Partial Least Squares (PLS) in Operations Management Research: Insights from a Systematic Literature Review

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Abstract:

Purpose: The present paper aims to analyze the Operations Management (OM) research between 2014 and 2018 that has made use of Partial Least Squares (PLS) to determine whether the trends shown in previous literature reviews focused on this topic are maintained and whether the analyzed papers comply with the recommendations for reporting.

Design/methodology/approach: A systematic literature review has been carried out of OM articles that use PLS as an analysis tool. A total of 102 references from 45 journals from 2014 to 2018, published in WOS and Scopus, has been analyzed. Bibliometric analysis and a review of the PLS reporting standards applied in the context of OM have been developed.

Findings: PLS is gaining importance and is widely adopted in OM as a statistical analysis method of choice. In general, certain aspects of PLS are correctly applied and adequately reported in the publications. However, some shortcomings continue to be observed in terms of their application and the reporting of results. A detailed comparison has been developed between the current research and previous OM research (as well as previous research on other disciplines) on this topic.

Research limitations/implications: OM researchers making use of PLS should be aware of the importance of correctly reasoning and justifying their choice and fully reporting the main parameters in order to provide other researchers with useful information and enable them to reproduce the performed analysis.

Originality/value: This article builds a study with results based on a greater number of articles and journals than the two previous literature reviews focused on this topic. Therefore, it provides a richer and more up-to-date evaluation of trends in the use and reporting of PLS. Additionally, the present paper assesses whether the studies follow the indications suggested in recent years triggered by significant changes in the standards of reporting results obtained through the use of PLS.

Keywords: PLS, SEM, PLS-SEM, systematic literature review, OM - operations management

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1. Introduction

Partial Least Squares (PLS) is a statistical regression method, first introduced and developed by the Swedish statistician, Wold, for econometrics in the late 60s (1966), extended by Lohmöller in the late 80s (1989) and introduced into business research by Chin (1998) in the late 90s, that has become increasingly popular in the last decade.

It is one of the methods of the family of variance-based structural equations modelling (SEM) developed in several stages. In the first stage, the Latent Variable Scores (LVS) are estimated iteratively; in the second, the measurement model is resolved, estimating the outer weights and loadings (based on the LVS estimated in the first stage); and, in the third, the parameters of the structural model are estimated (Marin-Garcia & Alfalla-Luque, 2019a; Ringle, Wende & Becker, 2015; Sarstedt, Ringle & Hair 2017)

There are many reasons for PLS' popularity. The method allows researchers to deal with more complex models with a large number of constructs and indicator variables (Ringle, Sarstedt, Mitchell & Gudergan, 2018); the mathematical and statistical procedures are rigorous and robust (Wold, 1980); the mathematical model is flexible (Falk & Miller, 1992); PLS is robust even with extremely non-normal data (Cassel, Hackl & Westlund, 1999; Hair, Hult, Ringle, Sarstedt & Thiele, 2017); it does not establish strict premises in data distribution or the measurement scale (Peng & Lai, 2012) and it provides a high level of statistical power for relatively small sample sizes (Mitchell & Nault, 2007; Reinartz, Haenlein & Henseler, 2009; Wold, Martens & Wold, 1983).

In fact, Partial Least Squares Structural Equation Modeling (PLS-SEM) has quickly spread to research in multiple disciplines such as accounting, human resources management, international business research, information systems, strategic management, marketing management, hospitality management, tourism, supply chain management, consumer behavior, healthcare, knowledge management, and Operations Management (OM), as indicated by Usakli and Kucukergin (2018). Undoubtedly, the availability of software applications has been a determinant factor in the popularity of PLS-SEM.

A detailed explanation of the different aspects of the PLS method can be found in current publications (Hair, Hult, Ringle & Sarstedt, 2014; Hair, Sarstedt, Ringle & Gudergan, 2017; Hair, Risher, Sarstedt & Ringle, 2019; Kaufmann & Gaeckler, 2015; Marin-Garcia & Alfalla-Luque, 2019a; Nitzl, 2018; Ringle et al., 2018; Usakli & Kucukergin, 2018). Therefore, the purpose of the present paper is not to focus on these aspects. Given the importance that the use of PLS is gaining in research, the objective of this paper is to analyze its use in research in OM from 2014 to 2018 to update and enhance previous research studies based on a smaller number of journals and articles (Kaufmann & Gaeckler, 2015; Peng & Lai, 2012). Peng and Lai (2012) researched 42 articles in OM in general from 8 journals spanning from 2000 to 2011. Kaufmann and Gaeckler (2015) focused on 75 articles in Supply Chain Management from 10 journals spanning from 2002 to 2013.

In contrast, the present article reviews 102 papers on OM taken from 45 journals and spanning from 2014 to 2018. This article builds a study with results based on more articles and journals than any previous research and therefore provides a richer and more up-to-date evaluation of the trends in the use and reporting of PLS. Additionally, this article assesses whether the studies follow indications given after the introduction in the said period, of the significant change in the reporting standards for results obtained through the use of PLS.

Therefore, the objective of this study is to fill the gap in recent OM PLS reviews by providing a comprehensive, detailed, and systematic review of the deployment and reporting of the PLS-SEM method in the area and to determine whether the tendencies shown in previous papers are maintained and the obtained results are adequately reported. For this, a systematic literature review has been carried out to select OM articles that use PLS as an analysis tool. An investigation will be carried out of these articles with a bibliometric analysis and a review of the PLS reporting standards applied to the context of OM.

To be more precise, we intend to answer the following research questions using a specific protocol (Marin-Garcia & Alfalla-Luque, 2019b):

- What characterizes OM publications between 2014 and 2018 that have used PLS?
- Do recently published articles comply with reporting recommendations?

- Are the results of previous reviews on the subject based on a very limited set of journals and conducted before substantial modifications to the PLS-based study reporting methods, still valid?

For this, we follow the methodology detailed in section 3. Then, the main results are set out in section 4 and the main conclusions are explained in section 5.

2. Previous Research

It is important to note that many disciplines have regularly reviewed the PLS method, used to ensure rigorous research and publication practices. This method has gained importance, particularly in the wake of the intense academic debate and controversy surrounding PLS that has taken place in recent years that led to the drafting of guidelines and recommendations for its use and reporting standards for articles that use PLS-SEM as an analytical tool (Hair et al., 2019). Despite the controversy and debate surrounding PLS, interest in PLS has been growing among OM researchers.

Some authors have reviewed and summarized the method's application in systematic literature reviews in diverse social science disciplines such as accounting (Lee, Petter, Fayard & Robinson, 2011; Nitzl, 2016), information systems (Hair, Hult, Ringle, Sarstedt et al., 2017), strategic management (Hair, Sarstedt, Pieper & Ringle, 2012), marketing management (Hair, Sarstedt, Ringle & Mena, 2012), hospitality management (Ali, Rasoolimanesh, Sarstedt, Ringle & Ryu, 2018), tourism (do Valle & Assaker, 2016) and healthcare (Avkiran, 2018), among others. Some of these reviews have also presented guidelines for evaluating and using PLS-SEM tailored to their specific fields.

