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Robustness checks in PLS-SEM: A review of recent practices and recommendations for future applications in business research

Santha Vaithilingam [a,*], Chu Sun Ong [b], Ovidiu I. Moisescu [c], Mahendhiran S. Nair [a]

[a] Sunway Institute for Global Strategy & Competitiveness & Sunway Business School, Sunway University, Malaysia
[b] Department of Innovation Science, School of Environment and Society, Tokyo Institute of Technology, Japan
[c] Department of Marketing, Faculty of Economics and Business Administration, Babeş-Bolyai University, Romania

A R T I C L E I N F O

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A B S T R A C T

For the last decade, scholars have employed partial least squares structural equation modeling (PLS-SEM) extensively in business research. However, when applying PLS-SEM, researchers need to perform various robustness checks before and after model estimation. This study showcases the findings of a review of PLS-SEM use in business research, by examining papers published between 2016 and 2021 in business journals. The study explores the extent to which researchers have performed robustness checks regarding nonnormality, endogeneity, unobserved heterogeneity, nonlinearity, and heteroskedasticity. The findings highlight that statistical rigor remains a serious problem in business-related studies employing PLS-SEM. Despite some encouraging improvements in the last few years, the vast majority of recent business-related studies using PLS-SEM have systematically overlooked robustness checks. This study calls for continued emphasis on the importance of robustness checks and the correct application of appropriate techniques, providing recommendations and guidelines for future PLS-SEM applications.

1. Introduction

For the last decade, partial least squares structural equation modeling (PLS-SEM) has risen in popularity as a method of choice for investigating intricate relationships between observed and latent constructs in social science research. This increased popularity is evidenced by the exponential growth in the number of PLS-SEM applications published in major social science journals (Hair et al., 2022). Within the domain, PLS-SEM is particularly appealing and it is employed extensively in business research in a wide range of subjects, such as marketing (Sarstedt et al., 2022a), international management (Richter et al., 2022), strategic management (Hair et al., 2012), supply chain management (Kaufmann & Gaeckler, 2015), operations management (Bayonne et al., 2020), human resource management (Ringle et al., 2020), family business management (Hair et al., 2021), management information systems (Hair et al., 2017), knowledge management (Cepeda-Carrión et al., 2018), technology adoption and use (Vaithilingam et al., 2022) and hospitality management (Ali et al., 2018).

Compared to other SEM methods that used to be more prominent in the past, particularly covariance-based structural equation modeling (CB-SEM), PLS-SEM provides several advantages to researchers. It facilitates the estimation of intricate models using relatively little data, with no imposed distributional assumptions, this being especially beneficial for business researchers who often rely on relatively small samples and nonnormal data (Hair et al., 2019b). In addition, PLS-SEM enables researchers to handle both reflectively and formatively specified measurements in their estimated models to test hypothesized relationships and to emphasize prediction, all at the same time (Cepeda-Carrión et al., 2016). This is of particular interest in business studies in which confirmation and explanation, as typical requisites of academic research, need to be accompanied by prediction in order to derive managerial implications (Henseler, 2018; Shmueli et al., 2016). Moreover, the availability of intuitive and user-friendly software packages (Sarstedt & Cheah, 2019), along with various papers and textbooks providing guidelines for applying the technique (e.g., Hair et al., 2022), has made PLS-SEM even more appealing to social science researchers, in general, and business researchers, in particular.

However, when applying PLS-SEM, researchers need to perform various robustness checks before and after model estimation, as there are several instances, such as nonnormality, endogeneity, unobserved heterogeneity, nonlinearity, and heteroskedasticity, that might threaten the validity of the results. Thus, even though PLS-SEM is a

* Corresponding author at: No. 5, Jalan Universiti, Bandar Sunway 47500, Selangor Darul Ehsan, Malaysia.
E-mail address: santhaav@sunway.edu.my (S. Vaithilingam).

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nonparametric method and does not require normally distributed data, extremely nonnormal data can lead to misleading results regarding the model parameters' statistical significance (Hair et al., 2022). Furthermore, endogeneity can lead to inaccurate path coefficients in PLS-SEM models. This is particularly problematic when testing hypothesized relationships, especially in studies focusing on confirmation and explanation (Hult et al., 2018; Papies et al., 2017). In addition, assuming that the investigated population is homogeneous, which is often unrealistic in business research, can lead to incorrect conclusions if a heterogeneous sample is analyzed on the aggregate level (Sarstedt et al., 2022b). Moreover, overlooking nonlinearities in the structural model when they can better depict the relationships between constructs, and erroneously assuming linearity for all paths in the PLS-SEM model, can lead to underestimating the true relationships or even wrongly flagging them as non-significant (Basco et al., 2022). Ultimately, although the method's nonparametric nature does not imply meeting rigorous homoskedasticity assumptions, extremely heteroskedastic data should be handled carefully, as PLS-SEM is a regression-based method.

Along with the rise of PLS-SEM as a method of choice, research has produced various additional methods for evaluating the robustness of PLS-SEM output. Nevertheless, despite their extensive documentation in the literature, business research using PLS-SEM has been slow in adopting those robustness checks. For instance, Latan (2018) and Sarstedt et al. (2020) highlighted the very limited use of robustness checks in hospitality and tourism research, providing guidelines to check for endogeneity, unobserved heterogeneity, and nonlinearity in a PLS-SEM framework.

Considering the utmost importance of robustness checks in PLS-SEM, this paper showcases the findings of a review of PLS-SEM use in business research, by examining papers published between 2016 and 2021 in high-quality journals. Our analysis examines the extent to which business research has incorporated robustness checks (i.e., concerning nonnormality, endogeneity, unobserved heterogeneity, nonlinearity, and heteroskedasticity) in the application of PLS-SEM, and provides recommendations and guidelines for conducting such checks before and after model estimation in future PLS-SEM studies. To achieve this objective, we attempt to answer the following questions: (i) What type of robustness checks were performed, (ii) which techniques were used, and (iii) is there a trend in performing and reporting results of robustness checks.

