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A brief review of partial least squares structural equation modeling (PLS-SEM) use in quality management studies

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Abstract

Purpose – Partial least squares structural equation modeling (PLS-SEM) has become an established social sciences multivariate analysis technique. Since quality management researchers also increasingly using PLS-SEM, this growing interest calls for guidance.

Design/methodology/approach – Based on established guidelines for applying PLS-SEM and evaluating the results, this research reviews 107 articles applying the method and published in eight leading quality management journals.

Findings – The use of PLS-SEM in quality management often only draws on limited information and analysis results. The discipline would benefit from the method's more comprehensive use by following established guidelines. Specifically, the use of predictive model assessment and more advanced PLS-SEM analyses harbors the potential to provide more detailed findings and conclusions when applying the method.

Research limitations/implications – This research provides first insights into PLS-SEM's use in quality management. Future research should identify the key areas and the core quality management models that best support the method's capabilities and researchers' goals.

Practical implications – The results of this analysis guide researchers who use the PLS-SEM method for their quality management studies.

Originality/value – This is the first article to systematically review the use of PLS-SEM in the quality management discipline.

Keywords Partial least squares, Structural equation modeling, Quality, Management, PLS-SEM, Review, Guidelines

Paper type Research paper

1. Introduction

Partial least squares structural equation modeling (PLS-SEM; Hair *et al.*, 2022; Hair *et al.*, 2018; Lohmöller, 1989; Wold, 1982) has become an established social sciences multivariate analysis technique (e.g. Hair *et al.*, 2018). Since quality management researchers – as we show in this article – also increasingly use PLS-SEM, this growing interest requires guidance. Consequently,

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we provide a critical review of PLS-SEM's usage in 107 studies published in leading quality management journals. Our review is based on established guidelines for applying the PLS-SEM method and evaluating the results (e.g. Hair *et al.*, 2019a; Sarstedt *et al.*, 2020). Furthermore, we refer to PLS-SEM applications' relevant criteria and aspects considered in prior review studies (e.g. Hair *et al.*, 2012; Ringle *et al.*, 2020; Sarstedt *et al.*, 2022a).

Our goal is not to provide a complete review, which previous studies have done, but a first insight into PLS-SEM's use in quality management. In addition, we offer the first suggestions for improving researchers' application practices. Consequently, our review focuses on four aspects: (1) *reasons* for using PLS-SEM, (2) *model characteristics*, (3) *structural model evaluation*, and (4) *advanced analysis techniques*. We exclude the complex topic of *measurement model evaluation* from this initial analysis in quality management, since our review clarifies that, at first glance, an appropriate PLS-SEM application in this discipline has comparable problems to those that review studies in other disciplines have already identified (see Table 1 in Cepeda-Carrión *et al.*, 2022, which provides an overview of PLS-SEM review studies in different research disciplines). Consequently, quality management researchers are advised to follow the established guidelines for measurement model evaluation (e.g. Hair *et al.*, 2019a; Legate *et al.*, 2022; Sarstedt *et al.*, 2021). For instance, it is important to fully apply the current and relevant criteria catalog to the evaluation and not to only highlight a few aspects when assessing PLS-SEM results.

In the following subsections, we explain how we selected articles comprising PLS-SEM quality management applications and present the results of our review of the four aspects (reasons, characteristics, structural model, and advanced techniques) on which it focuses. Our analysis reveals key findings regarding PLS-SEM's usage in quality management and the latter's potential for improving the method's application. We therefore provide guidance for the PLS-SEM method's utilization in quality management and related fields.