Regarding the discipline of OM, the most recent article (Peng and Lai, 2012) reviews papers published up to 2011. There is also a publication on Supply Chain Management (SCM) which revises publications up to 2013 (Kaufmann & Gaeckler, 2015). Therefore, an updated assessment of PLS-SEM use and reporting in OM seems timely and necessary to evaluate compliance with the recommendations by comparing and contrasting what is currently reported in OM literature with the suggested reporting protocols and guidelines. This review is particularly important given the intense academic debate and controversy surrounding PLS of recent years, which resulted in new guidelines and recommendations for its use and the reporting standards of articles that use PLS-SEM as an analytical tool (Cepeda-Carrion, Cegarra & Cillo, 2018; Hair et al., 2019; Marin-Garcia & Alfalla-Luque, 2019a; Sharma, Sarstedt, Shmueli, Kim & Thiele, 2019). The present article is especially focused on evaluating whether the procedures for using and reporting PLS follow the current recommendations and an exhaustive comparison has been made with two more recent review articles related to OM (Kaufmann & Gaeckler, 2015; Peng & Lai, 2012). There is also a third review article in the field of OM by Shah and Goldstein (2006). This article has not been analyzed and compared to the other two since it is older and predates the significant changes in PLS reporting whose implementation in articles we intend to analyze.

Peng and Lai (2012) select OM journals recognized as having published relevant and rigorous empirical research and review articles from 2000 to 2011. After narrowing the OM journals down to 10, they perform a keyword search using the following keywords: "partial-least-squares", "partial least squares", "PLS", "formative", "PLS Graph" "PLS-Graph", and "SmartPLS", resulting in the selection of 42 articles. They then conduct a review of the way that researchers have used PLS in these articles with the analysis of 20 specific aspects grouped into 6 categories (Table 1).

Items	Description
(1)	Rationale for using PLS
(2) to (6)	Sample size
(7) to (13)	Formative constructs
(14)	Bootstrapping
(15)	PLS software used
(16) to (21)	Reported results

Table 1. Number of items reviewed (Peng & Lai, 2012)

These authors conclude that some studies exhibit deficiencies or a lack of familiarity with certain aspects of PLS while others demonstrate a reasonably good understanding of the PLS method. However, overall, many of the reviewed articles do not adequately assess the properties of the formative constructs. Despite the importance of using the right criteria to evaluate formative constructs, 16% of the articles that use the latter do not perform any analysis of their measurement properties, 26% use techniques for evaluating reflective constructs, 37% examine formative construct item weights, 21% evaluate the multicollinearity of the formative measurement items (mostly using the variance inflation factor - VIF) and only 16% examine discriminant validity. It is also interesting to mention that, in some cases, the reasons for using PLS or the performed analysis are not fully consistent with the characteristics of the study carried out: only 42% of the articles that use formative constructs state that their use is the reason for using PLS; although a small sample size is the most cited reason for using PLS, only 5% of the articles perform a power analysis.

The second review, Kaufmann and Gaeckler (2015), focuses on ten OM journals, specifically in the discipline of SCM, and reviews 75 articles from 2002 to 2013. The authors perform a keyword search using the following keywords: "partial least squares" and "PLS". They examine the way that researchers have used PLS in these articles by analyzing 26 key dimensions comprising 46 specific aspects grouped into 7 categories (Table 2).

Items	Description
(1)	Reasons for using PLS
(2) to (6)	Sampling characteristics
(7) to (24)	Model descriptive analysis
(25) to (30)	Reported reflective measurement model statistics
(31) to (35)	Reported formative measurement model statistics.
(36) to (43)	Reported structural model statistics
(44) to (46)	Technical reporting (software and resampling method)

Table 2. Number of items reviewed by Kaufmann and Gaeckler (2015)

These authors conclude that not all of the reviewed articles provide sufficient or complete results, so the PLS analyses are not fully documented. Some researchers meticulously perform all the tests and report data on all necessary criteria, but others inadequately document their approach. Consequently, some important criteria and data seem to be underrepresented (see Table 11 for further details).

Despite the importance of using the right criteria to evaluate formative constructs, 23% use techniques for evaluating reflective constructs, 73% examine formative construct item weights and 19% report their sign and magnitude, 38% evaluate the multicollinearity of the formative measurement items (mostly using the variance inflation factor - VIF). More comparative details of the characteristics and conclusions of both articles are presented in Table 11.

3. Methodology

In order to conduct the analysis that is the object of the present investigation, we have followed a detailed procedure to perform a systematic literature review following Tranfield et al. (2003), Denyer and Tranfield (2009), and Medina-López, Marin-Garcia and Alfalla-Luque (2010).

3.1. References Selection

The first step is the identification of the field of the study - OM articles that have used PLS methodology in their research – and the choice of the period to be analyzed, 2014-2018. This period has been chosen as the last review in OM includes articles up to 2013 (Kaufmann & Gaeckler, 2015), as seen in the previous section, and, especially, due to a significant change being developed during this period in the standards for reporting results obtained from PLS use.

The next step is to define the information sources. In our case, we focus on articles published in scientific journals. To select the journals, we start from the list in Annex II of the article by Boronat-Soler (2018) and identify the journals labeled as OM. These authors perform an exhaustive classification of the journals indexed in the Web of Science and Scopus databases by these journals' sub-areas in the field of Economics and Business Sciences, particularly in the areas of OM and Human Resource Management (HRM). For this, they simultaneously classify the 715 journals in field D15 of the Spanish National Agency for Quality Assessment and Accreditation (ANECA) indexed in Scopus and JCR. After analyzing the public information in each journal and, in some cases where the classification was not clear, the subject matter of the articles published in the last two issues of the journal, they construct the classification of the journals (this classification is included in Annex II of the Boronat-Soler (2018) article mentioned above). We take the 67 journals labeled as OM as the basis for the present research. Our selected journals include all 10 journals used by (Kaufmann & Gaeckler, 2015) (journals that have received an Impact Factor rating above 1.0 by Thomson Reuters in the recent past). It also includes all journals defined by Peng and Lai (2012) as "journals that are recognized as publishing relevant and rigorous empirical research". As Peng and Lai (2012 state, these were cited as journals "whose missions involve publishing empirical research examining topics" (Barman, Hanna & LaForge, 2001; Goh, Holsapple, Johnson & Tanner, 1997; Malhotra & Grover, 1998; Soteriou, Hadjinicola & Patsia, 1999; Vokurka, 1996). Therefore, this present article includes the journals analyzed in previous studies and widens the spectrum by adding over 50 relevant journals in OM, some more recent articles and a more comprehensive analysis than the previous literature.

We perform a search of publications taking as the starting point for our selection the keywords used in previous reviews in OM with similar objectives to this research(Kaufmann & Gaeckler, 2015; Khan, Sarstedt, Shiau, Hair, Ringle & Fritze, 2019; Peng & Lai, 2012). The keywords are: "partial least squares", "partial-least-squares", "PLS", "PLS Graph", "PLS-Graph", and "SmartPLS". The term "formative" was not included to prevent any false positives (since they refer to training/learning and not to constructions of an alternative type to the common factor) and adding the term "ADANCO" (another software application currently used to analyze PLS models).

The two main journal databases have been considered: Web Of Science (WOS) and Scopus. Initially, important differences have been observed in the number of results obtained in the search in the two databases for the field "journal name". These differences were caused by the search by journal name generating false positives, as journals from other areas whose names include the search terms but only differ in a single word, are included in the results.

For this reason, we chose to carry out the searches by ISBN field (see Figure 1), limiting the search strategy by keywords to the OM journals that are simultaneously indexed in WOS and Scopus (Boronat-Soler, 2018). For this, we used the Boronat-Soler (2018) list filtered by the ISBN field.