While we acknowledge the importance of other robustness checks (e.g., necessary condition analysis, common method variance, confirmatory tetrad analysis, model comparisons), our selection is the result of deliberate prioritization based on the relevance of such checks within the conventional regression analysis framework, considering that PLS-SEM is a regression-based method. Practical considerations related to time constraints and data availability also played a role in the decision to highlight these selected checks.

In our investigation, the robustness checks are categorized according to the point of time at which the analysis is undertaken. Thus, normality is assessed before model estimation. This is to ensure that extremely nonnormal data does not lead to misleading results, and also to ascertain the suitability of PLS-SEM due to its robustness when analyzing nonnormal data. On the other hand, endogeneity, unobserved heterogeneity, nonlinearity, and heteroskedasticity are evaluated after model estimation to warrant the validity of the results.

The paper is structured as follows. We start by describing the protocols of the systematic literature review (SLR). We subsequently outline our SLR findings, depict the prevalence of robustness checks in the investigated papers, and discuss the techniques used for each robustness check. Finally, we provide recommendations for future PLS-SEM applications in business research.

2. Methodology

We conducted an SLR, following the guidelines of Kitchenham et al. (2009) who pointed out that the SLR functions as an important tool for assessing the methodological quality of research. Given the plethora of empirical studies that use PLS-SEM, and the guidelines published to help researchers use and report PLS-SEM results, the question of statistical rigor in those studies remains elusive (Hair et al., 2024; Hult et al., 2018; Sarstedt et al., 2020).

Since the scope of the review included all papers that employed the PLS-SEM methodology, the query had to contain all the different terminologies used to refer to PLS-SEM. Hence, to obtain a comprehensive list of results, the following search strings were used: "(PLS-SEM) OR (PLS) OR (PARTIAL LEAST SQUARES)." The search was conducted within Clarivate Analytics' Web of Science Core Collection, a database that covers more than 21,100 leading journals.

Several restrictions were applied to filter irrelevant results while maintaining the reliability of the SLR results. The initial search criteria were set to locate papers that are published (i) in English, (ii) in academic journals, (iii) in a business field of study, and (iv) for the past six years (2016–2021). Further criteria of inclusion applied to the search results are as follows:

(vi) The paper was published in a high-ranked journal, namely a Q1 journal as per the 2020 SCImago Journal Rank (SJR) indicator[1] (SCImago, n.d.), as methodological rigor characterizes high-quality journals (West & Rich, 2012); (vii) the paper was empirical in nature (only papers with applications of PLS-SEM were considered; theoretical, conceptual, or "guidelines" papers were excluded).

The initial search returned 2,725 articles. After the exclusion of articles based on the established selection criteria, a total of 1,228 articles remained. These articles were published in 76 unique business journals. Appendix A shows these journals, with the reported instances of robustness checks. The flow chart highlighting the different phases of our SLR is shown in Fig. 1.

To enhance comparability and enable the examination of the progression in robustness checks practices within the business literature, we subsequently partitioned the corpus of articles into two distinct subperiods, each comprising an equivalent span of years (i.e., 2016–2018 and 2019–2021).

3. Findings

Of the 1,228 papers selected, we found that 182 (14.9 %) reported at least one of the diagnostic checks within the scope of our review. In these 182 papers, a total of 245 instances of robustness checks were reported. In the next sections, we discuss our findings and their key implications for each category of robustness checks.

3.1. Normality

Researchers use bootstrapping for hypothesis testing in PLS-SEM (Hair et al., 2022), rendering PLS-SEM a distribution-free technique. Unlike CB-SEM, PLS-SEM does not require normally distributed data which is particularly appealing for business researchers who often rely on nonnormal data (Hair et al., 2019b). However, when using PLS-SEM, extremely nonnormal data can lead to misleading results regarding the statistical significance of the parameters (Guenther et al., 2023; Hair et al., 2022). For this reason, and also to support their method of choice, researchers employing PLS-SEM should assess the normality of their data. Nevertheless, motivating the choice of PLS-SEM over alternative methods primarily on the basis of nonnormality alone is not sufficient (Sarstedt et al., 2022a). Additional robust arguments may encompass considerations such as the meaningfulness of indicator residual variances for the constructs in the model (Guenther et al., 2023), or the

[1] Our classifications of "high quality" journals are based solely on the SJR score. Therefore, they may potentially exclude journals considered high quality by other ranking systems.

