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Innovative Application of Composite-based Structural Equation Modeling to Hospitality Research with Empirical Example

Abstract

Partial least squares path modeling (PLS-PM) and generalized structured component analysis (GSCA) are two key estimators derived from a full-fledged composite-based structural equation modeling (SEM). The analyses of PLS-PM and GSCA have been recently extended to mimic factor-based SEM, and the extended approaches are called PLS_C and $GSCA_M$, respectively. Simulation studies have confirmed that the relative performance of PLS-PM is comparable with that of GSCA. Similarly, $GSCA_M$, PLS_C, and the traditional factor-based SEM perform equally well in parameter recovery. Although composite-based SEM perfectly fits into the current research landscape that focuses on a prediction-oriented approach, empirical research in the hospitality context that uses PLS-PM, GSCA, PLS_C, and $GSCA_M$ estimators is extremely rare. To encourage hospitality researchers to adopt these methodologies, we demonstrate an illustrative example by using PLS-PM, GSCA, PLS_C, and $GSCA_M$ based on the confirmatory composite analysis (CCA) procedure. Measurement and structural invariances, applications of model fit, $PLS_{predict}$, and importance-performance map analysis are incorporated into our example. Lastly, practical management in the hospitality field based on this methodology is discussed.

***Keywords*:** composite-based structural equation modeling (SEM), partial least squares path modeling (PLS-PM), consistent partial least squares (PLS_C), generalized structured component analysis (GSCA), confirmatory composite analysis (CCA), invariance analysis

Introduction

Hospitality and tourism scholars have widely used structural equation modeling (SEM) as a crucial tool for investigating complex relationships among hypothesized conceptual variables (Han, Yu, & Kim, 2018; Hwang, Cho, & Kim, 2018; Hwang & Lee, 2019; Jeaheng, Al-Ansi, & Han, 2019; Xu, Kim, Liang, & Ryu, 2018). SEM has two major types: factor-based and composite-based SEM. In creating proxies to represent conceptual variables, factor-based SEM optimizes an unobserved factor to best explain the covariance of its indicators. By contrast, proxies in composite-based SEM are conceptualized as a weighted linear combination of indicators, called composites. Although factor-based SEM is regularly used in social and behavioral sciences, composite-based SEM has gained considerable attention in various fields, such as marketing (Hair, Sarstedt, Ringle, & Mena, 2012), strategic management (Hair, Sarstedt, Pieper, & Ringle, 2012), international management (Sinkovics, Richter, Ringle, & Schlägel, 2016), and tourism and hospitality (Ali, Rasoolimanesh, Sarstedt, Ringle, & Ryu, 2018; Manosuthi, Lee, & Han, 2020).

In the composite-based literature, partial least squares path modeling (PLS-PM) and generalized structured component analysis (GSCA) are comparable in terms of model specifications and estimation procedures. Similarly, the relative performance of these approaches has been evaluated in prior simulation studies. Given that the data-generating process (DGP) is created under the assumption of composite-based SEM, the relative performance of PLS-PM is comparable with that of GSCA (Cho & Choi, 2020; Hair, Hult, Ringle, Sarstedt, & Thiele, 2017). GSCA with reflective indicators and PLS-PM with mode A outperform GSCA with formative indicators and PLS-PM with mode B, respectively, in terms of parameter recovery and hypothesis testing (Cho & Choi, 2020). Moreover, given that type I error is controlled at 5% significance level, the statistical power of GSCA is marginally higher than that of PLS-PM. Implications from recent simulation studies suggest that the relative performance of PLS-PM and GSCA exhibits no significant difference.

The methodological advancement of PLS-PM and GSCA has evolved at a rapid pace in recent years. One of the extensions of PLS-PM and GSCA is the application of composite-based SEM to account for measurement errors in the same manner as that in the factor-based approach, although measurement errors in the traditional composite-based SEM is mitigated by extracting a weighted composite (Hair & Sarstedt, 2019a; Henseler et al., 2014). Such extensions are formally called consistent partial least squares (PLS_C) (Dijkstra & Henseler, 2015) and GSCA with incorporated measurement errors ($GSCA_M$) (Hwang, Takane, & Jung, 2017). On the basis of simulation studies, the relative performance of parameter recovery from PLS_C, $GSCA_M$, and the factor-based approach exhibits no difference given that model misspecification does not occur. When an experiment is conducted using empirical data, only $GSCA_M$ yields no inappropriate solution (Hwang et al., 2017). Hence, composite-based SEM can be used as an alternative method in case the traditional factor-based SEM suffers from the issue of inappropriate solution or identification.