After this initial search performed in March 2019, we obtained a preliminary list of OM articles: 362 articles in Scopus and 369 in WOS. A manual filter was then applied using the following inclusion criteria: (i) articles published in journals or conferences in the WOS core collection databases (which includes the journals contained in the Journal Citation Reports and in the Emerging Source Citation Index) and in Scopus; (ii) empirical studies that analyze models with PLS; (iii) research whose contribution focuses on the field of OM (in the scientific areas of business administration or engineering); (iv) articles indexed between 2014 and 2018 (both years inclusive). This 5-year time window starts immediately after the date of the last reference used by Kaufmann and Gaeckler (2015), (2013), and prevents any overlaps with the previous research.

The following exclusion criteria have been considered: (i) the theme of the article does not correspond to the area of OM. For example, topics such as a. civil or construction engineering, b. material or electrical or chemical engineering (i.e. surface treatments, mechanical process, etc.), c. ICT unrelated to OM, d. management issues unrelated to OM (corporate social responsibility, management capability, soft skills, retail, etc.); (ii) PLS does not stand for Partial Least Squares (e.g., product or process layout systems (PLS), Pareto Local Search (PLS)); (iii) PLS is not used as an SEM technique to test empirical models, e.g., analysis with PLS regression (to prevent false positives of this type, it is recommended to change the term "PLS" to "PLS-SEM" in the search strategy); (iv) Methodological articles on how to use PLS for topics not linked to our objectives or guidelines for the use of PLS; (v) The focus of the paper is solely on the PLS method and does not include any empirical results, e.g., editorials,

conceptual papers, method explanation. Following these considerations and after applying the acceptance and discard criteria, 102 references for PLS in OM were initially selected.

Scopus

TITLE-ABS-KEY ("partial least squares" OR "partial-least-squares" OR "PLS" OR "PLS Graph" OR "PLS-Graph" OR "SmartPLS" OR "ADANCO") AND PUBYEAR > 2013 AND PUBYEAR < 2019 AND ISSN(1619-4500 OR 1854-6250 OR 0254-5330 OR 0890-0604 OR 0217-5959 OR 0144-5154 OR 0964-4733 OR 1435-246X OR 0007-8506 OR 1535-3958 OR 0011-7315 OR 0305-215X OR 1751-5254 OR 0377-2217 OR 1936-6582 OR 0926-2644 OR 1090-8471 OR 2156-3950 OR 0018-9391 OR 1471-678X OR 1366-2716 OR 0092-2102 OR 0957-4093 OR 1367-5567 OR 0890-6955 OR 0144-3577 OR 0960-0035 OR 2288-6206 OR 0925-5273 OR 0020-7543 OR 0263-7863 OR 1756-6517 OR 0969-6016 OR 1881-3054 OR 0735-3766 OR 0925-5001 OR 1547-5816 OR 0956-5515 OR 1526-6125 OR 1087-1357 OR 0278-6125 OR 0924-0136 OR 0272-6963 OR 0022-3239 OR 0737-6782 OR 0895-562X OR 1478-4092 OR 1094-6136 OR 1757-5818 OR 1094-6705 OR 2055-6225 OR 1523-2409 OR 0160-5682 OR 1523-4614 OR 0361-0853 OR 1042-6914 OR 1432-2994 OR 0364-765X OR 0894-069X OR 1109-2858 OR 1936-9735 OR 0030-364X OR 0167-6377 OR 0171-6468 OR 0233-1934 OR 0269-9648 OR 0954-4054 OR 1059-1478 OR 0953-7287 OR 8756-9728 OR 0898-2112 OR 1684-3703 OR 0257-0130 OR 0033-6807 OR 0399-0559 OR 0934-9839 OR 1862-8516 OR 0264-2069 OR 0038-0121 OR 1696-2281 OR 1359-8546 OR 1478-3363 OR 0965-8564 OR 1366-5545 OR 1524-1904 OR 1976-1597 OR 0007-6805 OR 0305-0548 OR 0167-9236 OR 0424-267X OR 1077-2618 OR 0263-5577 OR 0378-7206 OR 1471-7727 OR 1047-7047 OR 1385-951X OR 1091-9856 OR 0268-3768 OR 0267-5730 OR 1530-9827 OR 0923-4748 OR 0268-3962 OR 0742-1222 OR 1546-2234 OR 0022-4065 OR 0963-8687 OR 1091-0344 OR 1540-1960 OR 0276-7783 OR 1532-9194 OR 0268-1072 OR 0748-8017 OR 0048-7333 OR 0895-6308 OR 0736-5845 OR 0883-7066 OR 1094-429X OR 0953-7325 OR 0166-4972)
Results 362

WOS

(TS= (("partial least squares" or "partial-least-squares" or "PLS" or "PLS Graph" or "PLS-Graph" or "SmartPLS" or "ADANCO")) AND IS=(1619-4500 OR 1854-6250 OR 0254-5330 OR 0890-0604 OR 0217-5959 OR 0144-5154 OR 0964-4733 OR 1435-246X OR 0007-8506 OR 1535-3958 OR 0011-7315 OR 0305-215X OR 1751-5254 OR 0377-2217 OR 1936-6582 OR 0926-2644 OR 1090-8471 OR 2156-3950 OR 0018-9391 OR 1471-678X OR 1366-2716 OR 0092-2102 OR 0957-4093 OR 1367-5567 OR 0890-6955 OR 0144-3577 OR 0960-0035 OR 2288-6206 OR 0925-5273 OR 0020-7543 OR 0263-7863 OR 1756-6517 OR 0969-6016 OR 1881-3054 OR 0735-3766 OR 0925-5001 OR 1547-5816 OR 0956-5515 OR 1526-6125 OR 1087-1357 OR 0278-6125 OR 0924-0136 OR 0272-6963 OR 0022-3239 OR 0737-6782 OR 0895-562X OR 1478-4092 OR 1094-6136 OR 1757-5818 OR 1094-6705 OR 2055-6225 OR 1523-2409 OR 0160-5682 OR 1523-4614 OR 0361-0853 OR 1042-6914 OR 1432-2994 OR 0364-765X OR 0894-069X OR 1109-2858 OR 1936-9735 OR 0030-364X OR 0167-6377 OR 0171-6468 OR 0233-1934 OR 0269-9648 OR 0954-4054 OR 1059-1478 OR 0953-7287 OR 8756-9728 OR 0898-2112 OR 1684-3703 OR 0257-0130 OR 0033-6807 OR 0399-0559 OR 0934-9839 OR 1862-8516 OR 0264-2069 OR 0038-0121 OR 1696-2281 OR 1359-8546 OR 1478-3363 OR 0965-8564 OR 1366-5545 OR 1524-1904 OR 1976-1597 OR 0007-6805 OR 0305-0548 OR 0167-9236 OR 0424-267X OR 1077-2618 OR 0263-5577 OR 0378-7206 OR 1471-7727 OR 1047-7047 OR 1385-951X OR 1091-9856 OR 0268-3768 OR 0267-5730 OR 1530-9827 OR 0923-4748 OR 0268-3962 OR 0742-1222 OR 1546-2234 OR 0022-4065 OR 0963-8687 OR 1091-0344 OR 1540-1960 OR 0276-7783 OR 1532-9194 OR 0268-1072 OR 0748-8017 OR 0048-7333 OR 0895-6308 OR 0736-5845 OR 0883-7066 OR 1094-429X OR 0953-7325 OR 0166-4972)) *AND* **DOCUMENT TYPES:** (Article OR Proceedings Paper OR Review)
Indexes=SCI-EXPANDED, SSCI, CPCI-S, CPCI-SSH, ESCI Timespan=2014-2018
369 results

Table 3. Search strategy in Scopus and WOS

3.2. Codification Process

We then encoded the full articles in the list of 102 PLS references in OM. For this, we had previously defined 46 codes (see full list in Marin-Garcia et al (2019b) designed to extract information from the articles. This information was grouped into 5 sections: (i) Reasoning behind the use of PLS-SEM; (ii) Data characteristics; (iii) Model characteristics; (iv) Model evaluation and (v) Reporting of other aspects.

