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Run! This road has no ending! A systematic review of PLS-SEM application in strategic management research among developing nations

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A B S T R A C T

Partial least squares structural equation modelling (PLS-SEM) is emerging as a prominent methodological tool in strategic management research. Although it offers various advancements to stay relevant with growing research needs, the pace of PLS-SEM adoption may differ in different parts of the world. In this paper, we conducted a systematic review using the PRISMA framework and extracted from the top-ranking strategic management journals 120 articles published between 2011 and 2022 that presented a microscopic view on developing nations. Our findings reveal that despite the astounding methodological solutions offered by PLS-SEM, the studies from developing nations are still trailing behind developed nations in terms of fully exploiting the advancements of PLS-SEM to provide substantial insights to strategic management literature. This review identifies discrepancies in the current application of the method, discusses the most recent advancements and provides the best practices, standard guidelines and recommendations for the best use of PLS-SEM in strategic management research.

1. Introduction

Structural equation modelling (SEM) has constructively penetrated the world of scientific research for at least five decades now since the seminal work of Jöreskog [1]. This statistical analysis method was initially introduced to assess the consistency between the theoretical covariance matrix and the empirical covariance matrix. The approach, known as covariance-based SEM (CB-SEM), aims to minimise the differences between the proposed theoretical model and the data [1–3]. This method was complemented with an alternative modelling of variance-based partial least squares structural equation modelling (PLS-SEM) [4]. Unlike CB-SEM, which focuses on the model fit, PLS-SEM focuses on predicting and estimating the model and maximising the explained variance of the target construct [5,6].

Currently, the application of PLS-SEM has become prominent in numerous disciplines [7], including business and management

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studies [8,9]. The method has evolved extensively to support researchers with the latest analyses to stay relevant with their growing research needs. Although PLS-SEM software developers and renowned scholars are consistently contributing new advancements and guidelines, the studies that capture and track such evolution are slim pickings [10]. Only a few scholars have made a blue-chip contribution by conducting systematic reviews in certain subject areas to keep track with the developments.

In this line, two-high impact review studies in the area of marketing and strategic management [10,11] were published between the year 1981–2010. Apart from these, PLS-SEM reviews in the areas of management information systems [12], production and operation management [13] and accounting [14] were also conducted. Other studies reviewed the use of PLS-SEM in management accounting research [15], assessed the application of PLS-SEM in hospitality research [16] and focused their PLS-SEM reviews in human resource management [8] and the higher education sector [17]. Recently [18], contributed to the knowledge by extending the work of Hair et al. [10] in marketing research from 2011 to 2020. However, to date, no succeeding work has been found in the area of strategic management after the systematic assessment of [11].

The importance of PLS-SEM for strategic management research is well delineated in prior work [11]. The authors argued that strategic management studies are highly reliant on the PLS-SEM approach compared to the CB-SEM because research in this field are often centred on predicting and explaining variance of the key target construct and incorporating the analysis of formative constructs that are useful to explain certain dependent constructs [11]. Accordingly, the correct understanding of PLS-SEM principles, its application techniques and reporting is important to provide accurate conclusions and guide strategic decisions in organisations. However, Hair et al. [11] argued that PLS-SEM studies in the field of strategic management are lacking in terms of utilising the properties available in the PLS-SEM analysis method, regardless of its advanced features and evolution. Thus, we find it highly useful to conduct a systematic review to learn how the method has been applied in the strategic management literature as well as what the latest developments and gaps are to provide corrective measures based on the standard guidelines and best practices available.

As the initial systematic assessment of PLS-SEM [11] was conducted a decade ago, voluminous developments have taken place in recent years [18,19] and it is high time that a subsequent systematic review in the field of strategic management be conducted. Our review mainly focuses on the problematic use of PLS-SEM method in strategic management research, particularly in the context of developing nations, where we find that researchers generally do not fully utilise PLS-SEM capabilities [11,20] and at times misapply the method [11,21]. Thus, we review the relevant studies that have applied the PLS-SEM method and published in top-ranked strategic management journals for the period of 2011–2022. Our study is unique compared to existing literature reviews, as we particularly highlight the ununiformed distribution of PLS-SEM knowledge by zooming into the discrepancies in its application in the context of developing nations for some important reasons.

First, although the methodological guidelines of PLS-SEM are well established internationally, most of the advancements emerged from developed nations. Therefore, the maturation of PLS-SEM in developing nations often takes a different pace and requires more attention and guidance. Moreover, a quick search in the Web of Science (WoS) and Scopus databases of the top 10 journals in the strategic management area using 'PLS' and 'partial least squares' keywords showed that only 34 % (138 out of 405) of the studies were published from the developing nations. Hence, a systematic review among developing nations may help enlighten researchers from this region to gain benefits from the application of PLS-SEM and contribute more to strategic management literature. Thus, while assessing the state of the art of PLS-SEM application in strategic management literature, this study aims to ascertain if the method has been applied appropriately and whether the most recent advancements of PLS-SEM are deployed by researchers in developing nations. Based on the findings, best practices and standard guidelines are suggested for identified discrepancies in practice. Recommendations for the future application of PLS-SEM are also discussed, and the related resources are furnished to enhance rigor in the forthcoming research.

Although our study focuses on the strategic management field within the context of developing nations, this does not limit its contribution to an extended group of audience. The audience of this study may include a diversified academic community, such as researchers who are also users of PLS-SEM, various journal editors and reviewers, as well as PLS-SEM software developers and trainers. While strategic management researchers or PLS-SEM users from developing nations can understand their common mistakes and gain knowledge of the actual rules of thumb and advance developments in PLS-SEM, the editors and reviewers may understand the knowledge discrepancies and different phases of PLS-SEM knowledge distribution among researchers and thus provide more careful attention and guidance while reviewing their studies. Indeed, new reviewers may gain more familiarity with the PLS-SEM approach as this study provides a comprehensive guideline from the basic up to the advance developments of the PLS-SEM method with complete references and examples, which can also be useful in different fields and contexts. The developers and trainers, on the other hand, can focus more on the researchers and academics from developing regions for their teaching and promotion activities to allow a more uniformed knowledge distribution of PLS-SEM and enhance the quality of research across geographical contexts.

2. Review methodology

This systematic review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) protocol [22] to select and review the articles. The protocol is widely used in various disciplines, as its ability to increase the accuracy of the review and reduce researchers' biases is well acknowledged in the literature [23]. Appendix 1 illustrates the PRISMA framework adapted in this study.

2.1. Search strategy and selection criteria

As guided by PRISMA protocols, the scoping procedures were performed to extract the most relevant articles from the literature. As this review focuses on PLS-SEM application in the strategic management discipline, the relevant articles were selected from the top 10 strategic management journals based on the 2020 ranking by Google Scholars Metrics (see Appendix 2). These articles were mainly indexed in two reliable and eminent databases, WoS and Scopus, and thus the search process was limited within these databases.

The keywords used during the search process were 'PLS' OR 'partial least squares', which are basic words that could provide the broadest coverage of studies as long as the studies apply the PLS-SEM method. Meanwhile, the study was limited to the 2011–2022 period to extend the previous work [11] that covered strategic management research from 1981 to 2010. This yielded a total of 400 articles in the WoS database and 5 articles in Scopus within the pre-selected journals. Next, the selections were limited by countries to filter the articles published in developing nations. The identification of developing countries in this study followed the classification provided by the International Statistical Institute in 2021 (https://www.isi-web.org/resources/developing-countries). The document source and type were limited to journals and articles, and only those in English language were extracted. At this stage, the total articles accumulated were 137 from WoS and only 1 from Scopus, and all the articles were published in only 4 out of the 10 pre-selected journals. These records were exported to a Microsoft Excel file for a detailed quality assessment.

2.2. Quality assessment

This study only included original articles published in reputable journals to ascertain the best quality of findings. Based on the records saved in the Microsoft Excel file, the documents were downloaded and vetted carefully to remove duplicate or irrelevant studies. To avoid potential biases in the article selection process, the abstracts were read thoroughly, and in cases of ambiguity, the entire papers were reviewed before inclusion to ensure proper filtering of the documents. Upon filtering, 18 articles were removed due to substantial irrelevance. For example, articles stating PLS-SEM without applying the method, presenting new methods or scale development or comparing PLS-SEM with other methods using simulation studies were excluded from the review [18]. This leaves 120 articles for inclusion in the review, as illustrated in the PRISMA framework in Appendix 1.

2.3. Eligibility and inclusion

As explained in the preceding section, a total of 120 articles were found eligible and thus included for qualitative synthesis. These articles complied with the inclusion criteria as outlined in Table 1.

These articles (see Appendix 3) represent an overall state of the art of PLS-SEM application in strategic management studies from the lens of developing nations, consistent with the aim of this study.