Relying on testing theories is insufficient in the current research landscape. Moreover, scholars should "offer managerial implications, which inherently follow a predictive paradigm" (Hair & Sarstedt, 2019a, p. 622). However, the traditional factor-based SEM is unsuitable for this paradigm. By contrast, composite-based SEM satisfies theory testing and the prediction-oriented approach. However, previous empirical studies in the hospitality literature tend to underuse composite-based SEM. To contribute to the methodology in the hospitality literature, we apply the confirmatory composite analysis (CCA) procedure (Hair, Howard, & Nitzl, 2020; Hair & Sarstedt, 2019b) with multigroup analysis (MGA), such as the measurement invariance of composite models (MICOM), by utilizing all available PLS-PM, GSCA, PLS_C, and $GSCA_M$ methods based on the modified empirical data in the restaurant context with a small sample size but acceptable statistical power. To realize the full potential of composite-based SEM, our example includes importance-performance map analysis (IPMA). To the best of our knowledge, this work is the first to present composite-based SEM that incorporates the most promising methods, including PLS-PM, GSCA, PLS_C, and $GSCA_M$, with IPMA in a single example. This example is presented in the next section.

Illustrative case

Case explanation

This example is modified from a real tourism dataset to facilitate the present case. That is, the perception of local restaurant owners toward Muslim customers visiting 2 non-Islamic districts in 2 non-Islamic countries, namely, the US and South Korea, is the analysis unit in our example. The number of local restaurants in the 2 districts is 189; thus, a sample of 136 local restaurants in the 2 districts (73 and 63 restaurants located in the US and South Korea, respectively) can be a good representative of local restaurant population. Local restaurants should adapt their menus to include Halal certification, and this implementation imposes costs to the owners. The hospitality and tourism literature suggests that if the perceived benefit of welcoming Muslim customers outweighs the cost of welcoming them, then owners will be willing to welcome Muslim customers. In line with previous empirical studies (Al-Ansi & Han, 2019; Egresi & Kara, 2018; Han, Al-Ansi, Olya, & Kim, 2019), the perceived benefit from international Muslim customers (BI) is assumed to induce the satisfaction of local restaurant owners (SAT), which triggers willingness to welcome (WTW). Notably, hospitality scholars must provide theoretical and empirical pieces of evidence during hypothesis development. Moreover, conceptual variables must be operationalized with the prespecified items used in the measurement based on the prior literature. Nevertheless, we exclude such practice because our objective is to provide an example of the application and a report of composite-based SEM based on the latest research. A set of hypotheses is developed as follows.

Hypothesis 1: BI exerts a positive effect on SAT.

Hypothesis 2: SAT exerts a positive effect on WTW.

Hypothesis 3: BI exerts a positive effect on WTW.

Rationale for using composite-based SEM

This section intends to provide an example of the rationale to support the application of composite-based SEM under PLS-PM and GSCA estimators. This example can be useful for the future research of hospitality scholars. The following is an example of the rationale.

Example for PLS-PM and GSCA This study aims to propose a causal–predictive model and identify the most salient driver in building WTW using IPMA, which requires a prediction-oriented approach. Thus, composite-based SEM fits this type of research because the composite score generated from the linear combination is deemed to be in a fixed and determinate form. Results from recent simulation studies suggest that findings estimated using PLS-PM and GSCA produce the same conclusion (Cho & Choi, 2020). However, the full information (FI) nature of GSCA tends to estimate a parameter more precisely than PLS-PM. Meanwhile, the limited information (LI) nature of PLS-PM is more robust to model misspecification. We use both estimators to ensure that our conclusions are robust across the two major types of composite-based estimators.