3.3. Analysis

Once the data had been exported, the R Bibliometrix package (Cuccurullo, Aria & Sarto, 2016; Garfield, 2004; Wulff Barreiro, 2007) (http://www.bibliometrix.org/index.html#header3-d) was used, enabling the following analysis: annual scientific production, most relevant sources, journals, single-author articles, citations per document, most productive authors, most productive countries. An analysis of the results is given in section 4.1.

Additionally, the 102 selected articles have been coded, for which 46 codes had previously been defined and grouped into 5 key dimensions: (i) reasoning behind the use of PLS (ii) data characteristics (iii) model characteristics (iv) model evaluation and (v) reporting of other aspects. The main outcomes are broken down in section 4.2.

4. Results

4.1. Bibliometric Study: Results

The 102 references analyzed are distributed over a total of 45 journals in the 2014-2018 period, 13 of which are proceedings papers. The number of articles per year (Figure 1) shows an increasing trend in the analyzed period, with a peak of 35 in 2018.
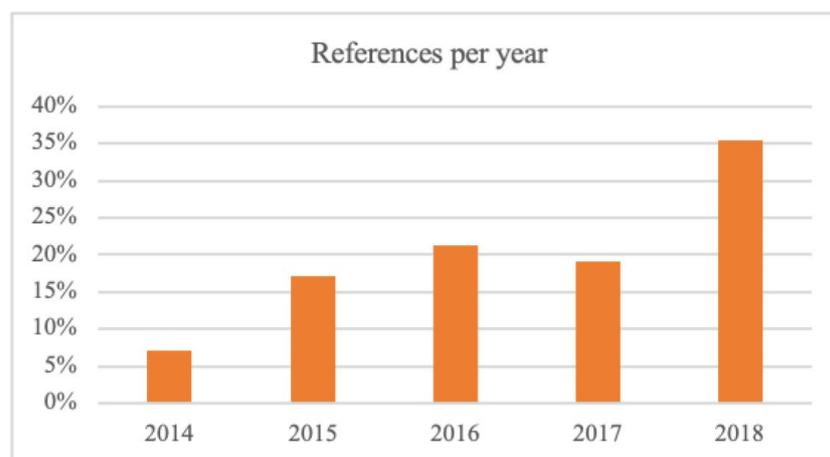

Figure 1. Time evolution of publications

With a total of 45 sources, the articles are not concentrated in any specific publications. Figure 2 shows the journals with the most published OM papers that concern PLS. Specifically, there are only 3 journals with 10 or more articles: Industrial Management & Data Systems (14), International Journal of Production Economics (13) and International Journal of Production Research (10). Following these are the Journal of Management in Engineering and the Journal of Manufacturing Technology Management, with 5 publications. Production Planning & Control has 3 articles and the remaining publications have 2 or 1.

Most of the research has been co-authored, with only conducted by a single author. On average, publications have 3 authors and 11.78 citations per document prior to the date that the search was conducted. Figure 3 shows the authors who have the highest number of publications that make use of PLS in the OM area during the analyzed period. In this figure, the size of the circle is proportional to the number of articles of the corresponding year, and the darker the color, the more cited the papers have been.