2.4. Qualitative synthesis

Upon the article selection was finalised in a Microsoft Excel file, descriptive analysis was carried out to understand the major trends of the publications in terms of distribution by year, source title and contributing countries. Subsequently, the articles and models were assessed on the basis of six criteria rooted from the previous review [11] in strategic management research. These criteria include (1) reasons for using PLS-SEM, (2) data characteristics, (3) model characteristics, (4) model evaluation, (5) advanced modelling and analysis techniques and (6) reporting. However, our systematic review is not the exact continuation of the work of Hair et al. [10] in terms of the journal selection because the ranking of strategic management journals changes over time. Based on the findings from our review, rooms for improvements were identified and best practices for future strategic management studies were recommended.

3. Analysis result and discussion

3.1. Descriptive analysis

The descriptive analysis result of all the 120 articles provided a comprehensive overview of PLS-SEM application in strategic management studies, particularly in the context of developing nations. The distribution of studies is presented by publishing year, source title and contributing country. Fig. 1 illustrates the number of publications by year. Overall, within a time frame of 12 years (2011–2022), the number of publications reflects an increasing trend, especially from 2018 to 2021. This trend indicates a strong adoption and movement towards the maturation of PLS-SEM in developing nations. The fall in 2022 is considered negligible as this study only captured publications until February 5, 2022.

Table 1
Eligibility and inclusion criteria.

Eligibility and Inclusion Criteria	
a.	Original articles published in journals
b.	Classified in the area of strategic management
c.	Applied the PLS-SEM approach in empirical investigation
d.	Published in the WoS or Scopus database
e.	Published within 2011–2022 (cut-off date: February 5, 2022)
f.	Authored by researchers affiliated in developing countries
g.	Published in the English language

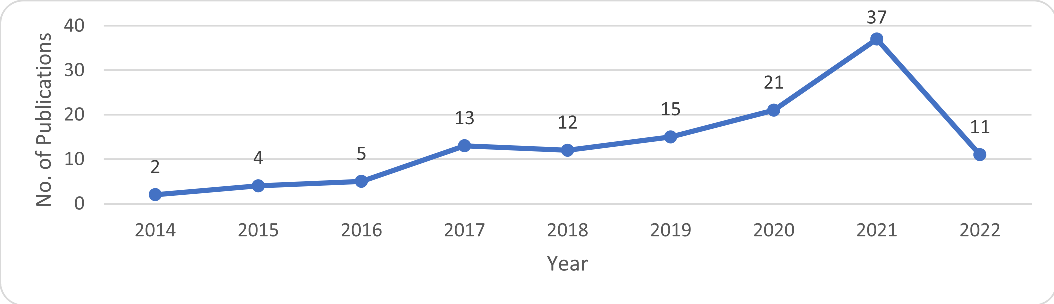

Fig. 1. Distribution of publications by year.

Next, the distribution of studies was divided into four top-ranking journals in the strategic management discipline as shown in Fig. 2. Despite the inclusion of all top 10 journals in the search list, only four journals included publications from developing nations. Among these journals, *Journal of Retailing and Consumer Services* (60 publications, 50 %) was the most preferred journal by strategic management researchers from developing nations.

The distribution of strategic management studies applying PLS-SEM by nation is depicted in Appendix 4. The top three productive nations in the context of the developing world for the theme under review are Malaysia (21 studies, 17.50 %), followed by China (19 studies, 15.83 %) and then India (17 studies, 14.17 %). The high number of publications in Malaysia shows that PLS-SEM is one of the most preferred methodological approaches among researchers in the country.

3.2. *Analysis result and discussion on the PLS-SEM application*

The six criteria explained in Section 2.4 represent the pillars of the state of the art of PLS-SEM use in the strategic management field, with a focus on developing nations. The present subsection will discuss each of the criteria based on the findings of 120 articles reviewed. Points of concerns are highlighted for the discrepancies found, and recommendations are provided based on the standard guidelines and best practices of PLS-SEM, as consolidated from the top publications.

3.2.1. *Reasons for using PLS-SEM*

Researchers are typically required to justify their reason for selecting the PLS-SEM analysis method over CB-SEM in publications [24]. Our review indicates that a majority of the articles (i.e. 95 out of 120 articles, 79.16 %) reported explicitly their rationale for selecting the PLS-SEM method in their studies. Table 2 presents the frequencies and percentages for each reason mentioned.

An important point of concern in this finding is that the studies mainly mentioned non-normal distribution of data and small sample size as the reasons for using PLS-SEM. Although PLS-SEM is more lenient in working with non-normal data, given that the algorithm is able to align non-normal data with the central limit theorem, this characteristic is insufficient to be cited as a primary justification for selecting the method over CB-SEM [25]. This is because highly skewed data can inflate the standard errors from bootstrapping, which may affect the significance of the model parameters [26].

In addition, a small sample size is a disadvantage for all types of statistical methods and PLS-SEM, as no other multivariate method can provide valid estimations using a non-representative sample [7]. According to Rigdon [27], a smaller sample size can only be considered based on the population's nature, for instance, in the situation where the population size is small. Indeed, a larger sample size is essential when the population is more heterogeneous in nature [28]. Thus, researchers should not take advantage of PLS-SEM's ability to work well with smaller samples when the population is large and easily accessible [5]. In fact, using a smaller sample size without a proper power analysis may produce a questionable and invalid result [26]. Scholars in strategic management field should be

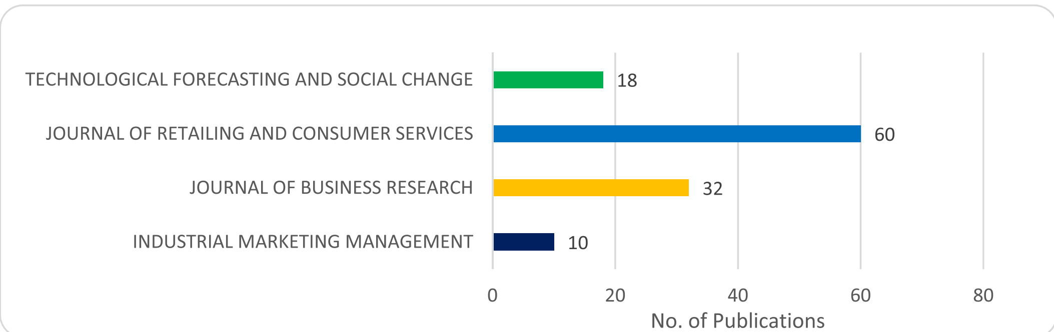

Fig. 2. Distribution of publications by journal.

Table 2
Reasons for using PLS-SEM.

Reason for using PLS-SEM	Number of Studies	Percentage (%)
Total number of studies reporting the reasons for using PLS-SEM	95	79.16
Reason reported		
1. Non-normal distribution of data	60	50.00
2. Small sample size	47	39.17
3. Theory development/exploratory research	44	36.67
4. Explanation/prediction-oriented	43	35.83
5. Model complexity	40	33.33
6. Formative measurement	19	15.83
7. Higher-order constructs	16	13.33
8. Mediation & moderation in a single model	9	7.50
9. Other reasons	18	15.00

Note: The total percentage exceeds 100 % as several studies mentioned multiple reasons for applying PLS-SEM.

more mindful of this point when justifying the reason for using PLS-SEM in their research.

A good point that can be observed in this finding is the use of several integral reasons for selecting PLS-SEM. For example, more than one-third of the researchers stated theory development/exploratory research, prediction-orientation and model complexity as their main reasons for using PLS-SEM. This result indicates that some researchers from developing countries within the strategic management discipline are aware of the calls from top PLS-SEM scholars to depart from data characteristics and focus on research aims and model complexity to rationalise the use of PLS-SEM [26,29]. However, only a small number of strategic management studies in developing nations have emphasised the inclusion of formative measurements, higher-order constructs (HOCs), analysis of mediation and moderation in a single model as the reasons for using PLS-SEM, which also represent adequate justifications for using PLS-SEM [18].

While accepting the above justifications, we strongly reject the reason given by several researchers that PLS-SEM is used due to its ability to test the measurement and structural models simultaneously. This justification requires correction because the capacity to test the measurement and structural models simultaneously should not be attributed to PLS-SEM alone but to the SEM as a whole [6,17]. With the reasons for using PLS-SEM now discussed, the following subsection proceeds with the discussion on data characteristics.