Example for PLS_C and $GSCA_M$

The objective of this study is to test the theoretical framework of the mediating role of SAT. We set the common factor proxies as representatives of the conceptual variables. However, the factor-based SEM with the maximum likelihood (ML) estimator yields a negative variance, which is an inappropriate solution due to the small sample size. Although the number of observations is extremely small, the results of the Monte Carlo simulation warrant a statistical power of 80%, which is considered an acceptable threshold. To mimic factor-based analysis, we disattenuate the correlation to account for measurement errors at the levels of measurement and structural models by using PLS_C. To increase the robustness of the results, we also estimate the uniqueness of the variation of the indicator residuals by using $GSCA_M$. Also, we evaluate model fit under the composite-based approach by using PLS_C and $GSCA_M$ estimators.

Statistical power analysis

Although sample size determination can be theoretically perceived as a function of three interrelated concepts, namely, type I error, type II error, and effect size, the 10× rule of thumb is generally accepted as a method for roughly estimating the number of observations in any study. Recommendations from the SEM literature consider statistical power based on the G*power, Cohen's table, or Monte Carlo simulation. In particular, Cohen's table (Cohen, 1992), which was summarized by Hair, Hult, Ringle, and Sarstedt (2016, p. 26), is highly recommended for hospitality researchers to support the minimum sample size based on the maximum number pointing at a construct and the minimum R^2 value to be detected from the analysis. On the basis of Hair et al. (2016), our example contains two independent variables (BI and SAT) with a tentative minimum R^2 of 0.1 regarding the 5% significance level. The minimum sample size recommended for this analysis is at least 90 observations.

Monte Carlo simulation is highly appealing to hospitality scholars because of its flexibility. It allows hospitality researchers to control a variety of parameters, such as skewness, kurtosis, and measurement error. To perform Monte Carlo simulation, the fully specified parameters of a data generation model (or population model) must be established on the basis of prior literature reviews. Then, the simulation must execute several runs to return the optimal number of observations depending on the specified statistical power. We also conduct Monte Carlo simulation with 80% statistical power level by using simsem, the R package for simulated SEM. The results of the Monte Carlo simulation suggest a minimum sample size of 96 to sustain a level of 80% statistical power. Hence, the 136 observations used in this case are sufficient for conducting composite-based SEM. We encourage hospitality academicians to consult Cohen's table or conduct Monte Carlo simulation to ensure statistical power before planning real data gathering. However, the obvious limitation of Monte Carlo simulation is that it requires researchers to know the value of parameters. If the values are unknown, then researchers must assume the conservative or probable values of a parameter.

Estimation and statistical package

Many statistical packages are currently available in the market, including SmartPLS, ADANCO, and XLSTAT-PLS. All these packages, particularly SmartPLS, can efficiently perform PLS-PM.

To the best of our knowledge, no commercial statistical package can conduct GSCA and $GSCA_M$. Hence, we use R programing version 3.6.1 with GESCA (Hwang, Kim, Lee, & Park, 2017), cSEM (Rademaker & Schuberth, 2020), simsem, semtools (Jorgensen, Pornprasertmanit, Schoemann, & Rosseel, 2019), and ggplot (Wickham, 2016) packages to conduct composite-based SEM on the basis of PLS-PM, PLS_C, GSCA, and $GSCA_M$ estimators. Moreover, four admissible conditions must be ensured when conducting the analysis: (1) convergence must be achieved, (2) all absolute standardized loading estimates must be less than or equal to one, (3) the model-implied variance–covariance matrix must be positive semidefinite, and (4) all reliability estimates must be less than one. The four admissible conditions are confirmed in the current example.

Heterogeneity investigation

Assuming the homogeneity of a dataset without investigating MGA can possibly result in a biased conclusion. The MGA literature suggests that scholars should examine observed and unobserved heterogeneous populations before conducting an analysis (Klesel, Schuberth, Henseler, & Niehaves, 2019). However, the current study focuses only on observable cases. Hence, we investigate the observed heterogeneity issue inherited in the dataset using an MGA procedure. To complete the procedure, we first examine MICOM. If measurement invariance is established, then the examination of structural invariance is executed.