Regarding authors' affiliations, there is a low concentration in a small number of universities, indicating that this tool is being used in different contexts (universities and countries). Figure 4 shows affiliations that appear in 2 or more articles. The University of Ciudad de Juárez stands out with 7 followed by the University of Seville with 5. The most active authors in Ciudad Juárez are Garcia-Alcaraz, JL (6 articles); Maldonado-Macias, AA (4); Avelar-Sosa, L (2) and Alor-Hernandez, G (2).
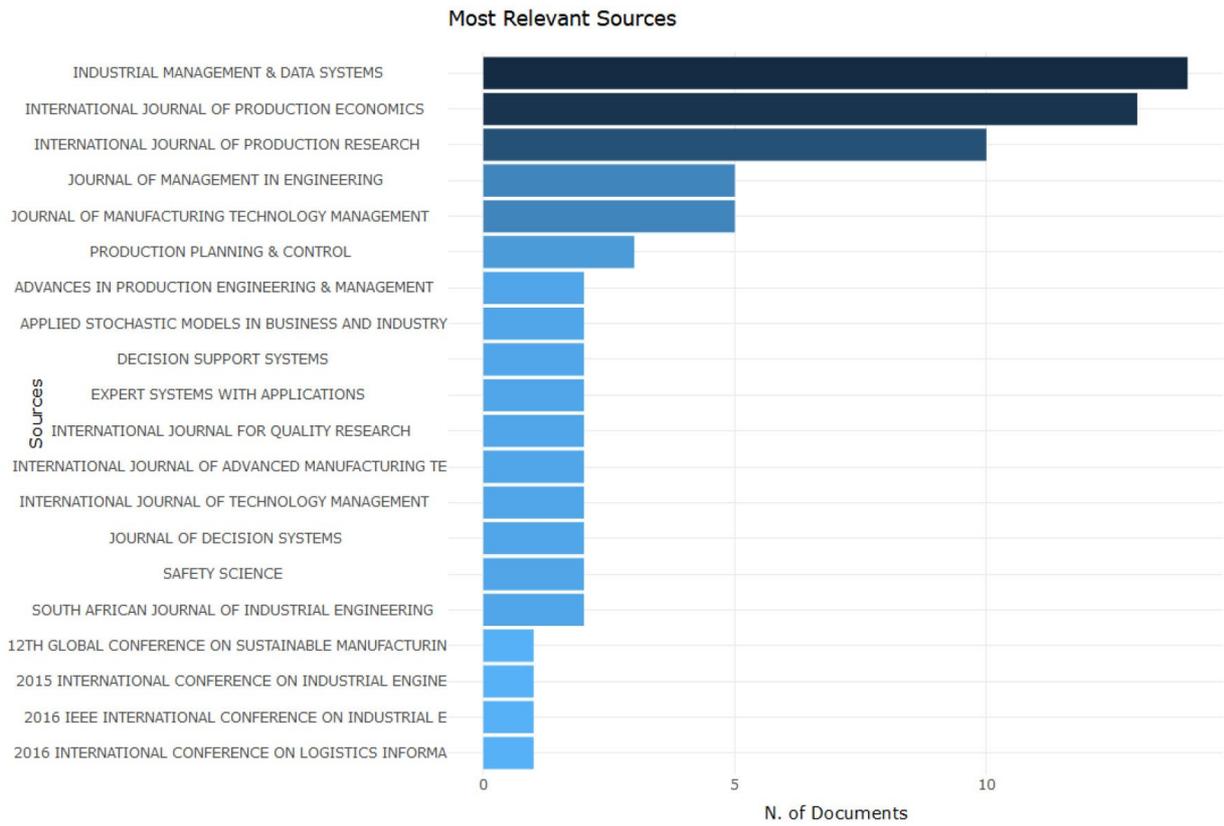
Figure 2. Journals with most analyzed publications
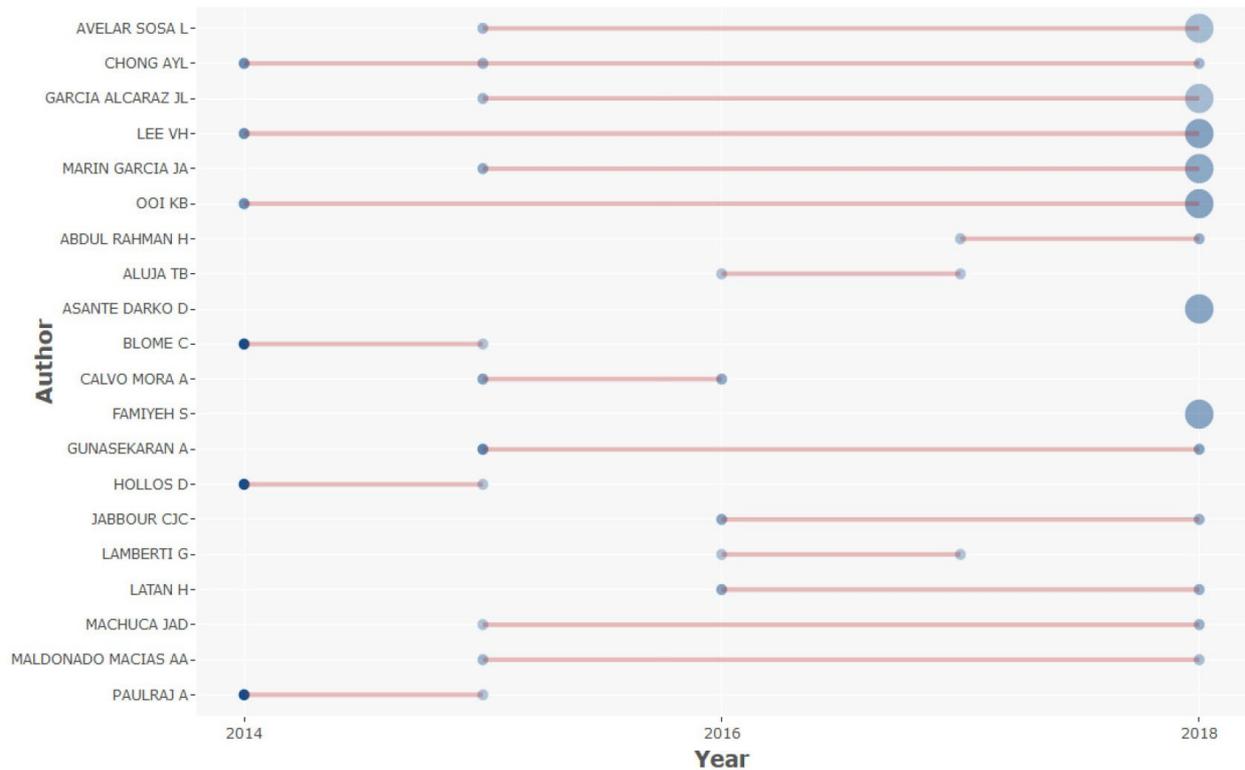
Figure 3. Top-Authors' production over time
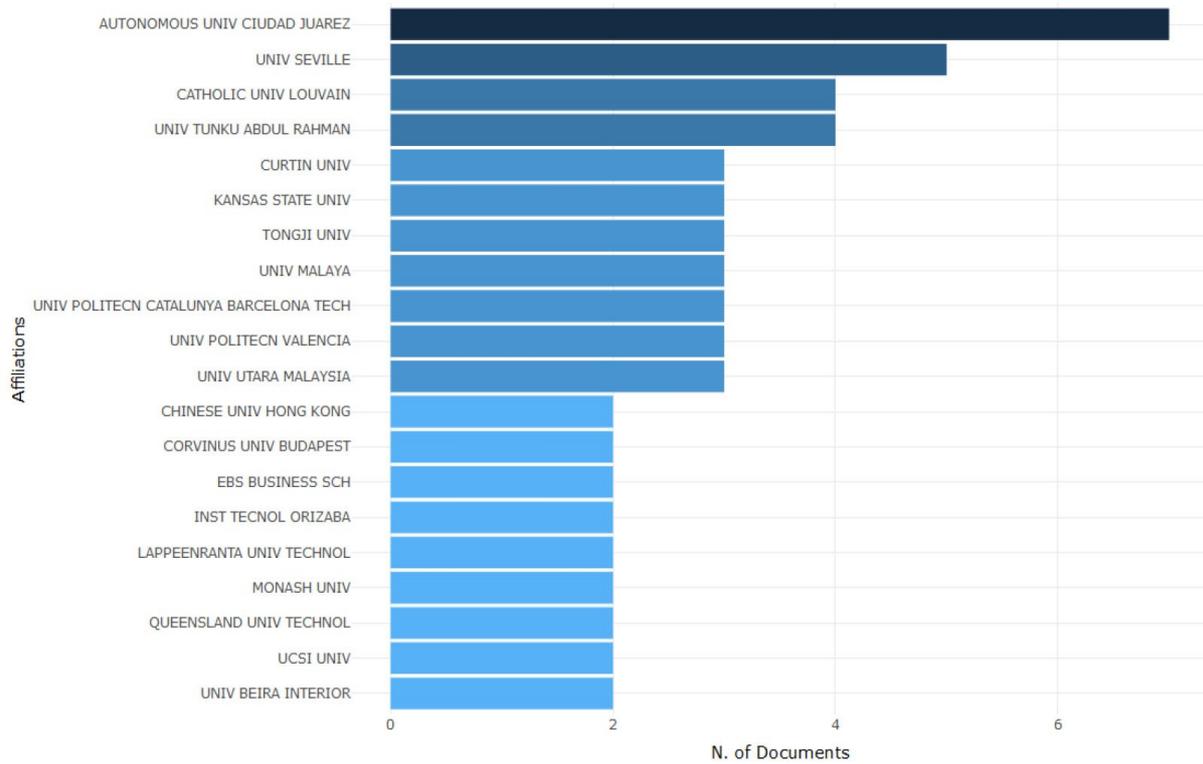
Figure 4. Most relevant affiliations
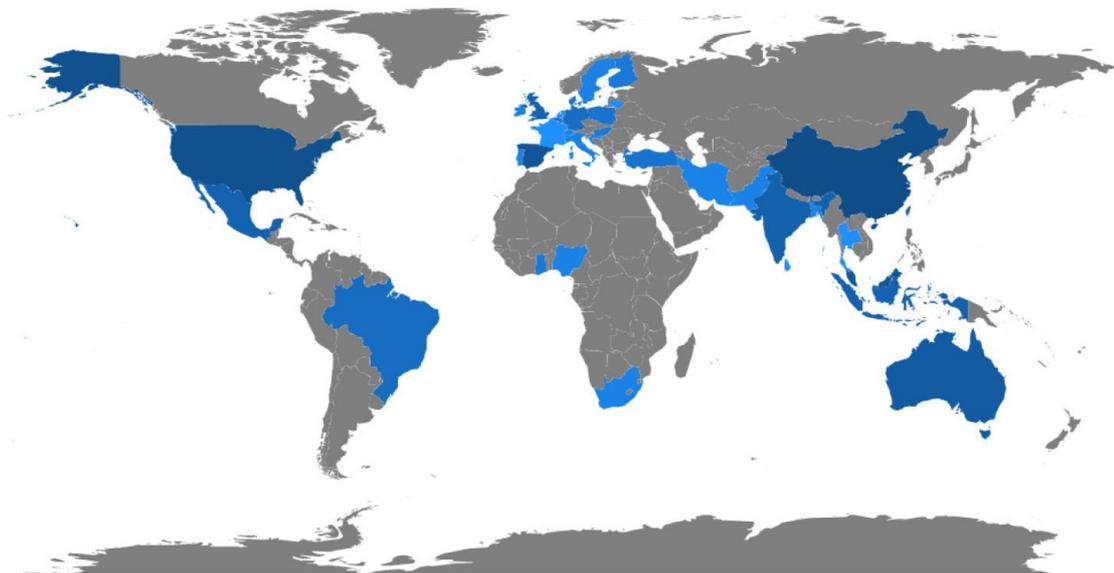
Figure 5. Scientific production by country