3.2.2. Data characteristics

All 177 models (100 %) presented in the reviewed studies documented the sample size used. As discussed in the prior subsection, several studies cited small sample size to justify the use of PLS-SEM. Accordingly, there were models with less than 100 samples (34 models, 28.33 %) in the reviewed articles, and the smallest sample size observed was as low as 36 samples. While PLS-SEM is technically more robust than CB-SEM in estimating models with small sample sizes, a larger sample is necessary to represent the population and minimise the standard errors [26,30]. Thus, a power analysis that takes into account the model complexity, data characteristics, expected significance level and effect size should be employed to make sample size decisions [26]. Unfortunately, only a small number of strategic management studies in developing nations (29 studies, 24.17 %) have reported the use of statistical power analysis in their research. Among the frequently used guidelines (12 studies, 10 %) is the ten times rule [31], which is criticised for providing a very rough estimation of the minimum sample size without considering important factors such as effect size, reliability and model complexity, all of which may impact the statistical power [7,32]. The rest of the studies used G*power application (7 studies, 5.83 %), specifically 2 studies (1.67 %) each for Kock and Hadaya [33] and Krejcie and Morgan [34] and 1 study (0.83 %) each for Green [35], Malhotra et al. [36] and Hinkin [37].

The lack of studies reporting statistical power analysis portrays a poor sampling design that requires serious attention. Hence, researchers are suggested to use appropriate sampling guidelines and power analysis to determine the minimum sample size requirements for achieving an accurate result. A further reading of Hair et al. [7] will be helpful for understanding the statistical power requirements.

Subsequently, our review indicated that only 16 studies (13.13 %) mentioned the multivariate non-normality of the data, although initially half of the studies (60 studies, 50.00 %) pointed at the non-normal distribution of data to justify the use of PLS-SEM. Of those 16 studies, only 13 (10.83 %) reported the skewness and kurtosis values of the data. Given such deficiencies in the finding, researchers are proposed to compute the multivariate normality of the data using WebPower software, which is available online at https://webpower.psychstat.org/models/kurtosis/, and report the values accordingly.

Another point of concern is that most of the strategic management studies in developing countries did not report the missing values, the patterns of missing values and the remedies applied. Only 21 studies (17.5 %) mentioned missing values, out of which 16 studies (13.33 %) included the choice of remedies used. More than half of these studies (9 studies, 7.50 %) took quick action by removing the missing data from their analysis. Grimm and Wagner [38] state that a case-wise deletion of 9 % is acceptable in PLS-SEM as long as the pattern of the missing values is not systematic. However, since such data are unavailable in the reviewed studies, further comments could not be provided if the deletion of missing data is a wise decision. Apart from deleting the missing data, other studies performed mean value replacement (4 studies, 3.33 %), expectation maximisation (2 studies, 1.67 %) and imputation using a neighbourhood approach (1 study, 0.83 %) [39].

In dealing with missing values, we highly encourage strategic management researchers to follow the recommendation of established scholars to use mean value replacement (i.e. when the missing data per indicator is below 5 %). In other cases, maximum likelihood or multiple imputation procedures are good options to utilise [7,18]. Other than missing data, extreme outliers are also capable of affecting ordinary least square regressions in PLS-SEM.

Therefore, researchers have to handle outliers attentively. Outliers can fall into three different categories [40]: error outliers, interesting outliers and influential outliers. A thorough check to detect influential outliers and the appropriate treatments is necessary to ensure a valid result. Our review reveals that the awareness among strategic management researchers in developing countries is very low, as only three researchers (2.5 %) mentioned outliers in their studies. Even worse, none of them reported if the outliers are random, non-random, influential or non-influential and how these were handled. Thus, we strongly suggest that researchers gain more understanding of outliers by referring to the resources from prominent scholars (e.g. Refs. [40–42]. With the completion of a thorough discussion about data characteristics, the next subsection centres its attention on the model characteristics.

3.3. Model characteristic

Our findings disclosed that an average number of 6.94 latent variables and 30.50 indicators per model were included in the strategic management studies in developing countries. These numbers are almost similar to the findings of PLS-SEM reviews in other disciplines. For instance, the average number of latent variables and indicators reported in marketing research [18] were 7.39 and 29.55, respectively, and in the field of human resource management [8], these were 7.8 and 34.97, respectively. A PLS-SEM review conducted in hospitality research [16] also indicated around the same range of average values (7.03 for latent variables and 24.69 for the indicators).

In the current review, the average number of structural paths is 10.51, which is also not very far from the result of PLS-SEM review in other disciplines (e.g. marketing research: 11.90, human resource management: 8.76, and hospitality research: 8.00). In sum, these values stipulate that the model complexity in the strategic management discipline, especially in the context of developing nations, is generally at par with other disciplines. To be more precise, the exact values are slightly higher than those in human resources management and hospitality research and closest to those in marketing.

PLS-SEM models may include both formative and reflective measurements, which are computed as composites from the linear combinations for indicators. Formative measurement models are estimated using regression weights, and the arrows point from the indicators to the latent variable. In contrast, reflective models are estimated on the basis of correlation weights, where the arrows point out from the construct to the indicators. Thus, any changes to the construct will be reflected in the indicators [43,44]. Our review finds that the majority of the studies (76 studies, 63.33 %) did not report the model specifications. Of the 44 studies that mentioned the type of measurement model used, 23 (36.67 %) reported the use of reflective measurement models, and rest stated that reflective and formative measurements were used in combination.

Given the whole arguments on measurement model misspecifications [45,46], scholars in the strategic management field should be more alert regarding this matter to avoid content validity issues. As both reflective and formative measurements stand on different sets of theoretical perspectives and indicators [47], the measurement models should be specified clearly. Failure to do so will result in misspecification assertions because each model involves different measurement criteria for assessment [26].

As far as this review is concerned, none of the studies used single-item constructs in the research models, except for the control variables. This reflects a good awareness among the researchers regarding the limitations in exploratory power of single-item measures, which tends to cause Type II errors [48]. Cheah et al. [49] reiterated that single items are only appropriate for measuring observable characteristics that often take the form of control variables. This view is consistent with the current practice of strategic management researchers from developing nations. With such impression, the next discussion focuses on the model evaluation.

3.4. Model evaluation

Model evaluation in PLS-SEM involves a two-step approach, namely the assessment of the measurement model and the structural model [24]. Measurement model assessment is conducted to ascertain the psychometric qualities of construct measurements. The

Table 3
Measurement model evaluation: Reflective model.

Criteria	Index	Threshold	References
Internal consistency	Composite reliability (CR) - upper bound of internal consistency reliability Cronbach's alpha (CA) - lower bound of internal consistency reliability Rho_A – between the upper and lower bounds (the best estimate)	Thresholds of all reliability measures: ≥0.70 (≥0.60 in exploratory research) Recommended: 0.80–0.90. Value > 0.95 may cause indicator redundancy and impact content validity	[7] [7,51,52]
Reflective indicator reliability	Indicator loadings	Loading >0.708 is recommended, but loading >0.70, 0.6, 0.5 or 0.4 is adequate if other items have high scores of loadings to complement AVE and CR	[7,21,54]
Convergent validity	Average variance extracted (AVE)	AVE ≥0.50	[7]
Discriminant validity	HTMT	HTMT <0.90 for conceptually similar constructs; HTMT <0.85 for conceptually different constructs Test whether HTMT is significantly lower than the threshold value	[7,55,56]

criteria used to assess measurement model differ depending on the type of construct (i.e. reflective or formative), as discussed in the previous subsection.

3.4.1. Assessment of reflective measurement model

Although a huge number of strategic management studies (76 studies, 63.33 %) did not directly report the type of measurement models used, the criteria for measuring measurement models were presented well in the studies. The standard criteria for assessing reflective measurement models are illustrated in Table 3. Reflective measurement involves measuring indicator reliability, internal consistency reliability and convergent validity. The matrices and cut-off points to confirm these criteria are shown in Table 3.

Our review shows that almost all the models (172 of the total 177 models, 98.29 %) reported the indicator loadings to affirm indicator reliability. A combination of Cronbach's alpha and composite reliability (CR) was the most used (109 models, 90.83 %) index, whereas the combination of Cronbach's alpha and rho_A was the least used index (1 model, 0.83 %). Subsequently, for convergent reliability, a total of 152 models (85.88 %) indicated the average variance extracted (AVE) values. Finally, for the discriminant validity checks, the studies generally referred to the Fornell-Larcker criterion [50], cross loading and Heterotrait-Monotrait (HTMT) values. The findings indicated that more than half of the models (68 models, 56.67 %) relied on the Fornell-Larcker criterion for discriminant validity assessments, while cross loadings deemed to be the least preferred criterion. The findings are summarised in Table 4.

Based on the above findings, there are several points to highlight for the reference of future strategic management researchers in developing countries. Firstly, although Cronbach's alpha is a popular measure of inter-correlation between the indicators for the estimation of reliability, there are some disparities in using it. This is because the measure assumes equal factor scores among the indicators [57] and is sensitive to the number of items in the construct [58]. CR is an alternative measure to Cronbach's alpha that considers the loadings of each indicator. While Cronbach's alpha represents the lower bound of the actual internal consistency reliability, CR represents the upper bound of it. Thus, Dijkstra [51] and Dijkstra and Henseler [52] recommended the use of rho_A, which takes the true value in between the lower and upper bounds as the best point and consistent measure of internal consistency reliability [7]. Even so, researchers should be aware that rho_A is only appropriate when a common factor model is assumed and a consistent partial least square is used for the model estimation [52,53].