[Insert Table 1]

[Insert Table 2]

[Insert Table 3]

To assess measurement invariance, three consecutive steps are executed: (1) configural invariance, (2) compositional invariance, and (3) invariances of mean and variance. First, the measurement and structural models of the US and South Korea are identical. Second, data treatment and algorithm settings are also identical in the two countries. Hence, configural invariance is established. To assess compositional invariance, let c denote the correlation between the composite scores of the US and South Korean groups.

As shown in Table 1, the null hypothesis is set to compositional invariance, which is equivalent to testing whether c is equal to one. With a permutation result of 5,000 rounds, PLS, GSCA, PLS_C, and $GSCA_M$ yield a similar conclusion that evidence is available to prove that compositional measurement invariance is established. Table 2 evaluates the invariances of the composite mean and variance. The null hypotheses of equality and mean and variance are not rejected, lending support to mean and variance equality. Subsequently, structural invariance is examined using an MGA that was recently proposed by Klesel et al. (2019). Table 3 presents five MGA tests. In accordance with Klesel et al. (2019), the first analysis tests the global model by using two distance measures: (1) geodesic distance (d_G) and (2) squared Euclidean distance (d_L). The null hypothesis is set as follows: the model-implied indicator covariance matrix is equal across groups. If we fail to reject this null hypothesis, then equality across groups is implied. The test statistics of the two distance measures report that their probability is higher than our threshold level of 0.05; thus, we fail to reject the null hypothesis for the global test. Subsequently, the separate path represented by Hypotheses 1–3 is examined on the basis of the methods proposed by Chin and Dibbern (2010); Keil et al. (2000); and Henseler, Ringle, and Sinkovics (2009). “Parameter k is equal across two groups” is set as the null hypothesis. Again, the four algorithms yield a similar result across all tests, confirming that no statistical difference exists between the two cultures. Therefore, we aggregate the two groups into a single dataset to improve statistical power because we do not have sufficient evidence to reject the null hypothesis.

CCA procedure

Measurement model assessment

Confirmatory composite analysis (CCA) is a specifically designed test for confirming measurement models embedded into a nomological network when these types of models are built on the basis of a composite-based paradigm. GSCA is another composite-based procedure used in this study that can follow CCA instructions (Benitez, Henseler, Castillo, & Schuberth, 2020; Hair et al., 2020). CCA has similar steps to but different details from confirmatory factor analysis (CFA). It begins with the assessment of measurement models. Such assessment includes loading estimation [$\hat{\lambda}$ and 95% confidence interval (CI, $\hat{\lambda}$)]; composite reliability (ρ_a); the convergent validity of the reflective indicator, i.e., average variance extracted (AVE); and the convergent validity of the composite–formative indicator, i.e., redundancy analysis and variance inflation factors (VIFs) for the formative case. Following the recommendation of Hair et al. (2020), the values of composite loadings must be greater than 0.7, those of all AVEs must be higher than 0.5, and that of Dijkstra–Henselers (ρ_a) must be higher than 0.7 but less than 0.95. Moreover, the estimated weight values are all positive and 95% CI does not include zero, signifying the relevance of each item. The findings presented in Table 4 indicate that all the reflective composites are reliable and valid. As indicated in Table 5, the strength of the discriminant validity, which is measured using the heterotrait–monotrait (HTMT) ratio of the correlation, is satisfactory because the HTMT ratio is less than 0.9. Nevertheless, the conservative threshold of HTMT analysis can be set to less than 0.85 (Henseler, Ringle, & Sarstedt, 2015). Moreover, we create a series of composite scores to test the nomological and concurrent validities following the recommendation of Hair et al. (2020). The correlation between composite scores is consistent with the theoretical direction, warranting the validity of the nomological net. Similarly, the significance tests of the path coefficients are in line with the hypotheses (H1 to H3), lending support to the concurrent validity.