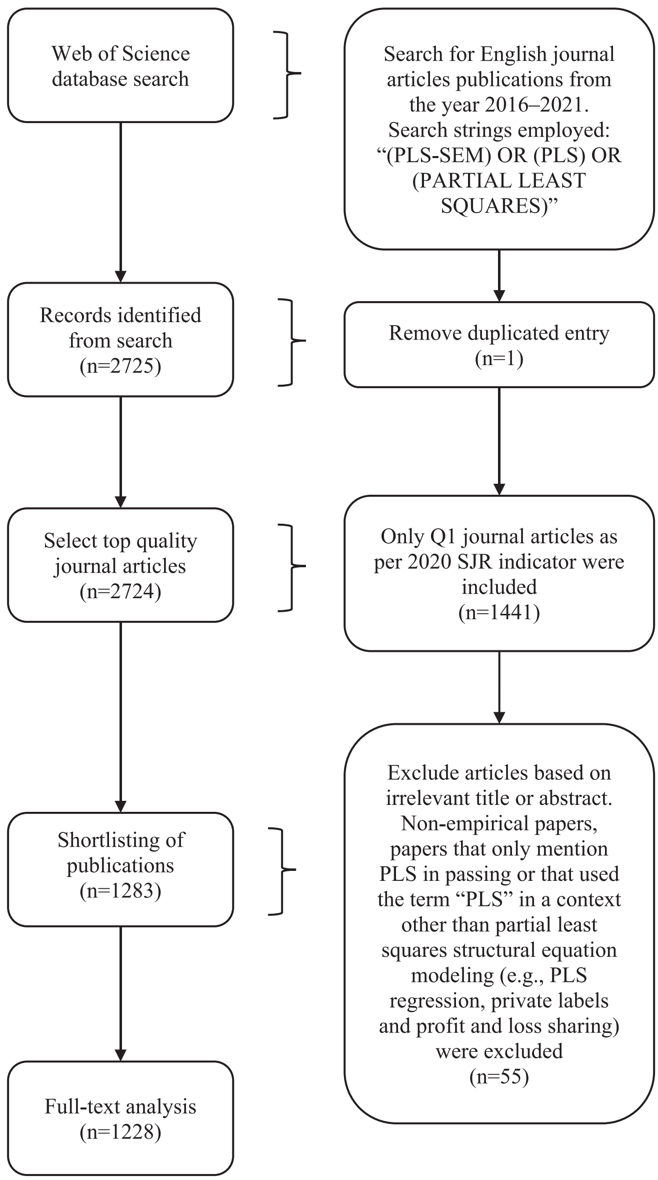

Fig. 1. Flow diagram.

predictive nature of the research objective (Hair et al., 2019c; Ringle et al., 2023).

Normality tests can be categorized according to the type of normality being tested, namely univariate or multivariate normality. Univariate normality is a requisite for multivariate normality (DeCarlo, 1997). Consequently, potential users of PLS-SEM should first assess univariate normality, checking whether individual indicators or items are normally distributed. If univariate normality is not rejected, users can then proceed to evaluate the stronger assumption of multivariate normality.

There are various approaches for univariate normality assessment, ranging from graphical methods to summary measures, and statistical tests. However, graphical methods including the Q-Q plot and P-P plot, have been criticized for the subjectivity of their interpretation (Loy et al., 2016). The common statistical tests that can be employed to assess normality are the Shapiro-Wilk and Kolmogorov-Smirnov tests. The former test has a higher power and is therefore recommended for small samples (Razali & Wah, 2011). Nevertheless, as these tests cannot indicate the extent of departure from normality, PLS-SEM users should examine skewness and kurtosis values. Skewness and kurtosis are summary statistics that measure the extent of departures from normality and can be used in both a descriptive and an inferential manner. Values of skewness and kurtosis outside the range of −1 to 1 denote significant deviation from normality. However, considering the robust performance of PLS-SEM when data are nonnormal, values between −2 and +2 can generally be considered acceptable (Hair et al., 2022).

As for multivariate normality assessment, researchers can employ tests, such as those developed by Mardia (1970, 1974), Small (1980), or Srivastava (1984). However, this assessment is not required if univariate normality, a prerequisite for multivariate normality, is rejected.

Our review of studies using PLS-SEM in business research shows that only 129 of 1,228 studies (10.5 %) assessed the normality of their data. Moreover, this situation has not improved in more recent years, with 90 of 858 studies (10.5 %) published between 2019 and 2021 performing such checks, compared to 39 out of 370 papers (10.5 %) published between 2016 and 2018.

As Table 1 shows, examining skewness and kurtosis values, as recommended by Hair et al. (2022), consistently proved to be the most used approach for normality assessment (54 of the 129 studies, 41.7 %). Statistical tests were also frequently performed to test for normality, the most common of which were the Shapiro-Wilk and Kolmogorov-Smirnov tests. Nevertheless, by not examining skewness and kurtosis values, more than half of the 129 studies failed to remove doubts associated with extreme nonnormalities that might have led to misleading results. Moreover, 23 of the 129 studies (17.8 %) explicitly claimed that normality checks were performed and that their data were nonnormal but provided no information on the type of assessment. In fact, studies that exploited the non-parametric nature of PLS-SEM to justify the use of the method, by making rhetoric statements (e.g., "PLS-SEM is chosen instead of CB-SEM, as PLS-SEM can handle nonnormally distributed data") without conducting the appropriate tests or reporting results of the tests, proved to be numerous (236 out of the total of 1,228 reviewed studies).

3.2. Endogeneity

Endogeneity occurs when a predictor (explanatory) variable in a regression equation is correlated with the error term of the dependent variable (Wooldridge, 2013). If that is the case, it can lead to inaccurate path coefficients in PLS-SEM models (Papies et al., 2017), which is particularly problematic when testing hypothesized relationships. Even though endogeneity can have several roots, it is usually the result of omitted latent variables that correlate with both the dependent variable and a predictor variable in the PLS-SEM model (Sarstedt et al., 2020). One of the approaches to address this is to employ control and instrumental variables (Ebbes et al., 2016). However, such variables are often unavailable or difficult to find and, consequently, PLS-SEM users can employ the more accessible Gaussian copula approach, which enables PLS-SEM users to assess the correlation between explanatory or predictor constructs and the error terms of dependent ones (Hair et al.,

Table 1
Number of instances normality checks were performed.

	2016–2018		2019–2021	
Technique used	**Count**	**%**	**Count**	**%**
Skewness and kurtosis	14	28	40	39
Details not provided	9	18	14	14
Kolmogorov-Smirnov	9	18	14	14
Shapiro-Wilk	7	14	11	11
Mardia	5	10	11	11
Graphical method	0	0	6	6
Jarque-Bera	0	0	4	4
Multivariate skewness and kurtosis	2	4	1	1
Kurtosis	0	0	2	2
Small	1	2	0	0
Srivastava	1	2	0	0
Others	2	4	0	0
Total	**50**	**100**	**103**	**100**

2024).