Secondly, the extensive use of the Fornell-Larcker criterion also raises concern as it has heavily been criticised for its inappropriateness in detecting discriminant validity [6]. Alternatively [56], introduced a new method known as HTMT ratio of correlations to measure discriminant validity. Other scholars in PLS-SEM literature have also affirmed the superiority of this new method in measuring discriminant validity (e.g. Refs. [55,59]). Researchers should be aware that there are two ways to use HTMT: (1) by performing bootstrapping to check if the values exceed HTMT 0.85 for similar concepts and HTMT 0.90 for dissimilar concepts and (2) by checking if the confidence intervals of HTMT for the structural paths include the value of 1. Lastly, HTMT2 was suggested as a more advanced approach for its ability to provide a more precise estimation when loadings of the indicators are heterogeneous [60]. This advancement expands the choices available for strategic management researchers in developing countries to measure the discriminant validity of constructs.

3.4.2. Assessment of the formative measurement model

The distinction between reflective and formative models relies on their conceptual differences, which require different criteria for measurement. Formative constructs are measured on the basis of convergent validity, indicator collinearity, statistical significance and relevance of the indicators' weights [24]. The cut-off values for each criterion are presented in Table 5. Convergent validity is assessed through redundancy analysis, which is performed by correlating a formative construct with a single global item or a reflective

Table 4
Findings on the reflective measurement model assessment.

	Assessment Criteria in PLS-SEM	Number of Models Reporting	Percentage Reporting
Indicator reliability	Indicator loadings	172	98.29 %
Internal consistency	Cronbach's alpha	3	2.5 %
	Composite reliability	44	36.67 %
	Rho A	–	
	Cronbach's alpha & Composite Reliability	109	90.83 %
	Cronbach's alpha & Rho A	1	0.83 %
	Composite reliability & Rho A	2	1.67 %
	All three	13	10.83 %
Convergent validity	AVE	152	
	Others	–	
Discriminant validity	Fornell-Larcker (FL)	68	56.67 %
	Cross loadings	3	2.5 %
	HTMT	39	32.5 %
	FL & Cross loading	14	11.67 %
	FL & HTMT	34	28.33 %
	Cross loading & HTMT	2	1.67 %
	All three	14	11.67 %

Note: Percentage (%) is computed using all 177 models, though HTMT was only introduced in 2015.

construct that measures the same concept. This procedure requires the alternative measurement to be included in the questionnaire [62]. The data collected are then used to examine the correlation between the same construct measured formatively (exogenous construct) and reflectively (endogenous construct) [6,49,62]. A correlation of 0.70 or higher, or at the minimum, a statistically significant relationship between the constructs, confirms convergent validity of the formative measurement model [61]. Among the 21 models (11.86 %) that specified the incorporation of formatively measured constructs, only 13 models (7.34 %) conducted redundancy analysis. Hence, we propose that strategic management researchers in developing nations should be more alert with the needs to conduct redundancy analysis and that the initiatives should be started from the design process.

Next, for the collinearity assessment, studies in the strategic management field in developing nations indicated a satisfactory understanding regarding the need to evaluate the variance inflation factor (VIF) when using a formative measurement model. A total of 18 from the 21 (10.17 %) studies reported VIF values for formative measurement. Finally, for the need to assess the significance and relevance of the indicators' weights, all the 21 models indicated a great familiarity by reporting the result. Indicator weight resembles the relative contribution of each item to its construct. In the absence of relative contribution, researchers should shift their focus to the absolute contribution, which is represented by the indicator's loading in order to remain an item in the measurement model. Since all the weights were significant in the models reviewed, there was no need to analyse the indicators' loadings to confirm their absolute contribution to the construct [7].

Overall, our review of the formative model assessment suggests that strategic management researchers from developing nations are well aware of the criteria applied for formative model assessment. However, more serious attention should be given to convergent validity (i.e. redundancy analysis) in future research as there is room for improvement. The findings on the formative measurement model from the review are summarised in Table 6.

3.4.3. Structural model

Upon completion of the review of measurement model, the next focus was on the structural model. Structural model involves the relationship between latent variables, which establishes the explanatory and predictive power of the model [6]. Table 7 illustrates the important indices for structural model assessment, and Table 8 presents our findings.

The assessment of the structural model begins with an examination of the potential prediction–criterion collinearity issue that may adversely influence the findings [63]. Our review of the strategic management studies in developing countries stipulated a critical deficiency at this stage, as only 53 of the 177 models (29.94 %) reported the findings. Thus, we admonish strategic management researchers to be seriously concerned about potential collinearity issues because the lateral collinearity may mislead the causal effect of the model [6].

Conversely, for path coefficients, the researchers have shown a perfect awareness as all the 177 models (100 %) presented path coefficients of the structural model in their analysis result. Almost all the models have also indicated the significance of the path coefficients (174 models, 98.31 %). Apart from that, the majority of models (158 models, 89.27 %) specified R^2 values, which indicate the explanatory power of the model. R^2 values are also known as the in-sample predictive power of a model. The amount of change in R^2 value due to the omission of an exogenous construct refers the effect size (f^2). Only less than half of the models (77 models, 43.5 %) reported the f^2 values. Nevertheless, this is not a serious concern, as scholars have recently argued that reporting f^2 values is optional because the value is redundant with the path coefficient in explaining the relative importance of an exogenous construct [7].

While R^2 and f^2 resemble in-sample prediction (i.e. explanatory power), out-of-sample prediction is computed using blindfolding based on Q^2 or PLS-predict. Blindfolding refers to a resampling technique that removes and predicts every data point of the indicators of the endogenous construct [64]. A total of 81 models (45.76 %) reported Q^2 values. Instead of reporting Q^2 values and its relative predictive effect, q^2 values, to demonstrate the predictive power of a model, we encourage strategic management researchers in developing nations to move beyond using the hold-out sample procedure. This is because the blindfolding technique is criticised for omitting and computing only the omitted data points rather than the entire case, and so the sample structure remains unchanged in its computation [64,65]. On the contrary, PLS-predict uses hold-out samples to provide a case-level prediction using parameter estimates from training samples [65].

The present review observed an inadequate exposure of the PLS-predict approach among strategic management researchers in developing countries, with only 19 models (10.73 %) having included the procedure. We suggest that strategic management

Table 5
Measurement model evaluation: Formative model.

Criteria	Index	Threshold	References
Convergent validity	Redundancy analysis	Correlation between a global single-item (or a reflectively measured multi-item scale) measuring same construct ≥0.70	Cheah et al. (2018); Chin, (1998)
Collinearity	Variance Inflation Factor (VIF)	VIF≤3: no collinearity issues VIF 3–5: collinearity issues are uncritical VIF ≥5: critical collinearity issues	Hair et al. (2022)
Indicator weights		Indicator weights are significant if the (i) t-values are greater than 2.576 (α = 0.01), 1.960 (α = 0.05), or 1.645 (α = 0.10) respectively (two-tailed) (ii) The 95 % percentile or bias-corrected confidence interval (α = 0.05) does not include zero	Aguirre-Urreta & Rönkkö (2018); Hair et al. (2022)
Indicator loadings of nonsignificant weights.		Loadings ≥0.5 and statistically significant	Hair et al. (2022)

Table 6
Findings on the formative measurement model assessment.

Criteria	Assessment Criteria in PLS-SEM	Number of Models Reporting	Percentage Reporting
Convergent validity	Redundancy analysis	13	7.34 %
Collinearity among indicators	Variance inflation factor	18	10.17 %
Significance and relevance of outer weights	Statistical significance of weights	21	11.86 %

Note: Only 21 from the total of 177 models explicitly specified the inclusion of formative constructs in the model. However, 177 models were used as the base for percentage computations.

Table 7
Structural model evaluation.