[Insert Table 4]

[Insert Table 5]

Structural model assessment

Collinearity. Although the regression assumption under ordinary least squares (OLS) does not assume the absence of (multi)collinearity to reach the best linear unbiased estimator (BLUE) condition, an adverse effect of this phenomenon is that obtaining a reliable beta coefficient becomes difficult due to the large variance and covariance. To explain how collinearity affects our results, the variances of $\hat{\beta}_{BI}$ and $\hat{\beta}_{SAT}$ and the covariances of these parameters can be written as

$var(\hat{\beta}_{BI}) = \frac{\sigma^2}{\sum BI^2(1-r_{BI,SAT}^2)}$,

$var(\hat{\beta}_{SAT}) = \frac{\sigma^2}{\sum SAT^2(1-r_{BI,SAT}^2)}$, and

$cov(\hat{\beta}_{BI}, \hat{\beta}_{SAT}) = \frac{-r_{BI,SAT}\sigma^2}{(1-r_{BI,SAT}^2)\sqrt{\sum BI^2 \sum SAT^2}}$.

As correlation $r_{BI,SAT}$ increases toward 1, the (co)variance approaches infinity, exerting pressure on the estimation of the beta coefficients. This problem of inflated variance and covariance can be perceived in terms of speed, called VIF, and defined as

$\text{VIF} = \frac{1}{1-r_{BI,SAT}^2}$.

Hence, we examine the structural model to address the multicollinearity issue by investigating the VIFs of all the exogenous constructs. The conservative threshold of VIF is 3.3 (Diamantopoulos & Siguaw, 2006). Therefore, the VIF value in our example exhibits no sign of a severe multicollinearity issue because the VIFs range from 2.06 to 2.68 (Table 6). Accordingly, no serious multicollinearity issue is involved in all the algorithms used in this work.

[Insert Table 6]

Significance and relevance of path coefficients. We follow the instructions of Hair et al. (2020) by performing a bootstrapping procedure with 10,000 samples. Our proposed causal–predictive model is empirically confirmed. As indicated in Table 6, the role of SAT as a mediator between BI and WTW (Hypotheses 1 and 3) is notable in PLS-PM (PLS-PM: $\hat{\beta}_{BI \to SAT} \in [0.6281; 0.7945]$ and $\hat{\beta}_{SAT \to WTW} \in [0.4704; 0.8064]$) and GSCA (GSCA: $\hat{\beta}_{BI \to SAT} \in [0.6363; 0.8040]$ and $\hat{\beta}_{SAT \to WTW} \in [0.4681; 0.8188]$) algorithms. However, the connection between BI and WTW is rejected by PLS_C (PLS_C: $\hat{\beta}_{BI \to WTW} \in [-0.0793; 0.4624]$) and $GSCA_M$ ($GSCA_M$: $\hat{\beta}_{BI \to WTW} \in [-0.0610; 0.4507]$) algorithms. Our example highlights the similarity and difference between the composite models (PLS-PM and GSCA) and the common factor-like models (PLS_C and $GSCA_M$).

In-sample predictive power. We adopt a criterion suggested by Benitez et al. (2020) to interpret different effect sizes, including a small effect size if $f^2 \in [0.02, 0.15)$, a medium effect size if $f^2 \in [0.15, 0.35)$, and a large effect size if $f^2 > 0.35$. The values of our reported effect sizes (f^2) vary from 0.064 to 1.675. Hence, the results for f^2 are satisfactory when a parsimonious model is given. We also report R^2 because of two reasons. First, R^2 provides the ratio between the variation explained by the model and the total variation. This value yields information about in-sample predictive ability. Second, R^2 can be used in the subsequent step to create a set of model selection criteria (Franke & Sarstedt, 2019; Sharma, Sarstedt, Shmueli, Kim, & Thiele, 2019). In line with the recent hospitality and tourism literature (Meng & Cui, 2020), the variance that explains the endogenous construct is within an acceptable range of 0.515–0.779, as indicated in Table 6.

In-sample model fit. In contrast with the traditional factor-based SEM, composite-based SEM is not highly concerned with testing model fit because its primary objective is to focus on in-sample explanation and out-of-sample predictive accuracy. Considering this logic, hypothesis testing can be implied from the assessment of in-sample predictive power as we have conducted in the previous section. However, we argue that the global model should still be tested when hospitality scholars use factor-like algorithms (e.g., PLS_C and $GSCA_M$). The results of a series of fit indices can assist researchers in developing a causal link and providing certain signs of model misspecification during the theoretical exploration stage (Benitez et al., 2020). Nevertheless, we do not support the idea of establishing a trade-off between improving fit indices and model predictive accuracy. This illustrative example is designed to mimic factor-based SEM (PLS_C and $GSCA_M$) in case a factor-based approach produces an inappropriate solution. Hospitality scholars are still requested to test the model.