Our review of papers employing PLS-SEM in business research shows that endogeneity checks were performed in only 28 of 1,228 studies (2.3 %). However, from this perspective, PLS-SEM users' rigor has improved significantly in more recent years, since endogeneity checks were performed in 25 of 858 studies (2.9 %) published between 2019 and 2021, compared to only 3 of 370 (0.8 %) published between 2016 and 2018. This is an encouraging finding, considering that a previous review of studies published between 2008 and 2017 in several of the highest ranked marketing journals revealed that none of the investigated PLS-SEM applications had considered any endogeneity assessment (Hult et al., 2018).

As Table 2 shows, studies that checked for endogeneity employed various tests, such as the Gaussian copula approach (Park & Gupta, 2012), the Durbin-Wu-Hausman (DWH) test, the Heckman test, or the nonlinear bivariate causality direction ratio (NLBCDR) (Kock, 2015). Among the endogeneity tests identified in our SLR, the Gaussian copula approach proved to be the PLS-SEM users' preferred test, most probably due to its instrumental variable (IV)-free nature. The DWH test, on the other hand, is less popular, as it requires identification of an appropriate instrumental variable. Moreover, the DWH is a parametric test, while PLS-SEM is known for its non-parametric nature.

Kock's NLBCDR method is still experimental (Kock, 2022) and is currently useful for testing endogeneity arising from reverse causality. Besides simultaneity, which comprises reverse causality, other sources of endogeneity include omitted variable, measurement error, and selection bias (Wooldridge, 2010). Endogeneity caused by these sources might not be detected using Kock's NLBCDR approach. The use of the Heckman test, on the other hand, is limited to detecting endogeneity caused by sample selection bias (Certo et al., 2016; Wooldridge, 2013). Ramsey's Regression Equation Specification Error Test (RESET) has also been suggested for endogeneity assessment. This application is, however, inappropriate, as RESET is a general misspecification test for linear regression models (Ramsey, 1969) and is only useful for detecting functional form misspecification, particularly the existence of neglected nonlinearities between dependent and independent variables that exist in the regression equation (for details, see Wooldridge, 2010).

Some papers account for endogeneity at the research design phase to ensure that all possible factors that have a potential impact on the outcome (dependent) variable are considered in their conceptual model. While a theoretical treatment of endogeneity was acceptable in the past (Guide & Ketokivi, 2015), the use of statistical evidence such as that based on the IV-free Gaussian copula approach (Park & Gupta, 2012) has become desirable. While it is IV-free, able to handle multiple endogenous regressors, and implemented in PLS-SEM software packages (e.g., SmartPLS 4.0 (Ringle et al., 2022)), Becker et al. (2022) advise researchers to be careful in applying the Gaussian copula approach. The authors highlight that the approach misleads if the following three conditions are not fulfilled: (i) nonnormality of the endogenous regressor(s), (ii) normality of the error term, and (iii) the error term and the endogenous variable follow a Gaussian copula correlation structure. The Cramér-von Mises (also implemented in PLS-SEM software packages such as SmartPLS 4.0 (Ringle et al., 2022)) and Anderson-Darling tests proved to have the best performance in testing for the nonnormality of the endogenous regressor (Becker et al., 2022). The normality of the error term condition can be tested by ensuring the regression residuals from the PLS-SEM structural model are normally distributed. However, the correlation structure required by the third condition cannot be observed whereby researchers must resort to theoretical considerations. Even when these three conditions can be justified, the Gaussian copula approach has a further minimum sample size requirement of 200 if skewness of the endogenous regressor is higher than 2; 1,000 if skewness is higher than 0.8; and 2,000 if skewness is below 0.8 (Becker et al., 2022).

Table 2
Number of instances endogeneity checks were performed.

Technique Used	2016–2018 Count	%	2019–2021 Count	%
Gaussian copula approach	0	0	10	38
Hausman/Durbin-Wu-Hausman	3	100	5	19
NLBCDR*	0	0	5	19
Heckman	0	0	2	8
Control variable approach	0	0	2	8
Ramsey*	0	0	2	8
Total	**3**	**100**	**26**	**100**

* Inappropriate technique for the intended robustness check.

Endogeneity assessment is not compulsory in all applications of PLS-SEM and is dependent on whether the objective of the study is confirmatory or predictive (Ebbes et al., 2011). In confirmatory-type studies, controlling for endogeneity is important to ensure the reliability of hypothesis testing results. In contrast, endogeneity is less of a concern in predictive-type studies where hypothesis testing is not the main objective of the research, and controlling for it may have an impact on the model's out-of-sample predictive power (Papies et al., 2017). Nonetheless, the line between confirmatory and predictive studies is often blurred in PLS applications (Schuberth et al., 2022). This calls for research to identify the approaches to handle endogeneity, by considering the interplay between the two research paradigms in the PLS-SEM context (Hair et al., 2019c). Nevertheless, it is still important for PLS-SEM users to determine, a priori, the prevailing intent of the study as either confirmatory or predictive, given the distinctive difference between the two types of studies in every stage of the statistical modeling process (Shmueli, 2010).

3.3. Unobserved heterogeneity

In PLS-SEM studies, assuming that the investigated population is homogeneous (which is often unrealistic in business research) can lead to incorrect conclusions if a heterogeneous sample is analyzed on the aggregate level (Sarstedt et al., 2022b). One way of addressing heterogeneity is to partition the data based on observable characteristics of the population and to estimate the model separately for each partition, thus accounting for observed heterogeneity. However, very often the cause of heterogeneity is unknown a priori and, consequently, unobserved heterogeneity needs to be accounted for. If such checks indicate no substantial repercussions affecting the results, the data can be analyzed on the aggregate level and their output can be generalized. However, if unobserved heterogeneity is detected, it needs to be treated accordingly.