The most published authors are affiliated with universities or research centers in the United Kingdom, China, India, USA, Spain, and Malaysia. Figure 5 shows the geographical distribution of the authors. Darker shading indicates countries with greater numbers of publications.

Finally, Figure 6 shows the main topics addressed in the publications in the different years. It should be highlighted that 2017 shows a clear orientation toward publications in supply chain management.

Figure 6. Trend Topics in the publications

4.2. Extraction of Articles Information

4.2.1. Reasoning Behind the Use of PLS

The first aspect to analyze in the coding process is the study of the arguments that the authors use as reasons for using PLS in their research. We found that out of the 102 articles analyzed, a total of 20 (19.61%) did not clearly explain the reasons why they chose to use the PLS method while 82 (80.39%) include one or more reasons for choosing the method. The reasons that predominate are related to the benefits of the method's ease of use and lower demands when tackling research, such as its ability to be used with a smaller sample size (cited in 56.44% of the articles) and the non-requirement of data normality (cited in 33.66% of the articles). Other reasons allude to the power of the method, mainly to its convenience when formulating hypotheses and predictions (cited in 35.64% of the articles) and to the power to implement more complex models (cited in 26.73% of the articles), as well as the possibility of using formative and reflective constructs (cited in 17.82% of the articles). 77.8% of the articles that include the possibility of using formative and reflective constructs as a reason make use of formative and reflective constructs, 11.1% use only formative constructs while 11.1% do not use any formative but only reflective constructs.

Table 4 gives an overview of the main reasons argued in favor of using the PLS method.

4.2.2. Data Characteristics

The second analyzed aspect includes the sample characteristics and serves as the basis for carrying out the study proposed by the authors. All the 102 analyzed articles report the sample size, which ranges from a minimum of 20 to a maximum of 533, with a mean of 186 and a median of 177. One aspect that is less cited in the publications is the response rate, which is not reported by 34.65% of the articles. It should be noted that even though the same name is used for this ratio in all the articles, in some cases it includes values discarded for not containing sufficient data to be included in the calculations, while in other cases it is only calculated with the complete values used for the study after discounting discarded values.

Regarding the normality of the distribution of the data, this is only assessed in 10.89% of the cases.

Tables 4 and 5 give an overview of the results.

Description	Articles reporting (%)
No reasons provided	19.6%
Most cited reasons	
small sample size	69.5%
not limited to a normal distribution assumption constraint	41.5%
suitable for complex hierarchical models	30.5%
to develop new knowledge and theories in an exploratory rather than a confirmatory study	28.0%
can handle formative and reflective constructs in the same model	22.0%
specifically designed for prediction purposes	15.9%
suitable for examining the relationships between multiple independent variables and multiple dependent variables	7.3%
less demanding premises, limiting soft modeling assumptions, less stringent assumptions	6.1%
previously used in similar studies	2.4%
suitable for analyzing higher-order constructs	2.4%
handles missing data	2.4%
deals positively with specific problems	
determines the relationships kept in the background due to multicollinearity problems and measurement errors	2.4%
independent equations that need to be estimated simultaneously	1.2%
more advisable when analyzing continuous scale moderators	1.2%
can solve issues (holdout sample, re-sampling, etc.), enabling researchers to estimate the robustness of the data	1.2%
maximizes the explained variance when independent variables are approximated as linear combinations of dependent variables	1.2%
maximizes the explained data-driven variance rather than estimation of model fit	1.2%
robustness check of maximum likelihood estimations	1.2%
great accuracy of parameter estimation and ease of model specification and interpretation	1.2%
avoids the limitations regarding improper solutions or empirical under-identification	1.2%

Table 4. Reasons given for using PLS (N=102)

Description	Values
Sample size	
mean	186
median	177
range	(20; 533)
fewer than 150 observations	29.4%
fewer than 100 observations	12.8%
Provides response rate	65.7%
response rate mean	40.6%
Response rate median	35.9%
response rate range	(9%; 85%)
Assess multivariate normal distribution	11.8%

Table 5. Data characteristics (N=102)

4.2.3. Model Characteristics

The third analyzed aspect includes the main features of models using PLS in OM research. In our analysis, we found that 82.3% of the articles include the description of the indicators while 17.7% do not include any description at all; 6.4% of the articles include latent variables with just one indicator. In 2.9% of the cases, the measurement model is only formative, in 21.6% it is formative and reflective and in 75.5% it is only reflective. 16.7% of the articles report the mean and standard deviation for the indicators while 31.4% report these only for constructs and 51.9% do not report them at all. 87.2% of articles make use of moderator latent variables and, of these, 46.1% evaluate the moderation effect.

Only 2% of the articles use the consistent PLS (PLSc) approach to remove the inconsistency of PLS estimates by correcting for measurement error; 7.8% check for heterogeneity, 2.9% use the finite mixture PLS (FIMIX-PLS) method, and 1% use the prediction-oriented segmentation in PLS (PLS-POS) method to identify and treat unobserved heterogeneity in PLS models. Advanced analysis regarding model assessment in PLS-SEM such as confirmatory tetrad analysis (CTA-PLS) (Gudergan, Ringle, Wende & Will, 2008) to test the mode of measurement and importance-performance map analysis (IPMA) are used in 0% and 3.9% of the articles respectively.

Table 6 gives an overview of the results.

Description	Values
Indicators	
provide item wording	82.3%
mean per variable	33.8
median per variable	29.0
range per variable	(9;80)
mean & standard deviation, items	16.7%
mean & std. dev., constructs only	31.4%
Latent variables	
mean	7.7
median	6
range	(2;17)
Latent variables, 1st order	
mean	7.1
median	6
range	(2;17)
Latent variables, 2nd order	30.4%
mean	2.1
median	2
range	(1;5)
Latent variables, 3rd order	3.9%
range	(1)
Reflective variables	
mean	6.9
median	6
range	(1;21)

Description	Values
Formative variables	
mean	3
median	2
range	(1;7)
Single-item variables	6.4%
Reflective model only	75.5%
Formative model only	2.9%
Reflective + Formative model	21.6%
Consistent PLS (PLSc estimator)	2.0%
Mediating effects	46.1%
Interaction effects / Multigroup analysis	20.6%
Check for heterogeneity	7.8%
FIMIX (Finite MIXture segmentation)	2.9%
POS (Prediction Oriented Segmentation)	1.0%
Confirmatory tetrad analysis	0%
Importance-performance matrix	3.9%
PLSpredict	0%

Table 6. Model characteristics (N=102)

A total of 806 latent variables have been proposed in the 102 analyzed articles. We have compiled all the names used for latent variables and have created a text cloud (Figure 7) which gives greater prominence to the words that appear most frequently, allowing us to easily recognize the top terms used as names for the latent variables in the analyzed OM-related articles.

