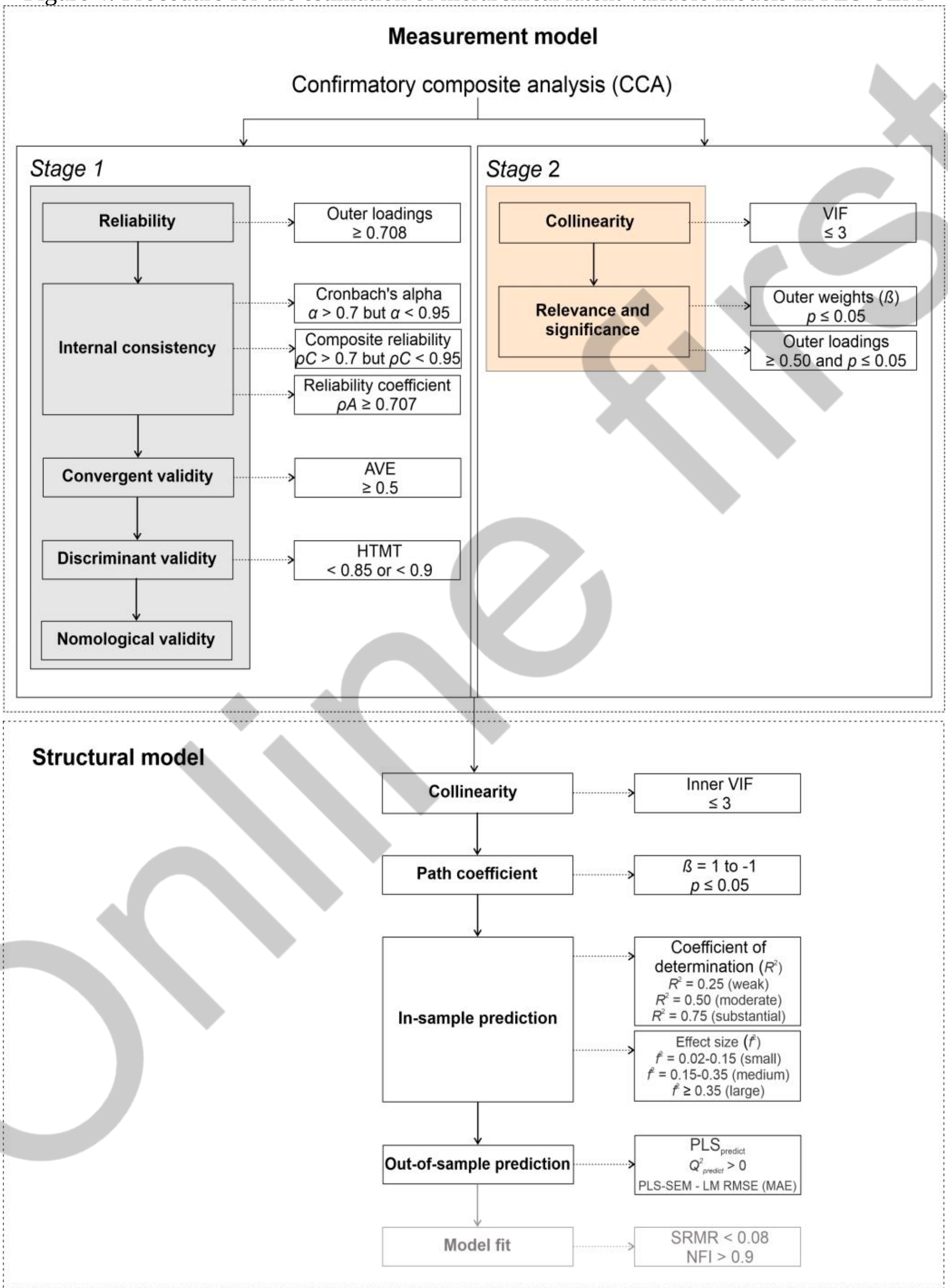
The coefficient of determination and effect size are considered in-sample prediction metrics, i.e., metrics that use the same sample to evaluate the model and predict the response, which according to Hair et al. (2020) suggests that "the model may have limited value in predicting observations not in the original sample" (p. 107). Shmueli et al. (2016) therefore proposed PLSpredict as a new approach for out-of-sample prediction, i.e., for determining "the model's accuracy when predicting the outcome value of new cases" (Shmueli et al., 2019, p. 2324). According to Richter et al. (2016a), this approach "sees the exogenous or independent latent variables' indicators as the data input layer and the endogenous or dependent latent variables' indicators as the data output layer" (p. 589). The input and output layers link a theoretically/conceptually well-founded structural model. Depending on context, time, customers, industry and the like, the input and output data change, but the structural model linking these two types of data remains unchanged. Therefore, this analysis attempts to predict the output layer based on the structural model and the input layer data.