2. PLS-SEM applications in quality management

We review PLS-SEM applications in quality management by considering the eight quality management journals included in the 2021 British Association of Business Schools (ABS, field: operations and technology management): *TQM journal* (Emerald, 1* ABS), *International Journal of Quality and Reliability Management* (Emerald, 2* ABS), *Total Quality Management and Business Excellence* (Taylor and Francis, 2* ABS), *International Journal of Productivity and Quality Management* (Inderscience, 1* ABS), *International Journal of Quality and Service Sciences* (Emerald, 1* ABS), *Journal of Quality in Maintenance Engineering* (Emerald, 1* ABS), *Quality and Reliability Engineering International* (Wiley-Blackwell, 1* ABS), and *Quality Progress* (American Society for Quality Control, 1* ABS). We subsequently undertook a full-text search of Elsevier's Scopus database for articles published in the eight journals during 2021 (last update, January 20, 2022), using the search terms "PLS-SEM" and "partial least squares." The query yielded 137 articles. Once we had assessed each of these articles to determine whether they applied PLS-SEM and contained the information required for the study, we excluded 30 articles from the review. This exclusion was due to articles not applying PLS-SEM (i.e. only mentioning PLS-SEM or using PLS regression, $n = 12$; not reporting sufficient information for an evaluation, $n = 11$; discussing the methodology, $n = 5$; and only using PLS-SEM for scale development, $n = 2$). A total of 107 articles were ultimately selected and reviewed. Six of them included more than one model, providing a total of 124 path models for our review. One of these 6 articles studied the relationship between the predictive value and the frequency of utilization of 12 maintenance measures and, for this purpose, estimated 12 different models (Gomes *et al.*, 2021). The other 5 articles included multiple models which differed with regard to some variables. For example, Ajami *et al.* (2018) first estimated the European customer satisfaction index (ECSI) model and then estimated a similar model merging two constructs.

An overview of the 107 articles by year of publication shows an upward trend in PLS-SEM's use in quality management studies (Figure 1). While the first article in the review dates

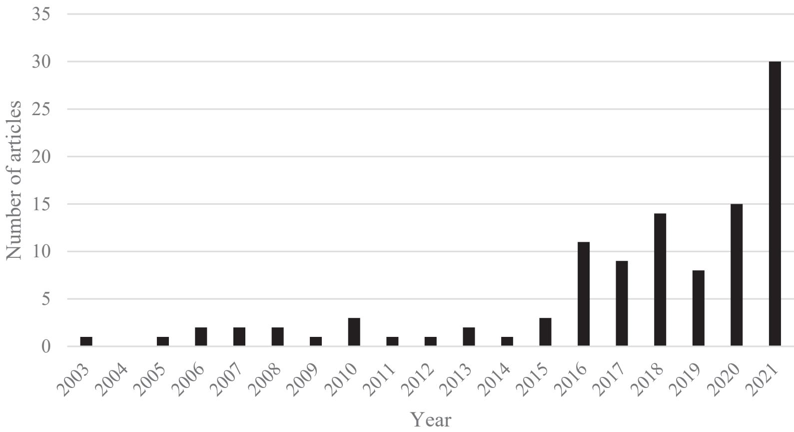

Figure 1.
PLS-SEM applications in the quality management field over time

to 2003, 87 of the 107 articles were published during the six-year period of 2016–2021. Compared to its use in other disciplines, such as marketing, PLS-SEM's use in the quality management field is rather new (Sarstedt *et al.*, 2022a). However, recent years have seen a particularly steep increase in the use of PLS-SEM.

A breakdown by journal shows that *Total Quality Management and Business Excellence* (29 articles), *TQM Journal* (28 articles), and *International Journal of Quality and Reliability Management* (22 articles) are the three journals that have published the most studies using PLS-SEM. Furthermore, the following journals show a relatively high number of hits: *International Journal of Quality and Service Sciences* (16 articles), *International Journal of Productivity and Quality Management* (10 articles), and *Journal of Quality in Maintenance Engineering* (2 articles). The journals *Quality and Reliability Engineering International* and *Quality Progress* have not published any articles with PLS SEM applications. In the period between 2016 and 2021, the *TQM Journal* published the most PLS-SEM applications (27 articles) by far.