Figure 7. Cloud text for Latent Variables names

4.2.4. Model Evaluation

The fourth analyzed aspect includes the two-stage approach for model evaluation in which stage 1 is the outer model evaluation and stage 2, the inner model evaluation.

4.2.4.1. Outer Model Evaluation

For stage 1, the outer model assessment differs depending on whether it is a reflective or formative measurement model. In our analysis, there are 99 reflective models and 25 formative models.

Regarding the outer model (reflective), we found that 81.4% of the articles report the indicator loadings when assessing internal consistency, but only 18.6% report their complete loading scheme (significance levels, t values/p values, confidence intervals). Composite reliability (CR), Cronbach's alpha and Average Variance Extracted (AVE) are used to assess the reflective models and are reported in the articles as 88.8%, 78.8%, and 91.9% respectively. A total of 4% of the articles do not report or mention any assessment or CR or Cronbach's alpha in only reflective models (while 6% (CR) and 8% (Cronbach's alpha) do not report their values but do mention their use in the research).

In relation to discriminant validity, only 20.2% of articles report cross-loadings (66.7% do not report these at all, while 13.1% do not report their values but mention their use in the research); the Fornell-Larcker criterion, which compares the AVE estimates with the inter-construct correlations, is reported in 53.5% of the articles (37.4% do not report it, while 9.1% do not report its values but mention its use in the research); the heterotrait-monotrait (HTMT) ratio of correlations is reported in 13.2% of the articles (83.8% do not report it and 3% do not report its values but mention its use in the research). Finally, 32.3% of articles do not report either the Fornell-Larcker criterion or AVE or HTMT.

Moving to the outer model (formative), we found that 24% of the articles report the redundancy analysis when assessing the convergent validity, 72% of the articles do not report it and 4% mention having conducted the redundancy analysis but do not report any value. For the assessment of collinearity among formative indicators, it is determined through the variance inflation factor (VIF) in 76.9% of articles, and 23.1% do not assess multicollinearity. Finally, 20% do not report either redundancy analysis or multicollinearity.

In order to examine the relevance and statistical significance of outer weights, 96% of articles report their values and 40% report their complete weighing scheme (significance levels, t values/p values, confidence intervals). 4% of the articles assess the formative constructs using the reflective criteria.

Table 7 gives an overview of the results.

Description	Articles reporting (%)	Articles not reporting (%)	Articles mentioning but not reporting (%)
Outer model: Reflective (N= 99 models)			
Indicator loadings	83.8%	16.2%	
Loadings data scheme	30.3%	69.7%	
Composite reliability (CR)	88.8%	5.1%	6.1%
Cronbach's Alpha Index (CAI)	78.8%	13.1%	8.1%
Average Variance Extracted (AVE)	91.9%	5.1%	3.0%
Fornell-Larcker criterion	53.5%	37.4%	9.1%
Cross-loadings	20.2%	66.7%	13.1%
Heterotrait – Monotrait (HTMT)	13.2%	83.8%	3%
Outer model: Formative (N= 25 models)			
Multicollinearity (VIF)	76.9%	23.1%	
Indicator weights	96%	4%	
Significance of weights	40%	60%	
Redundancy analysis	24.0%	72.0%	4.0%
Use reflective criteria to assess formative constructs	4%		

Table 7. Outer model evaluation

4.2.4.2. Inner Model Evaluation

Stage 2 is the inner model assessment. To examine the explained variance of endogenous constructs, 80.4% of the articles report the values of the coefficient of determination R2 (12.7% do not report it and 6.9% do not report its values but mention its use in the research) and 19.6% of the articles report the values of Cohen's effect size f2 (76.5% do not report it and 3.9% do not report its values but mention its use in the research).

For predictive relevance, 30.4% of the articles report the values of Stone-Geisser's cross-validated redundancy Q2 (61.8% do not report it and 7.8% do not report its values but mention its use in the research) and 3.9% of the articles report the values of effect size q2 (95.1% do not report it and 1% do not report its values but mention its use in the research).

In order to provide evidence of the quality of the inner model, 91.2% of articles report the path coefficients (8.8% do not give them) and 34.3% report their complete path scheme (significance levels, t values, p-value, confidence intervals).

Regarding a global fit index, 64.7% of the articles do not report any global measure, 2% mention having evaluated it but do not report it and 33.3% do report it at all. 44.4% of the articles that report the global fit index have done so using the Standardized Root Mean Square Residual (SRMR), 27.8% using the Tenenhaus Goodness of Fit (GoF) and 27.8% using the model fit indices that are calculated by WarpPLS software: Average Path Coefficient (APC), Average R-squared (ARS) and Average Variance Inflation Factor (AVIF).

Table 8 gives an overview of the results.

Description	Articles reporting (%)	Articles not reporting (%)	Articles mentioning but not reporting (%)
R² (coefficient of determination)	80.4%	12.7%	6.9%
f² (Cohen's effect size)	19.6%	76.5%	3.9%
Q² (Stone-Geisser value)	30.4%	61.8%	7.8%
q² (effect size)	3.9%	95.1%	1.0%
Path coefficients (β)	91.2%	8.8%	
Significance of paths	34.3%	65.7%	
Model fit	64.7%	33.3%	2.0%
Standardized Root Mean Square Residual (SRMR)	44.4%		
Tenenhaus Goodness of Fit (GoF)	27.8%		
Average Path Coefficient (APC), Average R-squared (ARS) and Average Variance Inflation Factor (AFVIF)	27.8%		

Table 8. Inner model evaluation (N=102)

A total of 368 R2 values has been reported in the 102 analyzed articles. Their distribution per interval is presented in Table 9.

R2 interval	0<R2<0.10	0.10 ≤R2<0.3	0.30 ≤R2<0.5	0.50 ≤R2<0.7	0.70 ≤R2
%	9.4%	23.0%	27.7%	24.8%	15.1%

Table 9. R2 value distribution

4.2.5. Reporting of Other Aspects

The fifth analyzed aspect comprises technical aspects, which are important for successfully understanding the way that the method is applied in the specified research and being able to replicate it.

In our research, the statistical power is only reported in 6.9% of the articles (92.2% do not report it and 1% do not report its values but mention its use in the research). Bootstrapping has been the only resampling method used in, and reported by, 60.8% of articles (39.2% do not mention its use). The number of bootstrap samples ranges from 100 to 5000, with the latter being the most employed (in 54.8% of articles), followed by 500 in 22.6% and 1000 in 14.5% of articles.

Since each PLS-SEM software program has a different set of default values, the software used should be reported. In 83.3% of the articles the software is reported, with SmartPLS the most commonly used (in 82.4% of articles), followed by WarpPLS (in 12.9% of articles). The PLS-SEM algorithm settings, which comprise weighting scheme, stop criterion and sampling weights, is only reported in 6.9% of articles while 3.9% of articles provide partial information.

The empirical covariance or correlation matrix has been reported for the indicator variables in only 5.9% of the articles. In 73.5% of the articles, it has been reported only for the constructs and in 20.6% of the articles it has not been reported at all.