Criteria	Index	Threshold	Reference
Collinearity	Variance inflation factor (VIF)	VIF≤3: no collinearity issues VIF 3–5: uncritical collinearity issues VIF ≥5: critical collinearity issues	[7]
Path coefficients	Significance and relevance of the path coefficients	Path coefficients are significant when (i) t-values are greater than 2.576 ($\alpha = 0.01$), 1.960 ($\alpha = 0.05$) or 1.645 ($\alpha = 0.10$) (two-tailed), OR t-values are greater than 2.33 ($\alpha = 0.01$), 1.645 ($\alpha = 0.05$) or 1.28 ($\alpha = 0.10$) (one-tailed). (ii) The 95 % percentile or bias-corrected confidence interval ($\alpha = 0.05$) does not straddle a 0. Additionally, f^2 values can be assessed to compare with the path coefficient and check if the rank orders are the same.	[7,72]
Explanatory power	R^2	R^2 values depend on the model complexity and the context of the research. A very high R^2 value such as 0.90 indicates that the model overfits the data. Several available thresholds are as follows: 0.26 – substantial 0.13 – moderate 0.02 – weak 0.67 – substantial 0.33 – moderate 0.19 – weak 0.75 – substantial 0.50 – moderate 0.25 – weak	[26] [73] [62] [7]
Predictive power	$PLS_{predict}$	Prediction errors (RMSE or MAE) produced by PLS-SEM are lower than LM for the following: (i) All the indicators (high predictive power) (ii) Majority or the same numbers of indicators (medium predictive power) (iii) Minority of the indicators (low predictive power) (iv) None of the indicators (no predictive power)	[65,74]

Table 8
Findings on the structural model assessment.

Quality Criteria	Assessment Criteria in PLS-SEM	Number of Models Reporting	Percentage Reporting
Collinearity issues	VIF	53	29.94 %
Path coefficients	β values	177	100 %
Significance of path coefficient	P values/T values/confidence intervals	174	98.31 %
Explanatory power	R^2	153	89.27 %
Effect size	f^2	77	43.5 %
Predictive relevance (Blindfolding)	Q^2	81	45.76 %
Predictive power	PLS-predict	19	10.73 %
Model fit	GoF/SRMR/dG/d-ULS/X^2/NFI/CFI/RMSEA/TLI	47	26.55 %

researchers explore PLS-predict method with the recent guidelines offered [65] for a decisive examination of the predictive power of their models.

Based on the review, more than a quarter of the models (47 models, 26.55 %) included model fit estimation in their analysis result. We emphasise that strategic management researchers are aware of the different meanings of the term "fit" in the contexts of CB-SEM and PLS-SEM. This is necessary as the fit statistic in CB-SEM focuses on the difference between the empirical and theoretical covariance matrix. Meanwhile, in PLS-SEM, the focus is on the differences between values of the endogenous variables and the model predicted values [6,66]. Additionally, certain model fit measures are meant for a common factor model because they assume uncorrelated outer residuals, which is inapplicable for composite models [67]. Therefore, there is an on-going debate whether model fits are meaningful in the PLS-SEM model.

Despite the gigantic criticism from prominent scholars [7,67] on the deficiencies of the use of model fits in PLS-SEM, another stream of scholars are strongly promoting its use [68,69]. We affiliate with the current practice of strategic management studies in developing nations that do not show much interest in model fit matrices, as only 26.55 % of the models included such matrices in the report. Most of those models opted for SRMR (32 of the 47 models, 18.07 %) and GOF (14 models, 7.91 %) rather than other matrices of model fit. At this point, we encourage the researchers to check out the larger sample size requirement on the basis of model complexity [7,70] to use SRMR and review the appropriateness of this matrix to their models.

Delving deeper into reviewing the strategic management studies in developing nations, we found a practice of combining CB-SEM (to obtain fit indices) and PLS-SEM (to examine for a structural model) in a single analysis. This practice is alarming, and such researchers certainly need to overhaul their understanding of the fundamental differences underlying CB-SEM and PLS-SEM approaches. CB-SEM statistically models constructs as common factors, while PLS-SEM models them as composite factors [71]; hence, combining both in a single analysis is unreasonable. A careful reading of [20,66] may help in creating awareness of the basic differences and rules of thumb involved in using the approaches.

3.5. Advance PLS-SEM modelling and analysis

With its remarkable momentum of dispersion, PLS-SEM offers an on-going refinement and advancement to analysis techniques to further improve validity, reduce bias and address more complex modelling [18,25]. In general, strategic management researchers in developing countries are still lagging in terms of utilising the advance analysis available in PLS-SEM. For instance, among the studies reviewed, only 21 studies (17.50 %) applied multi-group analysis (MGA). MGA is used to treat observed heterogeneity (i.e. a prior known difference) across groups in the population [75]. Although the attempt to use this technique is promising, our review showed a severe problem, as only 10 studies out of those that applied MGA tested for measurement invariance (MICOM), while the others failed perform the procedure. MICOM is an essential procedure [76] to confirm that the distinctions in the group-specific results do not arise from the differences in the construct or group-specific response patterns [26,77]. Thus, researchers are strongly urged to comply with this procedure when applying MGA.

While observed heterogeneity can be addressed using moderators, unobserved heterogeneity requires latent class analysis, in which finite-mixture (FIMIX) PLS is the most commonly used technique. Besides identifying heterogeneity, FIMIX-PLS can stipulate an appropriate number of segments that can be extracted from the data [78]. In the current context of strategic management research among developing nations, only 4 studies (3.33 %) applied FIMIX-PLS, one of which extended the procedure with PLS prediction-oriented segmentation (PLS-POS). The minimal usage of these techniques reveals a lack of awareness among the researchers about latent class procedures and their advantages in augmenting the validity of results.

Researchers have to understand that a homogenous population rarely exists because perceptions, attitudes and behaviours vary among individuals [79]. Thus, to ensure the validity of the findings, handling unobserved heterogeneity is highly essential in research. We suggest that researchers refer to Ref. [80] and master the novel techniques such as FIMIX-PLS, generic algorithm and hill-climbing to effectively handle unobserved heterogeneity in research. Researchers should take note that although FIMIX-PLS is a popular method for this purpose, it has some limitation in determining the segment structure defined by the group-specific path coefficients [81]. This limitation is more assailable when formative models are included. Given such limitation, prior scholars recommended using FIMIX-PLS jointly with other latent class techniques such as PLS-POS [82] to recover the segment structure or segment-specific parameters.

Next, almost one-third of the studies (37 studies, 30.83 %) included HOCs in the research. Nearly all these studies used second-order constructs except for one (0.83 %), which included a third-order construct. Among the issues found in these studies are the misstep to report measurement specifications, the techniques used and the failure to meet the evaluation criteria, especially for formative measures, and misinterpreting the relationship between the first- and second-order constructs as structural relationships. These severe deficiencies made the findings of the studies questionable. Hence, we remind strategic management researchers in developing nations to re-explore the techniques, procedures and requirements involved in the use of HOCs. Without a proper grasp of the procedures, the application of HOCs will only end up with sophisticated-looking research that do not have rigor. Sarstedt et al. [83] provides the most recent guidelines on the requirements of HOCs for users' reference.

Our review of strategic management research uncovered that a small number of studies (4 studies, 3.33 %) extended PLS-SEM analysis to include fuzzy-set qualitative comparative analysis (fsQCA). FsQCA is an asymmetric modelling that explains all the possible combinations of predictors that may produce the expected outcome [84]. It focuses on the combined effects of the predictors instead of the net effects on the basis of a configuration theory paradigm that allows the examination of multiple nonlinear relationships. The researchers' use of such complementary techniques with PLS-SEM is commendable. However, the recent trend in the literature has leaped ahead to use the necessary condition analysis (NCA), which identifies the extent of necessary conditions required to achieve a desired level of outcome [85,86]. We encourage the researchers to explore this method to further enrich their research findings in the future.

Following that, we found that an exiguous number of studies in our review dealt with endogeneity analysis (2 studies, 1.67 %) and nonlinearity effect (1 study, 0.83 %). Generally, endogeneity is a problem caused by the correlation of an error term with predictors and a dependent variable in the regression model, breaching the causal assumption of regression analysis [87]. The most appropriate way of addressing endogeneity is to specify the model accurately and use the experimental design. As this is not possible in every situation, researchers in the marketing field have proposed the use of the Gaussian copula approach to handle endogeneity [88,89]. It is promising to observe that one of the strategic management studies in developing nations applied the Gaussian copula approach to deal with the endogeneity issue. We recommend that other researchers who intend to address the endogeneity problem adopt this emerging method in their research.

The knowledge expansion among researchers in developing nations on handling nonlinear relationship is also important as there is growing interest in the strategic management field to understand curvilinear relationship effects (i.e. in U-shape & inverted-U-shape) [90]. Our review revealed that the examination of nonlinear relationships is almost non-existent as there is only one study involving such relationships, which also ended at using the Ramsey RESET [91] as there was no nonlinear effect identified. Therefore, researchers in the strategic management field have a huge unexplored room for future studies in this area.

Another interesting finding from our review is the application of a novel approach that uses PLS-SEM conjointly with artificial neural network analysis (SEM-ANN) [92–94]. This combination complements the limitations of both methods. ANN can be used to predict nonlinear relationships using non-compensatory models without a need for multivariate assumptions. Although ANN is unsuitable for hypothesis testing, it can be applied to test the predictive power of the significant antecedents identified by PLS-SEM with high accuracy by using sensitivity analysis. Since there is only one study (0.83 %) among those reviewed that applied this approach, we call for more researchers in the field of strategic management to explore the combination of PLS-SEM and ANN for further generalisation of the method.