3. Reasons for using PLS-SEM

Our review reveals that 17 articles do not report reasons for using PLS-SEM. The remaining 90 articles provide one or more reasons to motivate PLS-SEM's application (Table 1). The two most frequently mentioned reasons are the small sample size (50 studies) and the nonnormal

Table 1.
Reasons for using PLS-SEM

Reasons	Number of studies (n = 107)	Proportion (%)
Small sample size	50	46.72
Nonnormal data	47	43.92
High model complexity	23	21.49
Theory development and exploratory research	20	18.69
Predictive study focus	18	16.82
Theory testing	9	8.41
Formative measures	6	5.60
Explain variance in the endogenous constructs	5	4.67
PLS-SEM's popularity and standard use in the field	5	4.67
Other reasons (e.g. moderation effects; latent variable scores availability; mediation effects; higher statistical power than CB-SEM; multi-group analysis)	12	11.21

data (47 studies). However, current PLS-SEM guidelines consistently recommend that a study's purpose instead of its data characteristics should motivate the choice of PLS-SEM (Hair *et al.*, 2022). In fact, PLS-SEM's causal-predictive nature makes it a useful method when a study's purpose is to balance explanation and prediction, therefore "perfectly fitting today's research environment, which is not only concerned with testing hypothesized models but also with deriving managerial recommendations that are predictive by nature" (Becker *et al.*, 2022a).

The results of our review indicate that quality management researchers focus strongly on data characteristic-related arguments. Other, frequently reported reasons are the high model complexity (23 studies), theory development and exploratory research (20 studies), and the predictive study focus (18 studies). All these reasons are valid arguments for choosing PLS-SEM. However, PLS-SEM researchers should specifically emphasize the research goals of their studies (Sarstedt *et al.*, 2022b).

4. Model characteristics

As explained above, model complexity is a possible reason for selecting PLS-SEM. In fact, PLS-SEM can successfully handle complex models, such as those that include very many constructs and indicators, reflective and formative measurement models, mediation and moderation effects, higher-order constructs, and nonlinear relationships.

Our analysis of the 124 path models shows an average of 5.72 latent variables and an average of 7.60 path relationships (Table 2). These values are lower than those reported in fields such as marketing (Sarstedt *et al.*, 2022a), in which researchers started widely adopting PLS-SEM long before those in the quality management field did so. In addition, 119 of the 124 models only comprise reflectively measured constructs. A remarkable share of the reviewed models (43.54%) includes mediation effects. One or more higher-order constructs are present in 32 articles employing Type I (reflective-reflective; 17 studies), Type II (reflective-formative; 9 studies) or both Type I and Type II (2 studies) second-order constructs. Four studies do not provide information about the type of higher-order construct. Overall, most of the studies do not present plausibly comprehensible procedures for higher-order constructs' specification, estimation, and validation (for example, see Sarstedt *et al.*, 2019). For instance, only 10 of the 32 studies describe the approach for specifying and estimating higher-order constructs, revealing that the two-stage approach (7 studies) is more frequently applied than the repeated indicators one (3 studies). In only 3 studies are the higher-order constructs evaluated in a meaningful way (for example, see Becker *et al.*, 2022a; Sarstedt *et al.*, 2019). Moreover, in 13 studies, the assessment procedures are incompletely applied (e.g. they do not mention the discriminant validity evaluation between the lower-order components, nor are the formative higher-order constructs subjected to a redundancy analysis). In 13 studies, the higher-order constructs are not evaluated at all, and, in the remaining 3 studies, the evaluation criteria are misapplied (e.g. the relationships between the lower-order components and the higher-order components are considered structural paths).

5. Structural model evaluation

The evaluation of the structural model comprises assessing the model's explanatory and predictive power and the path coefficients' significance and relevance. The results of our analysis (Table 3) highlight that almost all models (123 and 122 models, respectively) report the path coefficients' values and significance. In 119 models, the path coefficients' significance is tested by means of the bootstrapping routine. Information about the number of bootstrap samples is only provided in 64 models (51.61%). Specifically, 5,000 bootstrap samples are used in the evaluation of 42 models, from 1,000 to 2,000 samples in the analysis of 6 models, and 500 or fewer samples in the assessment of 16 models. None of the reviewed PLS-SEM applications is therefore consistent with the more recent literature, which

