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USE *THE SILVER BULLET* ON THE RIGHT BEAST: A GUIDE ON USAGE OF PLS-SEM IN TOURISM AND GASTRONOMY STUDIES

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ABSTRACT

PLS based Structural Equation Modelling approach widens in social research with its benefits to ease some methodological struggles. As a matter of course, tourism and gastronomy fields gladly accept this advantage since the researchers mainly contain end-users in terms of statistical competence. However, this extensive use may come with some misunderstandings and errors during the conduction of the technique. Therefore, this editorial research note aims to point out common misunderstandings that appear while using PLS-SEM in tourism and gastronomy research and to guide to prevent them. The literature offered the basis of these misconductions but detected issues have mostly dug out from the unobtrusive statistical editorial experience of the authors.

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INTRODUCTION

PLS based structural equation modelling approach received a substantial correspondence in social sciences recently (Dash & Paul, 2021; Mateos-Aparicio, 2011). Besides the statistical power of the method, researchers prefer PLS according to perceived ease of the method as convenience with sample size and normality issues, model fit assumptions, and user-friendly usage of softwares (Dash & Paul, 2021; Hair, Hollingsworth, et al., 2017; Hair, Matthews, et al., 2017; Sarstedt et al., 2016; Sarstedt et al., 2014). There is even an understanding which calls the method as *the silver bullet* to

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overcome the struggles faced during research process (Hair et al., 2011). The most popular software to conduct PLS-SEM, SmartPLS is the common trigger to use this silver bullet (Hair, Hult, et al., 2017). It is not surprising to encounter SmartPLS in many different research areas like business, marketing, and more (Hair, Hollingsworth, et al., 2017; Sarstedt et al., 2014).

As interdisciplinary academic fields, firstly tourism, hospitality, and then gastronomy embrace the usage of PLS-SEM method in their articles recently published or sent to journals, too (do Valle & Assaker, 2016). SmartPLS mainly covers the research (e.g. Atsız & Akova, 2021; Khan et al., 2021; Kılıç et al., 2021; Sop, 2021) but with some alternatives like WarpPLS (e.g. Lacap, 2019). Same aforementioned conveniences on the method have welcomed by the referred fields since users mostly contain end-users of statistic methodology. That is natural since tourism and gastronomy research focus to usage of methods to realise a research question in contextual basis, but rarely focus to statistical basis.

Regardless of the field, researchers should be conscious using PLS as well as other statistical techniques. With its facilities provided, if those conveniences outweigh the statistical power, occurrence of some misunderstandings and/or evasiveness which cause this silver bullet to be questioned is almost inevitable (Marcoulides & Saunders, 2006). Therefore, this editorial research note aims to enlighten some possible methodological struggles and issues which tourism and gastronomy researchers may encounter while working with PLS-SEM specifically for SmartPLS. The awareness and detections of authors of this paper base on their limited experience as statistical editors in a specific tourism journal and the existing literature on PLS based SEM methodology. This research note intends to provide a useful guide on PLS-SEM with SmartPLS applications for tourism and gastronomy research. However, it should not be forgotten that, since there are already many respected publications in the literature, this note does not aim to explain the method with the gaze of a statistician, but with the gaze of a researcher who wants to use the method rightfully as an end-user. So, rather than a statistical explanation of the terms of PLS, the paper offers a checklist on conducting method properly especially for tourism and gastronomy researchers.

Even they have been referred as end-users, tourism and gastronomy researchers are quite successful at usage of PLS-SEM. Basic assumptions on convergent validity (with AVE, composite reliability etc.), discriminant validity (with recommended HTMT), and common method bias and multicollinearity (with VIF value) are most likely reported in relevant studies (e.g. Atsız & Akova, 2021; Khan et al., 2021; Kılıç et al., 2021; Sop, 2021). However, there are some common issues the authors noticed during their editorial adventure as follows: (1) sampling issue, (2) normality issue, (3) relationship formation issue, (4) modelling issue, (5) model fit issue, and (6) reporting and resulting issue.