In order to detect and handle unobserved heterogeneity appropriately, PLS-SEM users have a multitude of specific methods at their disposal, generally termed as latent class techniques. The most notable such technique is finite mixture PLS (FIMIX-PLS; Sarstedt et al., 2011). The method enables researchers to reveal the existence of heterogeneity reliably and to determine the number of segments correctly, using information criteria (e.g., jointly considering AIC3 and CAIC) and classification criteria (e.g., entropy statistic) (Sarstedt et al., 2022b). The technique's implementation in popular PLS-SEM software packages (e.g., SmartPLS), along with the many articles providing guidelines for applying it (e.g., Hair et al., 2016; Matthews et al., 2016), has made it readily available for PLS-SEM users for many years.

However, when heterogeneity is detected, identifying the actual segment structure correctly is an important limitation of FIMIX-PLS (Ringle et al., 2014; Sarstedt et al., 2022b), more so when formative constructs are involved (Becker et al., 2013). To overcome this limitation, research has proposed several additional techniques, such as the response-based procedure for detecting unit segments in PLS (REBUS-PLS, Esposito Vinzi et al., 2008), the prediction-oriented segmentation in PLS-SEM (PLS-POS, Becker et al., 2013), the PLS genetic algorithm segmentation (PLS-GAS, Ringle et al., 2014), and the PLS iterative reweighted regressions (PLS-IRRS, Schlittgen et al., 2016). However, instead of employing any of these additional techniques exclusively, researchers are advised to adopt a tandem approach (Sarstedt et al., 2022b), using FIMIX-PLS to detect heterogeneity and determine the number of segments, and to further use its results as a starting point for applying additional latent class techniques (i.e., using PLS-POS, PLS-REBUS, PLS-GAS, or PLS-IRRS). Moreover, since simulation studies have shown that PLS-POS provides favorable outcomes compared to its alternative techniques, and considering its availability in popular PLS-SEM software packages (e.g., SmartPLS), PLS-SEM users are recommended to use FIMIX-PLS and PLS-POS in tandem when heterogeneity is detected (Hair et al., 2024). Based on PLS-POS results, it is then mandatory to conduct ex-post analyses in order to link the latent segment structure to observable characteristics in the data (Sarstedt et al., 2022b), using techniques such as contingency table analyses and exhaustive chi-squared automatic interaction detector (CHAID) (Ringle et al., 2010), fuzzy-set qualitative comparative analysis (fsQCA) (Mikalef & Pateli, 2017), or logistic regression analyses (Dessart et al., 2019).

Our review shows that only 30 of 1,228 studies (2.4 %) performed unobserved heterogeneity checks for their data. Compared to a recent review on PLS-SEM use in marketing research (Sarstedt et al., 2022a), which found that 4.18 % of studies conducted latent class analyses, our review within the wider field of business research reveals an even less rigorous stand on this issue. Moreover, this situation has worsened in more recent years, with only 20 of 858 studies (2.3 %) published between 2019 and 2021 performing such checks, compared to 10 of 370 papers (2.7 %) published between 2016 and 2018.

As seen in Table 3, FIMIX-PLS dominates among the methods used for uncovering unobserved heterogeneity, which is in line with previous methodological recommendations. However, according to our review, only 4 of the 11 studies that had used FIMIX-PLS and that had detected unobserved heterogeneity further employed PLS-POS (or other additional latent techniques) to better depict the actual segment structure. In addition, among the five studies employing PLS-POS, two have done so without adopting the recommended tandem approach (i.e., FIMIX-PLS, followed by PLS-POS).

Unfortunately, our review emphasizes that business research has been slow in responding to recent calls to check for unobserved heterogeneity (e.g., Sarstedt et al., 2020, first publisehd online in 2019). This is despite the wide availability of latent class techniques, both considering software implementation, and guidelining papers. Hopefully, more recent calls (e.g., Sarstedt et al., 2022b), along with our current strong recommendation to account for unobserved heterogeneity, will have a significant impact in the near future.

3.4. Nonlinearity

Despite many past studies assuming monotonic positive linear relationships between constructs, Pierce and Aguinis (2013) pointed out that such relationships can become asymptotic and, consequently, negative with the increase in the value of the independent variables, resulting in a curvilinear relationship that they refer to as the "too-much-of-a-good-thing effect" (TMGT effect). For a nonlinear relationship between two variables, the effect size depends on the magnitude of change in the independent variable (Hair et al., 2024), that is, the changes in the slopes are dependent on the level of the variable (Basco et al., 2022). Thus, understanding the true underlying relationship between the independent and outcome variables is important, as the functional form will be dependent on the pattern of the relationship. Overlooking nonlinearities in the structural model when they can better depict the relationships between constructs, and erroneously assuming linearity for all paths in a PLS-SEM model can lead to underestimating the true relationships, or even wrongly flagging them as non-significant (Basco et al., 2022).

The RESET test (Ramsey, 1969) is the most prominent technique to be used for checking nonlinearities in PLS-SEM (Latan et al., 2018; Svensson et al., 2018). It involves estimating the PLS-SEM model and using the resulted latent scores as inputs for RESET, which can be implemented in standard software (e.g., SPSS, E-Views, or Stata; Sarstedt & Mooi, 2014). RESET tests are based on fitted values from a linear model. For this reason, the second stage is required to assess if a nonlinear specification for the relationships of the latent constructs in the structural model results in significant coefficients (Latan et al., 2018). This can be confirmed by adding the interaction terms in the structural model and reanalyzing the structural model based on bootstrapping (Hair et al., 2024). According to Hair et al. (2018), especially in social sciences, modeling quadratic effects should suffice, as other higher order polynomials of the independent constructs are very challenging.