Criterion	Results (n = 124)	Proportion (%)
Number of latent variables		
Mean	5.72	–
Median	5.00	
Range	(2; 14)	
Number of inner model path relations		
Mean	7.60	-
Median	7.00	
Range	(1; 24)	
Measurement model (first-order)		
Only reflective	119	95.97
Only formative	2	1.61
Reflective and formative	3	2.42
Total number of indicators in models		
Mean	32.58	–
Median	28.00	
Range	(3; 104)	
Number of models with single-item constructs	14	11.29
Number of models with control variables	11	8.87
Number of models with mediation effects	54	43.54
Number of models with interaction effects	11	8.87
Number of models with nonlinear relationships	1	0.80
Number of models with higher-order constructs	32	25.80
Type of second-order constructs		
Type I (reflective-reflective)	17	13.70
Type II (reflective-formative)	9	7.25
Type III (formative-reflective)	0	
Type IV (formative-formative)	0	
Both type I and II	2	1.61
Not specified	4	3.22
Specification and estimation of higher-order constructs		
Repeated indicators approach	3	2.41
Two-stage approach	7	5.64
Not specified	21	16.93
Other (mean value of the first-order components' indicators)	1	0.80
Evaluation of higher-order constructs		
Evaluate higher-order constructs using criteria documented in the extant literature	3	2.41
Do not evaluate higher-order constructs at all	13	10.48
Apply the relevant criteria incompletely	13	10.48
Misapply the evaluation criteria	3	2.41

Table 2.
Model characteristics

recommends drawing on at least 10,000 bootstrap samples (Becker *et al.*, 2022a; Streukens and Leroi-Werelds, 2016). The bootstrapping confidence intervals, as well as the standard errors, t values, and/or p values, are reported in 23 models. However, two models only provide the bootstrapping confidence intervals in respect of the indirect effects, but not the direct effects. More recent guidance on PLS-SEM applications recommends using bootstrap confidence intervals routinely when testing inference (e.g. Sarstedt *et al.*, 2022b). In addition, the f^2 effect size is evaluated in 37 models.

Predictive model assessment is a core motivation for selecting PLS-SEM (Hair *et al.*, 2019a). In this regard, the distinction between a model's explanatory and predictive power was a central argument in PLS-SEM's recent developments (Sarstedt *et al.*, 2022b). The explanatory power is assessed in 114 models by means of the value of the coefficient of

Criterion	Empirical test criterion in PLS-SEM	Number of models (n = 124)	Proportion (%)
Path coefficients	Values	123	99.19
Significance of path coefficients	Standard errors, significance levels, t values/p values	99	79.83
	Confidence intervals	0	0.00
	Both	23	18.54
Effect size	f^2	37	29.83
Explanatory power	R^2	114	91.93
Model fit	GoF	23	18.54
	SRMR	6	4.83
	Other	4	3.22
Predictive relevance (blindfolding)	Q^2	58	46.77
	q^2	14	11.29
Predictive power ($PLS_{predict}$)	$Q^2_{predict}$	0	–
	LM comparison	0	–
Predictive model comparison	BIC, GM, CVPAT	0[a]	–

Note(s): [a]One article mentions that AIC (Akaike's information criteria) were used to compare two different model specifications, but does not provide any data

Table 3. Structural model evaluation

determination (R^2). In some cases, the model fit measures are also reported, although they should be used cautiously in PLS-SEM (Hair *et al.*, 2019b). Specifically, the goodness-of-fit index (GoF; 23 models) of Tenenhaus *et al.* (2005), although criticized (Henseler and Sarstedt, 2013), and the standardized root mean square residual (SRMR; 6 models) are the most used model fit measures. In terms of their predictive relevance, a significant proportion of the models are evaluated by means of the Q^2 (58 models) and the q^2 (14 models), which are based on the blindfolding routine. However, recent research has advised against the use of Q^2 and q^2 resulting from Blindfolding to assess a model's predictive power with PLS-SEM and has recommended applying the $PLS_{predict}$ procedure (Shmueli *et al.*, 2016, 2019). Most certainly because of its novelty, none of the reviewed studies applied $PLS_{predict}$. In addition, no study compares competing models' predictive power by using novel procedures such as the cross-validated predictive ability test (CVPAT; Liengaard *et al.*, 2021; Sharma *et al.*, 2022). We expect the evaluation of models' predictive power and predictive model comparison to become an established routine in quality management studies applying PLS-SEM within the near future.