[Insert Table 7]

The current study extends traditional PLS analysis by providing a series of fit indices for the objective of testing a theory (Table 7). Apart from the absolute value of fit indices, we also improve the statistical inference of distance measures by using a bootstrapping procedure with 4,999 runs (Benitez et al., 2020). All distance measures, e.g., standardized root mean square residual (SRMR), geodesic distance, squared Euclidean distance, and ML distance, are above our threshold of 95% quantile of their reference distribution (HI_{95}). Hence, we have sufficient pieces of evidence to conclude that the population indicator covariance matrix is equal to the model-implied indicator covariance matrix, confirming satisfactory fit between the proposed model and the empirical test. Moreover, the results of the absolute fit indices from all the algorithms are acceptable based on the criteria of the factor-based approach.

Out-of-sample predictive power. We follow the suggestion of Shmueli et al. (2019) to examine the robustness of model predictive ability by using a cross-validation technique. This technique is called $PLS_{predict}$ in the literature, and it divides the dataset into training and testing datasets with k-fold cross-validation. Hair et al. (2020) recommended 10 folds and 10 repetitions. The indicator's prediction obtained using PLS-PM is then used to compare it with those obtained using LM and the simple mean ($Q^2_{predict}$) for all the exogenous indicators as benchmarking. We replicate this procedure using GSCA. To the best of our knowledge, this study is the first to introduce $GSCA_{predict}$ to the hospitality literature. Table 8 shows that all the $Q^2_{predict}$ values are greater than 0, indicating that the predictive power generated from the PLS-PM, GSCA, PLS_C, and $GSCA_M$ algorithms is considerably better than a simple mean prediction. In the $PLS_{predict}$ literature, scholars have proposed the criteria for choosing between mean absolute error (MAE) and root-mean-square error (RMSE) benchmarks by investigating the distribution of all the indicators' error terms. If the normality of residuals is evident, then MAE is better, and vice versa (Shmueli et al., 2019). We perform a univariate test for each indicator. All the target values are greater than the benchmark values; thus, we can conclude that the model generated from all the algorithms exhibits excellent predictive power. In addition, we square the difference between the target and benchmark values and sum them up to arrive at the sum of squared differences (SSD). The model generated from the PLS-PM estimator achieves the best predictive power (SSD = 0.043), whereas the model generated from the PLS_C algorithm (SSD = 0.053) exhibits the worst predictive power. Hospitality scholars should not improve model fit at the expense of predictive power. In this case, although the model generated from the PLS_C algorithm has better fit indices than the models generated from the PLS-PM and GSCA algorithms, its predictive power is considerably behind that of the model using total variance to form the composite.

[Insert Table 8]

Model comparison. We also search for and test alternative explanations to best explain WTW. Our proposed model (partial mediating model) is modified to reflect other plausible explanations. Our competing model is the full mediating model in accordance with the theoretical endorsement. $PLS_{predict}$ is modified to be tested at a composite level rather than at an indicator level. Model I represents the original (partial mediating) model, and Model II represents the full mediating model. All the $Q^2_{predict}$ values presented in Table 9 exceed zero, indicating that all the estimators outperform the simple mean. Subsequently, a similar normality criterion is applied to this analysis. Overall, the full mediating model (Model II) has stronger predictive power than the partial mediating model (Model I). Accordingly, the full mediating model is used in the subsequent IPMA analysis.