In this approach, a part of the total data set, the so-called analysis sample or training sample, is used to predict the data performance of the part of the total data set that was not included in the training sample (Sarstedt et al., 2022a). The model is thus evaluated on the basis of the training sample and the predictive ability is checked using the holdout sample (Hair et al., 2021). Shmueli et al. (2019) explain that "small divergence between the actual and predicted out-of-sample case values suggests that the model has a high predictive power", while large differences indicate low predictive power (p. 2325). The authors also point out that the prerequisite for conducting this analysis is that both the reflective and formative models meet the necessary quality criteria analyzed in the previous steps (reliability, convergent and discriminant validity for reflective, i.e., collinearity, significance and relevance of indicator weights for formative measurement models). Before performing the analysis, it is necessary to select the key endogenous variable for which the prediction needs to be made. Next, it is necessary to define the parameters for the *k*-fold cross-validation. In this procedure, the total sample is divided into a certain number of equal subgroups (*k*), with one subgroup becoming the holdout sample, while the remaining subgroups are used to predict this sample. The process is repeated until each group passes through the prediction process as a holdout sample. The total sample should be large enough to allow the formation of a holdout sample with at least 30 observations (Hair et al., 2020). The following step is to determine the number of repetitions of the algorithm. It is advisable to choose a larger number of repetitions, as in this case the prediction is made by averaging the values obtained in each repetition, thus providing more stable estimates of the predictive ability of the PLS model (Hair et al., 2019a).

Shmueli et al. (2019) point out that the first step in interpreting the predictive ability of a model is to check the $Q^2_{predict}$ statistic. If the value of this parameter is greater than 0, the next step is to interpret the predictive statistics. Several predictive statistics are used for this, of which the authors recommend using the mean absolute error (MAE) or the root mean squared error (RMSE). The MAE "measures the average magnitude of the errors in a set of predictions without considering their direction", while the RMSE can be explained as "the square root of the average of the squared differences between the predictions and the actual observations". The RMSE is recommended as the standard prediction statistic, except in a situation where the distribution of the prediction error is highly asymmetric. Smaller values of these statistics indicate higher predictive power. By comparing the values of these statistics obtained for the PLS-SEM model, which considers the entire structure of the model, i.e., both the measurement and structural models, with the "naïve value obtained by a linear regression model (LM) that generates predictions for the measured variables (indicators)" without considering the defined structure of the model, information about the predictive ability of the proposed model is obtained (Hair et al., 2020, p. 107). Comparing the RMSE or MAE statistics of PLS-SEM and LM models can lead to one of four results. First, if PLS-SEM does not have smaller prediction errors in terms of RMSE (or MAE) statistics for any of the indicators compared to LM, it means that the model has no predictive power. Second, if it has smaller prediction errors for a minority of the indicators, this means that the model has low power of prediction. Third, if PLS-SEM has smaller prediction errors than LM for most or the same number of indicators, it means that the model has moderate predictive power. Fourth, if all indicators have smaller prediction errors, the model can be said to have strong prediction power (Shmueli et al., 2019). Various authors (e.g. Hair et al., 2019a; Rasoolimanesh & Ali, 2018; Shmueli et al., 2019) point out that PLSpredict should be routinely used in PLS-SEM studies. Shmueli et al. (2019) add that this analysis is an extremely important part of the validation process of the newly developed scale.

To assess model fit, the authors use criteria such as the standardized root mean square residual (SRMR) and the normed fit index (NFI) (Sarstedt et al., 2022b). Henseler et al. (2016) recommend that the SRMR value should be below 0.08, as this value "typically indicate that the degree of misfit is not substantial" (Henseler, 2017, p. 185). Byrne (2008) considers an NFI value of more than 0.90 to be acceptable. While some authors recommend the use of criteria to assess model fit (e.g., Schuberth et al., 2018; Schuberth et al., 2023), Hair et al. (2019b) criticize their use. These authors point out that Henseler et al. (2016) and Henseler (2017) do not support their claim regarding the SRMR threshold and that many uncertainties remain to be resolved (e.g. whether values should be reported for the estimated or the saturated model), so they advise the authors not to reject or validate the model based on these metrics. Sarstedt et al. (2022a) support the view of these authors and state that the models in PLS-SEM often do not fulfill the necessary requirements for reliable misfit detection by checking the SRMR values. As an example, they give a model with only three variables and state that in the observed example, 500 observations are the minimum number required to reliably detect a model misfit.

Figure 4: Procedure for the estimation of hierarchical latent variable models in PLS-SEM



Source: Author

4. Discussion and conclusion

Examination of the articles referenced in the Web of Science database revealed that PLS-SEM as a statistical technique is not particularly well represented in papers from the field of tourism. Given the proven usefulness of PLS-SEM both for confirming, developing and extending theories and for developing and validating scales (Hair et al., 2017b; Hair et al., 2020), the contribution it can make to tourism studies is evident. With this in mind, this paper was written with the aim of serving as an incentive for future tourism studies to take advantage of PLS-SEM. First, the literature review conducted in this paper identified the areas where PLS-SEM has been applied so far to prove that it is suitable for different contexts and relationships in the field of tourism. Second, the weakest application of PLS-SEM in tourism was identified to provide a concrete and currently needed contribution for researchers. The analysis of the papers indexed in the Web of Science database has shown that there is a gap in the application of this technique in tourism studies for modeling hierarchical latent variables, which is also one of the most valuable assets of this statistical technique. Based on this discovery, further work aimed to present concrete steps for the assessment and interpretation of the model's hierarchical latent variables. Researchers are provided with a concrete guide, based on representative references, which they can use for further improvements in the application of this method that go beyond the scope of this paper.

Tourism researchers thus have a great tool at their disposal both to increase the rigor of empirical investigation and to make significant contributions to theoretical development. This study challenges researchers to address the complex dynamics of the tourism industry and to increase the rigor of empirical investigation through the use of PLS-SEM with hierarchical constructs. Subsequent research can use the insights gained here to examine relationships in specific tourism-related situations or phenomena. This in turn promises new transformative discoveries and paradigm shifts in our understanding of tourism dynamics, as well as significantly enriching and enhancing the application of PLS-SEM in tourism research.

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Conflict of interest

The author declares no conflict of interest.

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