Our review of articles applying PLS-SEM in business research shows that only 16 of 1,228 studies (1.3 %) accounted for nonlinearity in the investigated models, among which three studies did not actually report the results of their nonlinearity checks. There is, however, a slight improvement over time, with 12 of 858 studies (1.4 %) published between 2019 and 2021 performing such checks, compared to 4 of 370 papers (1.1 %) published between 2016 and 2018. Our findings are consistent with those of Sarstedt et al. (2020) who highlighted that most studies using PLS-SEM in hospitality and tourism research had not considered nonlinear effects, and also with those of Basco et al. (2022) who emphasized that family business research has only rarely considered nonlinear effects.

As Table 4 shows, the RESET technique for nonlinearity assessment has gained attention in more recent years, as all four studies employing the method were published between 2019 and 2021. However, only two of these studies have actually applied the recommended methodological rigor by completing both the RESET and quadratic effect assessments.

Just as in the case of unobserved heterogeneity, our review reveals once more that business research has been slow in responding to recent calls for robustness checks, including nonlinearity assessment. A possible explanation could be the cumbersome process of combining the use of several software packages (i.e., RESET), and the multi-staged nature of the full procedure (i.e., RESET followed by quadratic effect assessment). However, there is optimism that the recent calls for robustness checks (e.g., Sarstedt et al., 2022a), along with our strong recommendation to account for nonlinear effects, will give nonlinearity

Table 3
Number of instances unobserved heterogeneity checks were performed.

	2016–2018		2019–2021	
Technique Used	**Count**	**%**	**Count**	**%**
FIMIX-PLS*	9	82	16	73
PLS-POS	2	18	3	14
REBUS-PLS	0	0	2	9
Details not provided	0	0	1	5
Total	**11**	**100**	**22**	**100**

*Of the 25 studies that conducted FIMIX-PLS, 11 detected unobserved heterogeneity.

Table 4
Number of instances nonlinearity checks were performed.

	2016–2018		2019–2021	
Technique Used	**Count**	**%**	**Count**	**%**
Details not provided	1	25	2	17
Graphical method	1	25	1	8
RESET	0	0	2	17
Quadratic effect assessment	1	25	1	8
RESET and quadratic effect assessment	0	0	2	17
ANOVA (SPSS)	0	0	2	17
Curve estimation	1	25	1	8
Warp3 algorithm	0	0	1	8
Total	**4**	**100**	**12**	**100**

checks a boost in future studies.

3.5. Heteroskedasticity

PLS-SEM users might be unfamiliar with the concept of heteroskedasticity (HSK), even though the issue of observed or unobserved heterogeneity has been fairly established in the PLS-SEM literature. Heterogeneity is about the estimated path coefficient and if these coefficients vary significantly across subgroups of the population. HSK, on the other hand, refers to whether the variability around the estimated path coefficient differs across the different values of the antecedents or predictor variables in the model. Simply put, heterogeneity addresses the first moment (i.e., the mean), while HSK addresses the second moment (i.e., the variance). Given this property, HSK is also known as heterogeneity in the variance.

To account for HSK, PLS-SEM users can employ tests, such as the Levene test and the Breusch-Pagan and Koenker test. The Levene test is the most used HSK test and is meant for testing the univariate form of HSK. The test involves comparing the variance of a metric variable across levels of a nonmetric variable. The Breusch-Pagan and Koenker test, on the other hand, is meant for testing homogeneity of variance between two metric variables, which is a commonly faced issue in regression analysis (Hair et al., 2019a).

Although relatively few papers checked for the assumption of constant variance in the error terms or homoskedasticity, the numbers of studies came close to those checking for nonlinearity. Our review shows that 12 of 1,228 studies (1 %) performed HSK tests. Nevertheless, the adoption of such checks has improved in more recent years, since nine of 858 studies (1.1 %) published between 2019 and 2021 performed such checks, compared to three of 370 papers (0.8 %) published between 2016–2018. Table 5 shows that, as expected, the Levene test has been by far the most widely used to account for HSK.

A review of commonly cited PLS-SEM textbooks (e.g., Hair et al., 2024; Hair et al., 2022) and guideline articles (e.g., Hair et al., 2019b; Sarstedt et al., 2022a) did not mention whether the violation of the HSK assumption would pose a serious threat to the validity of PLS-SEM results. The fact that PLS-SEM is regression based but at the same time utilizes the bootstrapping procedure in generating the test statistics, makes the relevance of the HSK assumption as stipulated in the Gauss–Markov theorem unclear. In the interests of the diverse PLS-SEM community, which consists of researchers from many disciplines other than statistics, future research should address this gap.

4. Conclusions

Our study highlights that statistical rigor remains a serious problem in business-related studies using PLS-SEM. Only one in ten such studies published between 2016 and 2021 assessed the normality of their data, while endogeneity, unobserved heterogeneity, nonlinearity, or HSK checks were performed in only 2.3 %, 2.4 %, 1.3 %, and 1 %, respectively, of the 1,228 reviewed papers. Despite a significant improvement in what concerns endogeneity checks, as well as a slight advancement regarding nonlinearity and HSK examinations, the vast majority of studies using PLS-SEM in business research have largely ignored robustness checks.

Table 5
Number of instances heteroskedasticity checks were performed.