Our review also observed a sparse number of studies applying other advanced analysis techniques in PLS-SEM, such as moderated mediation (4 studies, 3.33 %), serial mediation (3 studies, 2.5 %) and moderated serial mediation (1 study, 0.83 %) in PLS-SEM. The limited number of studies utilising such analyses implies the limited exposure and practice of those analyses among strategic management researchers in developing countries. Hence, a thorough reading of related studies [29,95,96] is highly recommended to encourage the application of such analyses.

Overall, an eagle's eye view of the strategic management studies from developing nations indicates a huge room for refinement and advancement. This condition is not limited to exploiting the novel PLS-SEM approaches but also at applying them correctly using the appropriate procedures and rules of thumb. As the application of PLS-SEM advance methods is still at a nascent stage in developing nations, we strongly suggest that researchers explore other advanced analyses, such as model comparison, which is extensively used in other fields (e.g. marketing) (see Refs. [97–99]. Indeed, the recent advancement towards the cross-validated predictive ability test [100] also opens up more opportunities for greater interpretations. Additionally, untraveled advancements such as longitudinal data analysis [101], reciprocal relationship assessment [102,103], NCA [85,86], agent-based simulation [104], weighted PLS-SEM [95,105] and full latent growth modelling [102,106,107] unfold the new areas for expansion of strategic management studies. A list of advanced PLS-SEM modelling and analysis techniques with the corresponding references are exhibited in Appendix 5.

3.6. Reporting

With the indicator-level and construct-level correlation matrices discussed in Section 3.4, the present section focuses on the reporting of computational options, settings and software applications of the studies. The practices of reporting among the strategic management researchers in developing nations show a need for improvement in a number of aspects. Firstly, only 3 studies (2.50 %) reported the algorithm settings applied in the research. As for computational options such as weights, schemes and the maximum number of iterations, only 2 studies (1.67 %) reported them explicitly.

Subsequently, for bootstrapping settings, only 27 studies (22.50 %) reported whether they chose a one-tailed or two-tailed testing. Following that, 35 studies (29.17 %) reported the bootstrap confidence intervals used, and only 11 studies (9.17 %) reported the applications of the sign change option. In contrast, a substantial number of studies (80 studies, 66.67 %) reported the size of the bootstrap samples used. In a similar trend, over three-quarters of the studies (91 studies, 75.83 %) reported the significance level used in the bootstrapping procedure.

Although the differences in algorithm settings do not impose a significant change in the findings, this is not the case for bootstrapping setting [18]. Hence, we urge the researchers to report the bootstrapping settings completely. Prior scholars [108] revealed that sign change options may lead to Type 1 error. The necessity to use large bootstrapping subsamples and the type of bootstrap confidence interval are also highlighted by Streukens and Leroi-Werelds [109], which we recommend researchers refer to for further reading to close the gaps in reporting in future research.

Researchers should explicitly specify the software used to estimate the models. The review reflected a promising finding given that a large number of studies (106 studies, 88.33 %) reported the software used in the study. SmartPLS was deemed the most popular software among strategic management researchers in developing nations, with 96 out of the 106 studies (80.00 %) having applied the software to perform analyses. Only less than 5 % (5 studies) applied WarpPLS, followed by less than 2 % (2 studies) using ADANCO and XLSTAT, respectively, and only a single study (0.83 %) using the PLS package of R software. To keep up with the latest developments about software, we suggest that strategic management researchers look into new software such as cSEM [110] and SEMinR [111], which were developed for the R statistical environment to provide more user-friendly and costless options.

As transparent reporting is essential for the replicability of a study, we prompt the researchers to ensure a comprehensive reporting of the methods, procedures, settings and options they have used, which may influence the research findings. In this vein, several scholars [8,11,18] have repeatedly called for the inclusion of a correlation matrix of the indicators and the constructs in the reporting. Strategic management studies in developing countries partly comply with this, as the majority of the models (128 of the 177 models, 72.32 %) reported the correlation matrix at the construct level. However, none of models documented the indicator-level matrix. Such practices among the researchers may hinder the validation and replication of their analytical findings [8,11]. Thus, we urge the strategic management researchers in developing countries to take the necessary corrective actions in the forthcoming studies.

4. Conclusion and final remarks

This study provided a comprehensive state of the art of the current practices of PLS-SEM in the strategic management literature within the context of developing nations and identified several important gaps for improvement in future research. The major strengths of PLS-SEM stem from its statistical power, flexibility in dealing with complex models and formative measurements in comparison to CB-SEM [11]. Such qualities make PLS-SEM highly compatible for strategic management studies, which often include small sample sizes because their populations are generally firms and organisations rather than individuals. Furthermore, with the increasing complexity of today's organisational environment, the models dealt with by strategic management researchers are often more complex and involves many relationships and formative measures to analyse the driving factors of competitive advantage or organisational performance [11]. Accordingly, PLS-SEM emerges as a perfect methodological apparatus for strategic management research.

Nevertheless, it is highly integral for strategic management researchers to select the right options and adhere to the procedures and rules of thumb of PLS-SEM to preserve the validity of the results, which may have a substantial impact on the organisational decisions and may, in turn, influence its performance and competitiveness. Based on our review of the strategic management literature in developing nations, there seems to be numerous gaps for improvement to extract the best benefit from the application of PLS-SEM. We recap several salient issues and recommendations from our review which we believe will improve the future application of PLS-SEM in the strategic management literature among developing countries, in particular, and in other contexts and fields that apply the PLS-SEM approach, in general.

Firstly, the practice of using both CB-SEM and PLS-SEM in a single analysis for different purposes highlights a huge violation that leads to meaningless findings. Observing such practice in our review is appalling because there are ubiquitous resources and guidelines available for researchers. Besides, researchers should be more aware that taking advantage of a small sample size or skewed data may jeopardise the validity of their research result if the nature of the population and its accessibility do not justify such action. One fundamental but overlooked step by researchers in almost all strategic management research in the context of developing nations is the requirement for a preliminary test of multivariate assumptions [112]. Researchers should take note that PLS-SEM is also a multivariate regression method, which mean it is not exempt from basic multivariate regression assumptions. Thereby, the test of multivariate normality, normality of error terms, linearity, multicollinearity, constant variance and autocorrelation must be conducted before running the measurement and structural model analyses. On top of this, the identification and treatment of outliers and missing values are also imperative to ensure the best quality of findings and transparency in reporting.

Apart from data characteristics, proper attention should also be given to model specification issues and evaluation. The use of formative and reflective measurement models demands for different criteria of evaluation. The failure to use appropriate criteria will severely contaminate the rigor and validity of the research. This condition also applies for HOCs. Researchers must be extra careful when using HOCs as it requires a combination of different model characteristic evaluations when formative and reflective constructs are used co-jointly. The practice of mistreating the path connecting the first- and second-order constructs as a structural model is another serious mistake that may ruin the whole findings. We emphasise that the use of HOCs should only proceed when there is a strong theoretical reasoning; otherwise, the researcher will only end up adding meaningless complexity to their research.

Eventually, a complete reporting is necessary to provide the readers with adequate information to evaluate the research quality and facilitate replicability [8,11]. Our review found that the most commonly omitted parts of reporting by strategic management researchers in the context of developing nations are the PLS algorithm settings and bootstrapping settings. The researchers should understand that these elements must be made transparent as they are capable of affecting the findings. A further concern is the reporting of the statistical significance and substantive significance of the relationships. We encourage the researchers to follow the current developments in reporting substantive significance [113] resembled by the bootstrap confidence intervals (i.e. the upper and lower levels of CI do not straddle a '0') and effect size. The reporting of p-values alone is not sufficient because p-values are influenced by the sample size, which means it is inconsistent in nature and reduces the replicability of the research [114].

Finally, our review indicated that most of the researchers are still trailing behind the advancements and have not exploited the advanced analysis techniques of PLS-SEM. Therefore, they have not fully benefitted from the developments offered by PLS-SEM to further enhance their research findings. The application of advance techniques, as mentioned in Section 3.5, provides the strategic management researchers opportunities to amplify their research contribution by providing more substantial and accurate recommendations for the strategic improvements of management and organisations. Hence, we encourage strategic management researchers, especially those from developing nations, to move beyond the basic PLS-SEM analyses and explore the more recent advancements. However, in applying those advanced methods, researchers are always reminded to adjudge their appropriateness to the research aims and implement these correctly.

Altogether, PLS-SEM can provide a continued implication for the development of strategic management research with its on-going advancements and development. Therefore, we urge researchers, especially those from the developing countries, to be alert and updated with the developments and ensure strong adherence to the principles, procedures and rules of thumb of the method to enhance their research quality with improved validity, rigor and ability to deal with the increasing complexity of strategic management models.