RECOMMENDATIONS TO COMMON ISSUES

Sampling and Normality Issues

PLS-SEM does not require parametric assumptions and can operate analysis with smaller sample sizes (Hair, Hult, et al., 2017; Hair, Matthews, et al., 2017; Sarstedt et al., 2014). However, it would be an erroneous assumption to consider that PLS-SEM is used as a solution for all and/or only non-normal data and small sample sizes (Ali et al., 2018; do Valle & Assaker, 2016; Marcoulides & Saunders, 2006). Extremely abnormal data can pose problems in assessing the significance of the parameters since it inflates the standard errors from bootstrapping and decrease the likelihood of some relationships will be evaluated as significant (Hair, Hult, et al., 2017).

Contrary to popular myth, sample size considerations play a structural role to applying of PLS-SEM. Researchers may choose to decide subjectively whether the sample size is suitable for the nature of the aimed research. However, it is beneficial to take one of sampling requirement approaches in the literature as a guide. Sampling methods such as *Power Tables* (please see Cohen, 1992; Hair, Hult, et al., 2017, p. 21), *Monte Carlo Simulation* (please see Paxton et al., 2001), and *Inverse Square Root and Gamma-exponential* (please see Kock & Hadaya, 2018) rarely take place in the studies, because these methods possess some difficulties. Power tables method can lead to grossly inaccurate estimates of the required minimum sample size (Kock & Hadaya, 2018), Monte Carlo simulation is found very time-consuming, and equation based methods are too complicated to conduct. Therefore, mostly preferred techniques are (1) subjective assessment and (2) 10 times approach with their more user-friendly content.

While authors faced many studies that do not mention a sampling method and decide subjectively whether the sample size is efficient, it seems useful as long as researchers have in-depth understanding on variables. But for founding more methodological ground, according to Barclay et al. (1995), sample size should be 10 times larger than the largest number of formative indicators used to measure for construct or the largest number of structural paths directed at a particular latent construct in the model. The rule of thumb of 10 times can be meaningful just when strong effect sizes and high reliability of the measurement items conditions are met (Marcoulides & Saunders, 2006; Peng & Lai, 2012).

Relationship Formation and Modelling Issues

One of the main differences between CB-SEM and PLS-SEM is the logic behind the formation of hypothesised relationships. The reason of this statement belongs to PLS being more exploratory and predictive, working with relatively small sized samples, allowing no causal loops, and prone to producing higher R^2 than CB (Hair, Hult, et al., 2017; Hair, Matthews, et al., 2017; Sarstedt et al., 2014). Few researchers (e.g. Marcoulides & Saunders, 2006) find these features "risky" for quality of structure and indicators especially when the groundwork of the research hides under the methods itself as a *magical silver bullet* to the methodological assumptions. Nomological validity is the key assumption to prevent this risky situation. Forming and proposing the relationships between variables of the conceptual model according to contemporary literature is the basic approach to nomological validation of the research model (Cronbach & Meehl, 1955; Hagger et al., 2017) while there are also other statistical approaches (e.g. Liu et al., 2012). Most of the studies in tourism and gastronomy fields build their hypotheses through a conceptual framework, but interestingly, rare of them mention nomological validity as an assumption.