	2016–2018		2019–2021	
Technique Used	**Count**	**%**	**Count**	**%**
Levene	1	33	5	45
Graphical method	1	33	3	27
Details not provided	0	0	2	18
Breusch-Pagan	1	33	0	0
Koenker	0	0	1	9
Total	**3**	**100**	**11**	**100**

In addition, even when robustness checks were conducted, some studies showed uncertainty not only regarding the techniques to be used, but also regarding their appropriate context. This is more concerning, as misapplying such techniques can result in misleading conclusions or failing to fully depict the relationships between constructs in PLS-SEM models.

When performing robustness checks, researchers are advised not to be selective or adopt a "cherry-picking" behavior, but to be rigorous and transparent in performing and reporting the results of the checks performed. Otherwise, the validity of their findings will be called into question.

In line with recent calls for robustness checks (e.g., Sarstedt et al., 2022a), our strong recommendation for business researchers using PLS-SEM is to assess data normality and to account for endogeneity, unobserved heterogeneity, and nonlinearity. Table 6 provides a summary of the recommended techniques for each type of robustness check.

As for HSK, our SLR revealed several instances of such checks being performed. However, to date, no studies have addressed the extent to which HSK can affect the validity of PLS-SEM results. Hence, considering that PLS-SEM is a regression-based method, future research should examine the consequences of using extremely heteroskedastic data when assessing models in the PLS-SEM framework.

Moving forward, in order to encourage rigor among business researchers using PLS-SEM, PLS-SEM software developers should strive to include built-in functions for all relevant robustness check procedures. In addition, editorial boards and reviewers should consider adopting a more conservative stance when it comes to reviewing PLS-SEM studies, ensuring that appropriate robustness checks are performed where applicable.

This study has certain limitations. First, the journals included in our SLR may not be representative of all journals that published PLS-SEM studies within the investigated timeframe and field of study. Owing to the impracticality of considering all such journals, we considered only selected high-ranking publications.

Second, even though we conducted our SLR search within Clarivate Analytics' Web of Science Core Collection, we did the selection of high-ranking publications, using Elsevier's SCImago. Nevertheless, by doing so, we have broadened the range of journals that were taken into account, as SCImago is less conservative than Clarivate's Journal Citation Reports (JCR) when it comes to ranking journals in the top-tier zone.

Third, even though some scholars (e.g., Hair et al., 2020) suggest that robustness checks should also include multicollinearity, by examining bivariate correlations between formative indicators or between exogenous constructs, multicollinearity was not part of our analysis, as its assessment is generally associated to PLS structural and measurement model assessment. Moreover, the necessity of bivariate correlations between independent variables in a regression model as a condition for multicollinearity is a subject of debate (e.g., Gujarati & Porter, 2009). Nevertheless, further research and refinement of techniques for examining multicollinearity in PLS-SEM models would be beneficial.

Finally, the robustness checks covered in this paper are not meant to be exhaustive; rather, they were selected based on their relevance within the conventional regression analysis framework. When using PLS-SEM, researchers should also consider other relevant robustness checks. For instance, they should check for issues related to common method variance (Chin et al., 2013), assess whether any independent variable in the model is necessary to produce a specific outcome for a dependent variable (necessary condition analysis - NCA; Richter et al., 2020), and examine whether the specification (i.e., formative/reflective) of the measurement model is correct (confirmatory tetrad analysis - CTA; Gudergan et al., 2008). Additionally, researchers should assess whether their model, when compared with other competing models, performs better in terms of information criteria (Sharma et al., 2019), or predictive ability (PLSpredict; Shmueli et al., 2019; cross validated predictive ability test - CVPAT; Liengaard et al., 2021). Future research exploring

Table 6
Robustness checks recommendations.

When to Test	Recommended technique(s)	Tool(s)	Additional technique(s)	Tool(s)
Normality – univariate				
At all times	Examination of skewness and kurtosis values	✓ PLS-SEM programs (e.g., SmartPLS) ✓ Microsoft Excel functions - SKEW() and KURT() ✓ *skewness()* and *kurtosis()* in R '*moments*' package	Shapiro-Wilk Kolmogorov-Smirnov	✓ *shapiro.test()* in R '*stats*' package ✓ *ks.test()* in R '*stats*' package
Normality – multivariate				
Univariate normality failed to be rejected	Mardia's multivariate normality test	✓ Webpower website https://webpower.psychstat.org/models/kurtosis/ ✓ *mvnTest()* in R '*MVN*' package	Small (1980), Srivastava (1984)	R codes not available in any existing packages
Endogeneity				
Objective of study is confirmatory rather than predictive	Gaussian copula approach (if assumptions of the approach are met)	✓ PLS-SEM programs (e.g., SmartPLS) ✓ R codes are available at https://www.pls-sem.net/downloads/gaussian-copula-files/	Durbin-Wu-Hausman Test	✓ Using the generic *summary()* where the object is an instrumental variable regression estimated using R '*ivreg*' package
Non-linearity				
At all times	RESET testfollowed by Higher order polynomial fitting (quadratic)	✓ *resettest()* in R '*zoo*' package ✓ PLS-SEM programs (e.g., SmartPLS) – Assess the significance of quadratic terms	–	–
Unobserved heterogeneity				
At all times	FIMIX-PLS followed by	✓ PLS-SEM programs (e.g., SmartPLS) – Detect unobserved heterogeneity and number of segments	–	–
	PLS-POS	✓ PLS-SEM programs (e.g., SmartPLS) – Determine the actual structure of the segments	REBUS-PLS PLS-GASPLS-IRRS	✓ *rebus.pls ()*in R '*plspm*' package R codes not available in any existing packages

the use of such robustness checks in business-related studies would be beneficial for enhancing PLS-SEM rigor in business research.