While the comprehensive coverage of the present systematic review, we acknowledge its inherent limitations. One of the limitations is that, even though we extended the PLS-SEM review in the strategic management field from the work of Hair et al. [11], our systematic review is not an exact continuation of the prior work in terms of journal selection. This is because the ranking of strategic management journals is not static but changes over time, which may reduce the replicability of the current study in the future. Apart from that, our focus was centred on developing nations because the number of publications applying PLS-SEM in this region was generally lesser than that in the developed nations, particularly within the top 10 journals in the area of strategic management. However, this is not empirically sufficient to assert that research from the developed nations have lesser or are free from issues in the application of the PLS-SEM approach. Therefore, we recommend that forthcoming review studies analyse PLS-SEM applications in the context of developed nations to identify the actual knowledge gap of PLS-SEM between the two regions and provide more context-specific recommendations to the academic community, PLS-SEM software developers and trainers.

Data availability statement

No data was used for the paper. List of articles used for the study are available in the online supplement.

CRediT authorship contribution statement

V. Shela: Writing – original draft. **T. Ramayah:** Conceptualization. **Kalisri Logeswaran Aravindan:** Formal analysis. **Noor Hazlina Ahmad:** Conceptualization. **Ahmed Ibrahim Alzahrani:** Formal analysis.

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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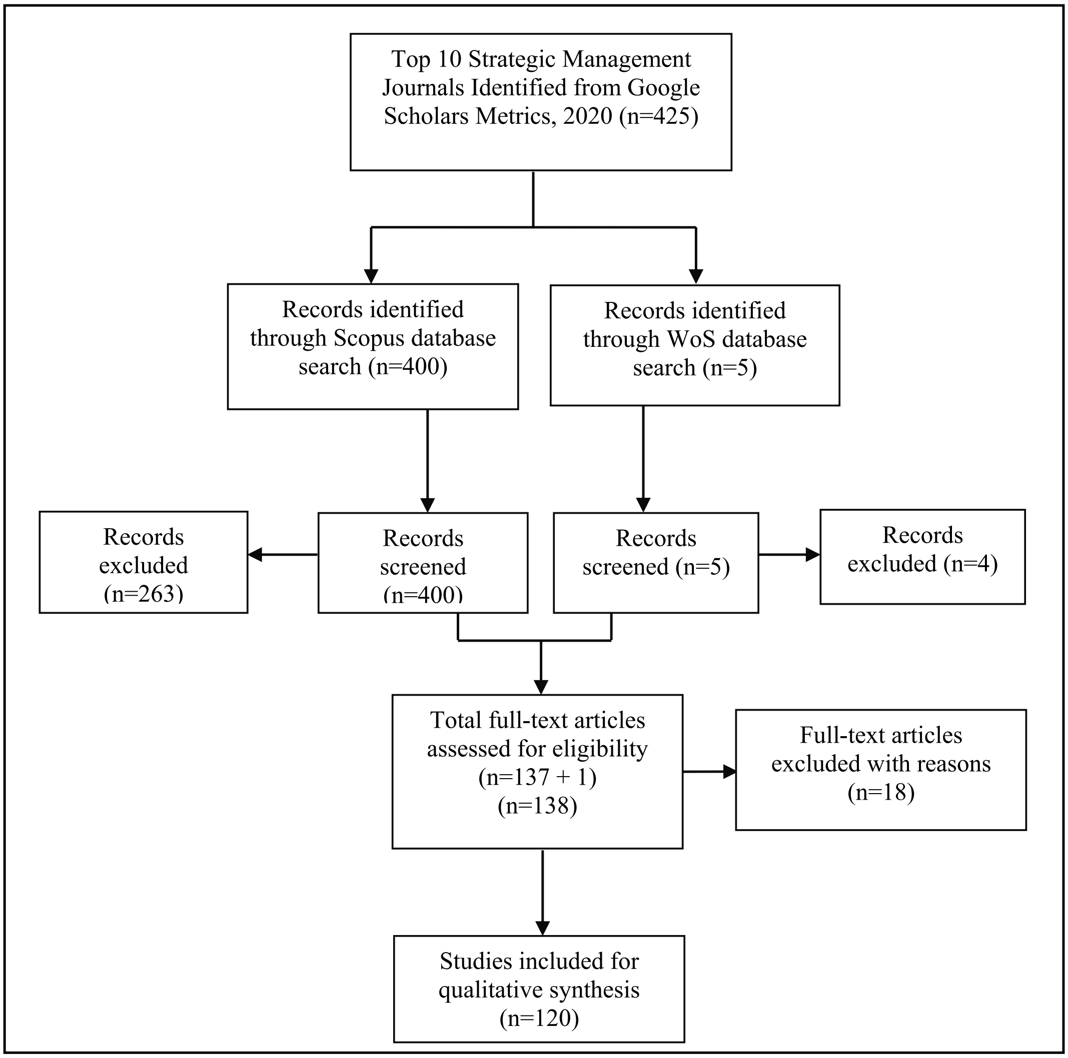
Appendix 1. PRISMA framework of the study selection process



Appendix 2. Top publications in the strategic management field (Google Metrics 2020)

	Publications	h5-index	h5-median
1	*Journal of Business Research*	140	199
2	*Technological Forecasting and Social Change*	106	165
3	*Management Science*	103	145
4	*Journal of Management*	98	175
5	*Strategic Management Journal*	96	140
6	*Journal of Retailing and Consumer Services*	90	138
7	*Academy of Management Journal*	90	132
8	*Industrial Marketing Management*	84	131
9	*Journal of Business Venturing*	70	110
10	*Academy of Management Review*	66	119
11	*Omega*	66	92
12	*Entrepreneurship Theory and Practice*	64	135
13	*Journal of the Academy of Marketing Science*	64	107
14	*Journal of Corporate Finance*	64	104
15	*Management Decision*	61	83

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	Publications	h5-index	h5-median
16	*Journal of Management Studies*	58	97
17	*Long Range Planning*	55	84
18	*European Management Journal*	54	87
19	*Organization Science*	54	84
20	*Harvard Business Review*	53	114

Appendix 3. PLS-SEM studies included in the qualitative synthesis

Journals	References
Industrial Marketing Management	Kumar & Bhatia (2021)
	Jain, Khalil, Johnston & Cheng (2014)
	Harmancioglu, Saaksjarvi & Hultink (2020)
	Stekelorum, Laguir & Elbaz (2020)
	Genc, Dayan & Genc (2019)
	Yeniaras, Kaya & Dayan (2020)
	Niu, Deng & Hao (2020)
	Ali, Ali, Salam, Bhatti, Arain & Burhan (2020)
	Jabbour, Vazquez-Brust, Jabbour & Latan (2017)
	Gupta, Drave, Dwivedi, Baabdullah & Ismagilova (2020)
Journal of Business Research	Ali, Kan & Sarstedt (2016)
	Valaei, Rezaei & Ismail (2017)
	Kaya, Abubakar, Behravesh, Yildiz & Mert (2020)
	Ali, Ali, Leal-Rodriguez & Albort-Morant (2019)
	Zhang, He, Zhou & van Gorp (2019)
	Alonso-Dos-Santos & Llanos-Contreras (2019)
	Suhartanto, Dean, Nansuri and Triyuni (2018)
	Tomar, Baker, Kumar & Hoffmann (2021)
	Ciampi, Demi, Magrini, Marzi & Papa (2021)
	Esfandiar, Sharifi-Tehrani, Pratt & Altinay (2019)
	Lin, Jing-Qin & Higgins (2016)
	Oubrich, Hakmaoui, Benhayoun, Soilen & Abdulkader (2021)
	Ali & Park (2016)
	Ogbeibu, Pereira, Emelifeonwu & Gaskin (2021)
	Yee, Miquel-Romero & Cruz-Ros (2021)
	Wang, Sharma & Cao (2016)
	Ali, Ali, Grigore, Molesworth & Jin (2020)
	Aw & Chuah (2021)
	Banik, Gao & Rabbanee (2019)
	Wang, Thai, Ly & Chi (2021)
	Cuevas-Vargas, Aguirre & Parga-Montoya (20220
	Bai, Johanson, Oliveira & Ratajczak-Mrozek (2021)
	Roy, Balaji, Soutar, Lassar & Roy (2018)
	Yeh, Wang, Hsu & Lin (2020)
	Al-Omoush, Orero-Blat & Ribeiro-Soriano (2021)
	Al-Omoush, Simon-Moya, Al-ma'aitah & Sendra-Garcia (2021)
	Chatterjee, Chaudhuri & Vrontis (2022)
	Xiong, Zheng, Germon, Susini & Chang (2021)
	Ogbeibu, Senadjki & Gaskin (2018)
	Leong, Hew, Ooi & Chong (2020)
	Akter, Babu, Hossain & Hani (2022)
	Hossain, Akter & Yanamandram (2021)
Journal of Retailing and Consumer Services	Rezaei (2015)
	Schmidt, Mason, Steenkamp & Mugobo (2017)
	Ting, Thaichon, Chuah & Tan (2019)
	Hallak, Assaker, O'Connor & Lee (2018)
	Graciola, De Toni, de Lima & Milan (2018)
	Lin, Tseng, Yeh, Liao & Wang (2020)
	Chi, Huang & Nguyen (2020)
	Dirsehan & Cankat (2021)
	Diaz, Gomez & Molina (2017)
	Roy, Balaji, Quazi & Quaddus (2018)
	Londono, Davies & Elms (2017)
	Driediger & Bhatiasevi (2019)
	Jiang, Rashid & Wang (2019)
	Roy, Shekhar, Lassar & Chen (2018)
	Ameen, Tarhini, Shah & Nusair (2021)