Another struggle appears during modelling process is to decide whether using a formative or a reflective construct (Coltman et al., 2008; Hair, Hult, et al., 2017; Hair, Matthews, et al., 2017). It is useful to keep in mind, constructs do not only represent a theoretical concept, but they are also the variables that are placed in the statistical model which is prepared to be tested (Sarstedt et al., 2016). Consequently, the ken of researchers on the variables are not only essential for nomological validity but also conceptualizing process. As subjected to Becker et al. (2012) and Sarstedt et al. (2016), causal and/or composite variables should be considered formative, and perceptual and/or effect variables should be considered reflective conceptualization approach. In simpler words, if the latent variable caused by and affected by its indicators, researchers should conduct a formative model; whereas in the reflective modelling, they should consider the indicators as the functions of the latent variable (Duarte & Amaro, 2018). Diamantopoulos and Siguaw (2006) draw attention to possible manipulation of constructing process since some researchers may alter formative and reflective construct to each other for gathering desired results.

do Valle and Assaker (2016) reveals reflective conceptualization is widely preferred when using PLS in tourism-related literature which is logical since the scholars preferably work with data of variables rooted by perceptual scales (e.g. Khan et al., 2021; Wang et al., 2021). It is like an old habit from previously used CB-SEM approach, and therefore some researchers do not even mention or visualize the formation process (e.g. Atsız & Akova, 2021; Kılıç et al., 2021; Sop, 2021). However, it is obvious these examples used reflective approach from the way they handle their variables.

Model Fit Issue

As acknowledged before, one of the main reasons to usage of PLS algorithm for methodological purposes in tourism and gastronomy studies is the perceived ease that contains as well as model fit assessments with other validity concerns (do Valle & Assaker, 2016; Hair, Hollingsworth, et al., 2017; Hair, Matthews, et al., 2017). However, this perceived ease may develop itself through a perception that there is "no need" to assess any model fit concept. To concern to authors' knowledge, the kind of an attitude has appeared in minds of researchers who worked in addressed fields. Even this body of consensus has referred user friendly in some respects, not referring any goodness of fit or model fit indices actually weakens the method's power in general (Marcoulides & Saunders, 2006). Therefore, in this phase, we offer 3 strategies in respect with model fit assessment as (1) common approach, (2) traditional approach, and which this study recommends (3) alternative approach with Tennenhaus et al.'s (2004) Goodness-of-Fit index.

Common Approach

As Hair, Hult, et al. (2017) humbly highlight, there is not a well-established group of model fit indices for PLS, especially in SmartPLS. The mistaken consensus that sees no need to concern any goodness of fit issue bases on this statement. Yet, the motive behind this statement is not stressing a redundancy on model fit concepts, in fact, the authors illustrate that the convergent validity parameters like AVEs and reliability coefficients, discriminant validity assumptions (preferably HTMT), and finally, path analysis' outcomes such as R^2 and β coefficients should be interpreted to assess model fit -or goodness of fit- of the research's measurement model

(Hair, Hult, et al., 2017; Hair, Matthews, et al., 2017; Sarstedt et al., 2016). There are many examples in the tourism field used this approach to conduct model fit (e.g. Atsız & Akova, 2021). But frankly, lack of the model fit indices is still the Achilles' heel for PLS. Therefore, the traditional model fit indices have also been introduced to the PLS based SEMs (Hu & Bentler, 1998).

Traditional Approach

As immanent in the name, traditional approach contains the most known indices like NFI, SRMR, and other values (please see Model Fit by SmartPLS) and finds a place in gastronomy and tourism studies which benefit PLS with SmartPLS (e.g. Khan et al., 2021; Kılıç et al., 2021; Sop, 2021). The mentioned indices have developed accordingly to the needs of Covariance-Based SEM approach (Hair, Matthews, et al., 2017). Therefore, Hair, Hult, et al. (2017) prompts to be careful when building the model fit assumptions on these indices since these are developed for CB-SEM approach. To further the model fit decisions, there is an alternative approach that developed specifically for PLS-SEM.

Alternative Approach

Tennenhaus et al. (2004) developed an approach to assess model fit through a calculation named as Goodness-of-Fit (GoF) index. Since it is developed specifically for PLS-SEM, it is encouraged to use as the main approach for PLS based confirmatory factor analysis and structural equation modelling by this study. The equation can be written down as follows:

$$GoF = \sqrt{\overline{\mathrm{AVE}} + \overline{\mathrm{R}^2}}$$

It is not concealed that the index bases on the common approach's elements as AVE and R^2. GoF uses those two coefficients to reveal a more valid and statistically explainable indicator on model fit. The cut-points of GoF take values as < 0.10 unacceptable, ≥ 0.10 low fit, ≥ 0.25 moderate fit, and finally ≥ 0.36 high fit.