6. Advanced analysis techniques

Finally, the articles' review examines the application of advanced analysis techniques. While PLS-SEM research is continuously evolving and developing new advanced analysis techniques (e.g. Hair, 2021; Hair *et al.*, 2018) and robustness checks (e.g. Richter *et al.*, 2020; Sarstedt *et al.*, 2020), our review reveals that quality management researchers scarcely apply them. For example, none of the articles uses latent class analyses (e.g. FIMIX-PLS, PLS-POS) to evaluate unobserved heterogeneity (Becker *et al.*, 2013; Hahn *et al.*, 2002) or confirmatory tetrad analysis (CTA-PLS) to support the choice of reflective or formative measurement model specification (Gudergan *et al.*, 2008).

Overall, of the 107 articles, only one includes PLS-SEM's importance-performance analysis (IPMA; Ringle and Sarstedt, 2016). Specifically, Raharjo *et al.* (2016) apply IPMA to assess predecessor constructs' performance and importance in shaping patient and care provider satisfaction, and extend their analysis on the indicator level. While multigroup analysis is reported in 9 studies, the MICOM procedure is only used in 3 of them to assess measurement invariance (Henseler *et al.*, 2016). This finding raises concerns, because measurement invariance is a prerequisite for multigroup analysis (e.g. Hair *et al.*, 2022). Finally, 2 articles mention endogeneity assessment briefly, but the authors do not provide the results and/or any other information about the applied procedure.

7. Conclusions and future research

The PLS-SEM method is increasingly used in quality management and has established itself as a standard method with growing relevance. This method has a special importance in the discipline, especially for models with success factors (Aquilani *et al.*, 2017; Carmona-Márquez *et al.*, 2016) or for investigating the sources of a competitive advantage (El Shenawy *et al.*, 2007; Sciarelli *et al.*, 2020). Simultaneously, however, PLS-SEM's use in quality management reveals various areas of improvement, which we specifically uncovered in the following areas: (1) reasons for using PLS-SEM, (2) the model characteristics, (3) structural model evaluation, and (4) advanced analysis techniques. Authors and reviewers should follow the established guidelines more closely (e.g. Hair *et al.*, 2019a; Sarstedt *et al.*, 2022a) to improve the application of the method in the future.

In addition, it is noticeable that in the quality management area, methodological PLS-SEM innovations are adopted very late. This specifically applies to robustness checks (Sarstedt *et al.*, 2020), which include, for example, nonlinear effects, endogeneity, and unobserved heterogeneity but also the confirmatory tetrad analysis (Gudergan *et al.*, 2008). Moreover, extended PLS-SEM analyses, such as the IPMA (Ringle and Sarstedt, 2016), have been established for some time, but are hardly taken into account. In more recent methodological developments, prediction-based model evaluation (Sharma *et al.*, 2022; Shmueli *et al.*, 2019), prediction-based model comparison and selection (Liengaard *et al.*, 2021; Sharma *et al.*, 2019), the detection and treatment of endogeneity issues by means of Gaussian copulas (Becker *et al.*, 2022b; Eckert and Hohberger, 2022; Hult *et al.*, 2018; Park and Gupta, 2012), the necessary condition analysis (Dul, 2016, 2020; Richter *et al.*, 2020) and the conditional mediation analysis (Cheah *et al.*, 2021) have, however, received particular attention. Finally, researchers should employ appropriate methods to assess observed heterogeneity via moderator (e.g. Becker *et al.*, 2022a; Becker *et al.*, 2018) and multigroup analyses (e.g. Chin and Dibbern, 2010; Hair *et al.*, 2018), as well as unobserved heterogeneity (e.g. Sarstedt *et al.*, 2017; Schlittgen *et al.*, 2016) to ensure their results' validity. The methodological extensions are also of great interest for quality management research and current studies should also adopt them in a timely manner.

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