[Insert Table 9]

Additional analysis: IPMA

IPMA is used by practitioners to identify the most salient driver by prioritizing the total effects regarding their mean. At the construct level, the performance of a predictor is computed by averaging the mean of the composites. In the important dimension, we bootstrap the total effect of all the drivers. The results are provided in Table 10. To increase the interpretability of the results, IPMA is modified to be analyzed at the indicator level. The result is presented in Figure 2. The most important factor should exhibit the property of high importance but requires further improvement at present (low performance) (Schloderer, Sarstedt, & Ringle, 2014). SAT2 is the most important driver of WTW, and it has more room for improvement compared with the other drivers. Although BI3 can be significantly enhanced, it may not be worth the investment because it exhibits the least importance. Similarly, practitioners should not focus on BI1 given that it already exhibits very high performance but low importance. In terms of order, all the estimators produce similar results: SAT2 > SAT1 > BI2 > BI1 > BI4 > BI3.

[Insert Table 10]

[Insert Figure 2]

Discussion

Before composite-based SEM was developed as an independent procedure, it was used to share similar assessment criteria with factor-based methods (e.g., CFA). During that period, composite-based SEM was criticized for its inability to control measurement errors (Rönkkö & Evermann, 2013). A year later, however, this claim was verified as false (Henseler et al., 2014). Under a factor-based framework, the common factor is implicitly assumed as a perfect proxy for a conceptual variable, autonomously inferring that common factor proxies have greater significance than composite proxies. Given this assumption, the sole source of measurement errors in the factor-based paradigm is assumed to originate from the discrepancy between the factor proxy and its indicator's unique residual. However, the factor-based approach has recently been found to generate a significant degree of uncertainty between a conceptual variable and the factor itself partly due to the problem of factorial indeterminacy (Rigdon, Becker, & Sarstedt, 2019). Hence, claiming that factor-based SEM does not produce measurement errors is an invalid argument for opting for the common factor model.

Another false claim is the inconsistency issue of the composite-based approach given that DGP is developed from the factor-based perspective. With the specific DGP design for a composite-based methodology, simulation studies have confirmed the consistency between PLS-PM and GSCA estimators (Cho & Choi, 2020). Interestingly, Sarstedt, Hair, Ringle, Thiele, and Gudergan (2016) compared the case of an incorrectly specified DGP between factor-based and composite-based methods. Their findings indicated that, on the average, PLS-PM estimates a parameter more precisely than a factor-based ML estimator. The implication drawn for the hospitality context is that if hospitality scholars have an unknown population model, then composite-based SEM should be selected because it is more robust to the incorrectly specified DGP than factor-based SEM.

In terms of practicality, hospitality scholars tend to limit an analysis within the scope of confirmatory tests and model fit evaluation. Hair, Risher, Sarstedt, and Ringle (2019) addressed the benefit of using composite-based SEM as follows: it "… overcomes the apparent dichotomy between explanation—as typically emphasized in academic research—and prediction, which is the basis for developing managerial implications. In order to fulfill the call for rigorous and relevant research, scholars not only need to test theories but also offer managerial implications, which inherently follow a predictive paradigm" (Hair et al., 2019, p. 3). Hospitality researchers can leverage their application to touch the base of a prediction-oriented objective by applying a full-fledged composite-based approach. In addition, this approach can mimic the traditional factor-based SEM based on the PLS_C and $GSCA_M$ algorithms. Although the flexibility features of composite-based SEM are noticeable, examples in the hospitality context are highly limited in guiding hospitality researchers to follow prediction-oriented (PLS-PM and GSCA) and theory testing-oriented (PLS_C and $GSCA_M$) approaches.

Our illustrative example contributes to the hospitality methodology. It applies the CCA procedure with MICOM and MGA tests by utilizing the PLS-PM, GSCA, PLS_C, and $GSCA_M$ algorithms on the basis of the modified empirical data in the restaurant context regarding a small sample size but acceptable statistical power. We encourage hospitality researchers to initiate the adoption of composite-based SEM because practitioners can use composite scores for subsequent analysis. In conclusion, if making a prediction is the primary objective, then PLS-PM or GSCA should be selected. However, if testing a theory with an acceptable level of fit indices is the primary objective, then $GSCA_M$, PLS_C, or the traditional factor-based SEM can provide the solution.