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CRediT authorship contribution statement

Santha Vaithilingam: Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Chu Sun Ong:** Writing – original draft, Writing - review & editing, Methodology, Formal Analysis. **Ovidiu I. Moisescu:** Writing – review & editing, Writing – original draft, Conceptualization. **Mahendhiran S. Nair:** Writing – review & editing, Supervision, Methodology.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Robustness checks in PLS-SEM empirical studies published between 2016 and 2021 in business journals

	Number of PLS-SEM empirical papers	Number of papers performing *at least one* robustness check	Number of instances robustness checks were performed
Journal of Business Research	139	23	32
Technological Forecasting and Social Change	51	12	21
Journal of Retailing and Consumer Services	108	11	18
Journal of Entrepreneurship in Emerging Economies	29	11	13
European Journal of Marketing	19	8	11
Journal of Business & Industrial Marketing	60	7	8
Journal of Product and Brand Management	39	6	7
Business Strategy and the Environment	29	6	7
Internet Research	50	4	6
Journal of Services Marketing	36	6	6

(*continued on next page*)

(*continued*)

	Number of PLS-SEM empirical papers	Number of papers performing *at least one* robustness check	Number of instances robustness checks were performed
Journal of Intellectual Capital	38	4	5
Corporate Social Responsibility and Env. Management	34	4	5
Industrial Marketing Management	23	5	5
European Business Review	22	3	5
Journal of Business Ethics	17	4	5
South Asian Journal of Business Studies	11	3	5
International Journal of Accounting Information Systems	7	2	5
International Journal of Retail & Distribution Management	37	3	4
Journal of Service Theory and Practice	14	3	4
Journal of Small Business and Enterprise Development	11	2	4
EuroMed Journal of Business	10	3	4
Journal of Hospitality Marketing & Management	9	3	4
Long Range Planning	8	2	4
Thunderbird International Business Review	8	2	4
Research in Transportation Business and Management	6	3	4
Small Business Economics	4	2	4
Journal of Vacation Marketing	17	3	3
International Journal of Managing Projects in Business	14	3	3
Electronic Commerce Research and Applications	13	1	3
International Business Review	9	3	3
Management Decision	44	2	2
European Management Journal	21	2	2
Journal of Asia Business Studies	19	2	2
Journal of Marketing Management	13	1	2
Journal of Electronic Commerce Research	11	1	2
Business Strategy and Development	9	1	2
IEEE Transactions on Engineering Management	7	2	2
British Journal of Management	6	2	2
Journal of Engineering and Technology Management	6	2	2
R & D Management	4	2	2
Business Process Management Journal	31	1	1
International Entrepreneurship and Management Journal	24	1	1
Young Consumers	16	1	1
Int. J. of Entrepreneurial Behavior & Research	14	1	1
Electronic Markets	9	1	1
Journal of Fashion Marketing and Management	8	1	1
Journal of World Business	5	1	1
Journal of Entrepreneurship	3	1	1
Emerging Markets Finance and Trade	2	1	1
International Journal of Advertising	2	1	1
Journal of International Business Studies	2	1	1
Journal of the Academy of Marketing Science	2	1	1
Asian Business & Management	1	1	1
European Research on Management and Bus. Economics	12	0	0
International Journal of Management Education	11	0	0
Psychology & Marketing	10	0	0
International Marketing Review	9	0	0
Journal of International Entrepreneurship	9	0	0
Journal of African Business	8	0	0
Service Business	7	0	0
BRQ-Business Research Quarterly	6	0	0
Eurasian Business Review	4	0	0
Journal of Innovation & Knowledge	3	0	0
International Small Business Journal	2	0	0
Journal of Global Fashion Marketing	2	0	0
Journal of Interactive Marketing	2	0	0
Journal of Media Business Studies	2	0	0
Multinational Business Review	2	0	0
Journal of Business and Psychology	1	0	0
Journal of Family Business Strategy	1	0	0
Journal of Management Analytics	1	0	0
Journal of Marketing	1	0	0
Journal of Personal Selling & Sales Management	1	0	0
Journal of Product Innovation Management	1	0	0
Journal of Service Research	1	0	0
Public Relations Review	1	0	0
Total	**1,228**	**182**	**245**

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Santha Vaithiligam is Professor of Econometrics and Policy Modelling, at Sunway Institute for Global Strategy and Competitiveness, Sunway University. She is trained in mathematical modeling. Her current research interest revolves around behavioral econometrics, using mathematical and statistical modeling to understand human behavior and the decision-making process. Her research work is also focused on developing research instruments and using robust data analytics & advanced statistical tools to research technology, innovation, and economic policy modeling for enhancing sustainable economic development.

Chu Sun Ong is a Ph.D. student at the Tokyo Institute of Technology. His doctoral research focuses on modelling the societal implications of digital inequality. He holds a bachelor's degree majoring in Econometrics and Business Statistics and a master's degree in Economics.

Ovidiu I. Moisescu is Professor of Marketing and Branding at the Marketing Department, Faculty of Economics and Business Administration at Babeș-Bolyai University of Cluj-Napoca, Romania. He completed his PhD in Marketing at the West University of Timișoara (Romania), as well as a postdoctoral research project at Babeș-Bolyai University of Cluj-Napoca (Romania) and Corvinus University of Budapest (Hungary). His research focuses on consumer behavior, brand loyalty, CSR, and methodological issues in PLS-SEM.

Mahendhiran S. Nair is Professor and Pro Vice-Chancellor (Research Engagement and Impact) at Sunway University. He is trained as an econometrician and data scientist. His expertise and research interests include data science; econometrics; behavioral economics; foresighting, science & technology policy modeling; planetary health; and sustainable development. He has been a subject matter expert for government agencies, public policy organizations and 'think-tanks' in Malaysia and regional economies. He has led to the formulation of several national economic & technology plans and studies for Malaysia.