Reporting Issue and Understanding the Results

The systematic evaluation of PLS-SEM studies follows a two-step process that includes separate evaluations of the measurement models and the structural model (please see Hair Hult, et al., 2017). At the measurement model stage, the reliability and validity of the PLS-SEM estimates are examined and evaluated. There are two flows for reporting the measurement model, depending on whether the structural model type is reflective or formative. Reliability and validity assessment is an important issue for reflective measurement models. For reflective measurement model assessment, it is necessary to discuss indicator reliability, composite reliability, convergent validity, and discriminant validity. On the other hand, for the evaluation of formative measurement models, the convergent validity of the measurements, the importance and relevance of formative indicators, and linearity should be tested and reported.

After the reliability and validity explanations of the structural measurements, second part of the reporting is the evaluation of the structural model results. This section includes examining the predictive power of the model and the relationships between structures. The first element expected from researchers at this step is to understand and interpret the concept of model fit in the context of PLS-SEM. Then, the researchers can evaluate the path coefficients in the structural model and interpret the model's determination coefficients (R^2 and β), effect size (f^2) (Cohen, 1988; Hair Hult, et al., 2017), and predictive fit (Q^2) (Henseler et al., 2009; Hair Hult, et al., 2017) of the path model (reference points mentioned in Annex A). Hair et al. (2017) present a detailed map of how the data to be presented in the specified steps are obtained through the program in the evaluation of the results in a Smart PLS-based study.

CONCLUSION

It is expected that this research note will be a guide for researchers who conduct PLS-SEM-based research, especially in the field of tourism and gastronomy, in all steps from sample selection to reporting the results. Due to the increasing interest of PLS-SEM in recent years, this article aims to clarify the model building, analysing, and reporting parts with key criteria. Conscious use of the PLS-SEM technique by especially tourism and gastronomy researchers, who are generally the end users of statistical methodology, will contribute to the creation of qualified resources for future research with this technique. All key elements for understanding, conducting, and reporting for researchers when using PLS-SEM are listed in the checklist mentioned in the last part of the article (see Annex A). Thus, the researcher will be able to present his results in a fluent format by following these steps.

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Annex A. *Checklist to usage of PLS-SEM with SmartPLS for tourism and gastronomy studies*

Issue	Indicator		✓
Nomological Validity	Forming and proposing the relationships between variables of the conceptual model according to contemporary literature		
Modelling Validity	Formative modelling (if the conceptual variable shows the feature of a causal or a composite indicator)		
	Reflective modelling (if the conceptual variable shows the feature of perceptual or effect indicator)		
Sampling Assumption	Subjective assessment 10 times approach		
Normality Assumption	Does not require parametric assumptions if the following issues have been met	Detection of missing data	
		Detection of incorrect responds	
		Detection of biased responds	
		Fixing extremely abnormal data	
Convergent Validity	Factor Loadings	> 0.6 (if other indicators allow) > 0.7	
	t value	> 1.96 ($p < 0.05$) > 2.58 ($p < 0.01$)	
	Composite Reliability	> 0.7	
	AVE	> 0.5	
Discriminant Validity	HTMT	< 0.9	
Multicollinearity Common Method Bias	VIF	< 3	
Model Fit	Goodness-of-Fit	> 0.25	
Reporting	Mention R^2		
	Mention β		
	Mention Q^2	> 0.35 high between 0.35- 0.16 moderate between 0.15 – 0.02 low	
	Mention f^2	> 0.35 high between 0.35- 0.16 moderate between 0.15 – 0.02 low	

Source: Based on the evaluation of authors on existing literature