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Journals	References
	Sarker, Mohd-Any & Kamarulzaman (2021)
	Pillai, Sivathanu & Dwivedi (2020)
	Jee (2021)
	Japutra, Roy & Pham (2021)
	Zhu, Sun & Chang (2016)
	Le, Ly, Nguyen & Tran (2022)
	Ramirez-Correa, Rondan-Cataluna, Arenas-Gaitan & Martin-Velicia (2019)
	Kimiagari & Malafe (2021)
	Singh, Singh & Mishra (2021)
	Uzir, Al Halbusi, Thurasamy, Hock, Aljaberi, Hasan & Hamid (2021)
	Lima, Cheah, Ng, Basha & Liu (2021)
	Xu, Islam, Liang, Akhtar & Shahzad (2021)
	Osakwe, Ruiz, Amegbe, Chinje, Cheah & Ramayah (2020)
	Baumann, Hoadley, Hamin & Nugraha (2017)
	Taneja & Ali (2021)
	Olavarria-Jaraba, Cambra-Fierro, Centeno & Vazquez-Carrasco (2018)
	Kumar, Purani & Viswanathan (2018)
	Purani, Kumar & Sahadev (2019)
	Suki & Suki (2017)
	Natarajan, Balasubramaniam, Stephen, Jublee & Kasilingam (2018)
	Cheah, Waller, Thaichon, Ting & Lim (2020)
	Terblanche & Kidd (2021)
	Ghantous, Das & Chameroy (2018)
	Chaouali, Souiden & Ladhari (2017)
	Dorai, Balasubramanian & Sivakumaran (2021)
	Yeo, Goh & Rezaei (2017)
	Tran (2021)
	Wu, Vassileva, Noorian & Zhao (2015)
	Herjanto, Amin & Purington (2021)
	Cheung, Pires, Rosenberger, Leung & Sharipudin (2021)
	Kasiri, Cheng, Sambasivan & Sidin (2017)
	Wang & He (2022)
	Gupta & Arora (2017)
	Ogonowski, Montandon, Botha & Reyneke (2014)
	Laato, Islam, Farooq & Dhir (2020)
	Abdelmoety, Aboul-Dahab & Agag (2022)
	Rajabion, Khorraminia, Andjomshoaa, Ghafouri-Azar & Molavi (2019)
	Idoko, Ukenna & Obeta (2019)
	Yan, Tan, Loh, Hew & Ooi (2021)
	Jayasimha & Srivastava (2017)
	Wang, Cheah, Lim, Leong & Choo (2022)
	Hsieh, Lee & Tseng (2021)
	Izogo (2015)
	Singh, Singh, Kumar & Mathur (2021)
	Rosenbaum, Friman, Ramirez & Otterbring (2020)
Technological Forecasting and Social Change	Andrade-Valbuena & Torres (2018)
	Acquah, Naude & Sendra-Garcia (2021)
	Ashaari, Singh, Abbasi, Amran & Liebana-Cabanillas (2021)
	Falahat, Ramayah, Soto-Acosta & Lee (2020)
	Shi, Evans & Shan (2022)
	Alraja (2022)
	Chatterjee, Chaudhuri, Vrontis, Thrassou & Ghosh (2021)
	Hajli, Shanmugam, Powell & Love (2015)
	Chopdar, Paul & Prodanova (2022)
	Dubey, Gunasekaran, Childe, Papadopoulos, Luo, Wamba & Roubaud (2019)
	Lim, Cheah, Ng, Basha & Soutar (2021)
	Bugshan & Attar (2020)
	Mahmood & Mubarik (2020)
	Afraz, Bhatti, Ferraris & Couturier (2021)
	Ferraris, Devalle, Ciampi & Couturier (2019)
	Chitsaz, Liang & Khoshsoroor (2017)
	Papa, Mital, Pisano & Del Giudice (2020)
	Arias-Perez & Velez-Jaramillo (2022)

Appendix 4. Distribution of strategic management studies applying PLS-SEM by nation

(*continued on next page*)

(*continued*)

Country	No. of Publications	Country	No. of Publications
Country	No. of Publications	Country	No. of Publications
Malaysia	21	Bangladesh	2
China	19	Jordan	2
India	17	Mexico	2
Saudi Arabia	6	Morocco	2
Taiwan	6	Nigeria	2
South Africa	5	Oman	2
Chile	4	Brazil	1
Vietnam	4	Egypt	1
Colombia	3	Ghana	1
Indonesia	3	Lebanon	1
Iran	3	Pakistan	1
Qatar	3	Thailand	1
Russia	3	Tunisia	1
Turkey	3	UAE	1

Appendix 5. Guidelines for Advanced Analysis Techniques in PLS-SEM

	Advanced Techniques	Explanation	References
1	Multi-group analysis & measurement invariance	Measurement invariance as an essential procedure for multi-group analysis. The differences across groups in model estimation do not stem from group-specific response patterns or differences in the constructs.	Henseler et al. (2016) Hult et al. (2008), Hair et al. (2019)
2	Latent class analysis	The use of latent class analysis (e.g. FIMIX-PLS, PLS-POS, PLS-IRRS) to identify differing segments in a model as a result of unobserved heterogeneity. Latent class analysis for robustness check to confirm the aggregate-level result is free from unobserved heterogeneity.	Becker et al. (2013), Sarstedt et al. (2022) Becker et al. (2013), Sarstedt et al. (2020)
3	Model comparison	Comparing a set of theoretical plausible models that provide alternative explanations of the phenomena being studied. Using cross-validated predictive ability test	Sharma et al. (2019), Sharma et al. (2021), Danks et al. (2020) Liengaard et al. (2021)
4	Higher-order constructs (HOCs)	The latest guidelines for the model specification, estimation and assessment of HOCs.	Sarstedt et al. (2019)
5	Nonlinear effects	The assumption of a linear relationship in PLS-SEM does not exist in every situation. The relationship can be nonlinear, which requires nonlinear estimations.	Basco et al. (2021), Sarstedt et al. (2020)
6	Moderated mediation and conditional process analysis	Combining moderator analysis and mediator analysis to moderated mediation and conditional process analysis.	Cheah et al. (2021), Sarstedt et al. (2020)
7	Necessary condition analysis (NCA)	Combining PLS-SEM and NCA to identify necessary conditions that must be present to achieve a certain level of outcome.	Richter et al. (2020)
8	Endogeneity	Addressing endogeneity using the Gaussian copula approach as the experimental design is not feasible in every situation.	Park & Gupta (2012), Becker et al. (2022)
9	Longitudinal data analysis	Applying PLS-path modelling in longitudinal studies.	Roemer (2016)
10	Weighted PLS-SEM	Another version of the PLS-SEM algorithm that includes sampling weights in estimations.	Cheah et al. (2021), Becker & Ismail (2016)
11	Reciprocal relationship assessment	Analysing reciprocal relationships using instrumental variables in WarpPLS	Kock (2022), Morrow & Conger (2021)
12	Full latent growth modelling	Applying full latent growth analysis techniques in WarpPLS Analysing a complete model with many moderated-mediation relationships using WarpPLS Using full latent growth analysis of moderating effects where the moderating variable is latent and does not disrupt the model.	Kock (2022) Hubona & Belkhamza (2021) Kock (2020)
13	Artificial Neural Network (ANN)	Using PLS-SEM and SEM-ANN conjointly to complement the limitations of both methods. ANN can predict nonlinear relationships using non-compensatory models. It can test the predictive power of the significant antecedents identified by PLS-SEM using sensitivity analysis.	Talukder et al. (2020), Abbasi et al. (2021), Ashaari et al. (2021)
14	Agent-based simulation	Combining PLS-SEM with agent-based simulation (ABS) to extend PLS-SEM prediction from an individual level to the population level through a network-based diffusion process.	Schubring et al. (2016)

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