Practical implications

Facilitate managers in allocating their resources efficiently and effectively

Our illustrative example is the first attempt to provide an innovative application of composite-based SEM with a full range of analyses in the hospitality context, including an example of a prediction-oriented objective (PLS-PM and GSCA) and a theory-testing objective (PLS_C and $GSCA_M$). IPMA is one of the innovative applications available in the field of composite-based methodologies. Although it adds a significant value beyond that of the traditional SEM analysis, this innovative application is underused (Ringle & Sarstedt, 2016) in the hospitality and tourism field. By identifying the most important driver that can further enhance the performance of IPMA, practitioners can better manage company resources because the right focus is allocated to foster the potential driver. Such information might be hard to be provided by the traditional factor-based analysis. However, we also illustrate the expansion of IPMA to the indicator level, enriching the useful information for practitioners.

Facilitate managers in accurately predicting the outcome based on available resources

In according with (Hair & Sarstedt, 2019a, p. 622), "PLS-SEM and GSCA's emphasis on prediction in estimating statistical models whose structures are designed to provide causal explanations (Shmueli et al., 2019) make them fit perfectly in today's research landscape." However, previous empirical studies in the hospitality literature tend to overgeneralize factor-based SEM with the pre-assumption that such SEM can perform efficiently in drawing predictive power (e.g., Kim, Kim, & Goh, 2011), contradicting the recommendation from the recent literature (Hair et al., 2020; Hair et al., 2016; Hair et al., 2017; Hair et al., 2019; Hair & Sarstedt, 2019a, 2019b; Sarstedt et al., 2016). Although factor-based SEM can be deemed suitable for a theory testing-oriented objective, a perfect fit model does not guarantee acceptable predictive accuracy (Hwang & Takane, 2015). We argue that practicality in the hospitality business can reap more benefits in predicting the desired outcomes (e.g., satisfaction or revisit intention) generated from a causal–predictive model. Hence, composite-based SEM is a full-fledged approach that facilitates practitioners in making a prediction of the desired outcomes on the basis of a company's available resources. Such approach is ideal for practitioners.

Provide an alternative analysis for testing a proposed causal–predictive model

The PLS_C and $GSCA_M$ algorithms are selected as examples to test our illustrative model with a small sample size but acceptable statistical power level. Testing the model in this manner is consistent with the traditional factor-based framework because it can estimate the unique part of the indicator and provide fit indices, such as SRMR and the goodness-of-fit index (GFI), generated from the difference between the model-implied correlation and empirical correlation matrices, as shown in our analysis. Distance measures, such as geodesic distance, can facilitate analysts in evaluating their proposed model under a theory testing-oriented objective. Therefore, when factor-based SEM is unable to run (e.g., under-identification problem, inappropriate solution, or convergence issue), this type of composite-based SEM can be used as an alternative method to traditional analysis.

Limitations

Although this application of composite-based SEM incorporates examples derived from PLS, GSCA, PLS_C, and $GSCA_M$ estimators, our example disregards two important cases that hospitality researchers should consider. First, our illustrative example does not cover other innovative applications that can be merged with IPMA (e.g., unobserved heterogeneity detection). We argue that the information extracted from unobserved heterogeneity can reveal new hidden clusters of potential customers. For example, a customer satisfaction index (e.g., SAT) may be implemented by some marketing divisions. Assuming that a single dataset is a homogenous mass can possibly lead to implementing a wrong strategy. Potential sources of heterogeneity in a dataset can be due to unobserved heterogeneity, such as latent customer preference, which cannot be as easily perceived as observed heterogeneity, such as nationality, as demonstrated in our example. Hence, hospitality practitioners can implement the appropriate strategy or marketing initiative to the right latent customer segments that are identified through the analysis of unobserved heterogeneity by using the composite-based approach.

The second case missing from our example is the application of a composite–formative model. Given the different paradigms used in constructing reflective and formative models, the assessment of a measurement model in the case of formative indicators is unique. For example, convergent validity is assessed on the basis of a redundancy analysis rather than traditional AVEs. Emphasis also shifts to the evaluation of indicator multicollinearity and the significance of indicator weights. Although our example can facilitate hospitality researchers in conducting composite-based SEM as a prediction-oriented approach (PLS and GSCA) or in applying composite-based SEM to mimic factor-based SEM (PLS_C and $GSCA_M$), future research on the guidelines of composite-based SEM should consider unobserved heterogeneity and a formative measurement model.

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