Table 10 gives an overview of the results.

Description	Articles reporting (%)	Articles not reporting (%)	Articles mentioning but not reporting (%)
Statistical power	6.9%	92.2%	1.0%
Bootstrapping	60.8%		
sign change options, etc.	9.8%		
100 samples	1.6%		
≤500 samples	22.6%		
1000 samples	14.5%		
1500 samples	1.6%		
2000 samples	4.8%		
5000 samples	54.8%		
Software used	83.3%		
SmartPLS	82.4%		
WarpPLS	12.9%		
R	2.4%		
Adanco	1.2%		
G*Power	1.2%		
			Partially Reported (%)
PLS-SEM algorithm settings	6.9%	89.2%	3.9%
			Only for Constructs
Covariance / correlation matrix	6%	20.6%	73.5%

Table 10. Reporting of other aspects (N=102)

5. Findings

5.1. Reviews Results and Findings

The use of PLS-SEM in OM has increased over time. We have reviewed and coded 102 articles published in 45 OM-related journals indexed in Scopus and WOS during the 2014-2018 period in which the PLS-SEM approach was applied. The obtained results have been compared with the two previous studies carried out in OM in 2012 and 2015 (see Table 3) and with similar studies carried out in other research areas.

With respect to the authors' reasoning for the use of PLS-SEM, 19.6% of the papers did not give any reasons for the choice of PLS-SEM, a significantly lower percentage than the two studies in OM (29% in both cases). The reasoning is that they benefit more from the method's lower demands (small sample size, non-normal distribution, less demanding) than its strengths (suitable for complex hierarchical models, develops new knowledge and theories, predictive purposes, handles formative variables). We also find that the 11.1% of articles that give the use of formative variables as their reason, do not in fact include any.

The second question analyzed in the coding process was the data characteristics. Following the above, with regard to sample size, it is important to emphasize that if PLS use is based on small samples, it should be verified that the statistical power is adequate for the sample size in question (in our case 29% of articles used a sample of 150 observations or less and only 13%, of 100 or less; the smallest sample was 20 observations). If PLS use is based on non-normal data, it is important to note that extremely non-normal data reduce statistical power and that, therefore, parameters such as skewness and kurtosis should have been reported at the very least. Lastly, we also find that the response rate is not included in 34.65% of cases.

The third question analyzed in the coding process was the model characteristics. 17.7% of the articles do not provide the indicator wording used in the models and only 16.7% provide their mean and standard deviation (31.4% for constructs). Very small numbers of articles use methods to remove inconsistency from PLS estimates, to identify and treat unobserved heterogeneity in PLS models but hardly use any methods for advanced model assessment analysis, which results in valuable information missing about the choice of the measurement model and the importance of one exogenous construct's influence on another endogenous construct of interest. There is almost no substantiation for (i) heterogeneity-related issues (heterogeneity, FIMIX-PLS, PLS-POS); (ii) inconsistency (PLSc); (iii) the choice of measurement model, reflective or formative (CTA-PLS); (iv) the importance of one exogenous construct's influence on another endogenous construct of interest (IPMA). These are verifications that need major improvement in the reporting.

The fourth question analyzed in the coding process was model evaluation. Starting with the outer model evaluation, while the loadings (in reflective models) and weights (in formative models) are reported in 83.8% and 96% of articles respectively, the reporting of their data scheme falls to 30.3% and 40% respectively. In reflective models, 11.2% of articles do not report CR, 21.2% do not report Cronbach's alpha and 4% do not report either of these two values, which raises an important concern about the assessment of their reflective outer models. Convergent validity (AVE) is not reported in 8.1% of the articles and, regarding discriminant validity, only 20.2% of articles report cross-loadings, 53.5% the Fornell-Larcker criterion, and 13.2% HTMT. Besides, 32.3% of the articles with reflective models do not report any of these, so they do not include any discriminant validity assessment at all. In formative models, redundancy analysis is not reported in 24% of articles, 23.1% do not report multicollinearity and 20% do not report either redundancy analysis or multicollinearity. OM researchers using PLS-SEM should improve the reporting and the assessment of formative measurement models. Although for the most part they assess potential collinearity issues and the indicator weights, they give almost no consideration to any other important aspects.

Continuing with the inner model evaluation and starting with the endogenous constructs' explained variance, 80.4% report R^2 values while only 19.6% report the f^2 effect size. As for predictive relevance, only 30.4% of articles report Q^2 and 3.9% q^2 effect size.

Regarding the global fit index, 64.7% of the articles do not report this (2% report its use but do not provide any values) while the most used index among those who have reported it is the Standardized Root Mean Square Residual (SRMR), followed by Tenenhaus Goodness of Fit (GoF) (27.8%) and indices calculated by WarpPLS

(APC, ARS, AVIF). There is an ongoing debate about the appropriateness of these global indices. In fact, some articles argue that no index is provided because these indices are required by CB-SEM but not by PLS-SEM.

The fifth question analyzed in the coding process was the reporting of other technical aspects. It is important to note that only 6.9% of articles report the statistical power, hence hardly any of the analyzed studies provide proof that the sample size is adequate. Although PLS-SEM relies on resampling procedures (Efron, 1979), only 60.8% of articles report the bootstrapping method and 17.6% of articles do not report the software used. 89.2% of articles do not report the PLS-SEM algorithm settings (weighting scheme, stop criterion, and sampling weights) and only 20.6% of articles provide the empirical covariance/correlation matrix.

5.2. Comparison with the Previous OM Research

Table 11 presents a comparison between this review and the two previous reviews in the OM area (Kaufmann & Gaeckler, 2015; Peng & Lai, 2012). Only the main aspects that we were able to extract from the latter two reviews are included Answering our first and second research questions, our findings indicate that the reasoning behind the use of PLS is basically similar, with the main reasons being the sample size, non-normal data, and the use of formative variables. The number of articles not providing reasons has fallen by a third in our review.

Referring to	Peng and Lai (2012)	Kaufmann and -Gaeckler (2015)	Present research
Journals	8 journals	10 journals	45 journals
Keywords	"partial-least-squares", "partial least squares", "PLS", "formative", "PLS Graph" "PLS-Graph", "SmartPLS"	"partial least squares", "PLS"	"partial least squares", "partial-least-squares", "PLS", "PLS Graph", "PLS-Graph", "SmartPLS"
Time frame	2000 to 2011	2002 to 2013	2014 to 2018
Articles selected	42 articles	75 articles	102 articles
Reasons for using PLS	29% do not provide reasons 33% small sample size 26% exploratory or predictive nature of the study 19% the use of formative constructs 14% non-normal data 10% high model complexity	29% do not provide reasons 58% small sample size 42% non-normal data 32% formative measures 30% exploratory research 25% focus on prediction	19.6% do not provide reasons 69% small sample size 41% non-normal data 22% formative measures 28 exploratory research 16% focus on prediction 30 for hierarchical models 7% relationships between multiple independent and dependent variables 6% less demanding premises 12% solves some specific problems
	in addition to which … only 5% of articles perform a power analysis only 42% of the articles using formative constructs mention this as the reason for using PLS	in addition to which… only 65% of the articles using formative constructs mention that as the reason for using PLS	in addition to which 90% of the articles using formative constructs mention that as the reason for using PLS
Assessment of formative constructs	26% use techniques for evaluating reflective constructs; 21% evaluate the multicollinearity of the formative measurement items, for the most part using the variance inflation factor (VIF);	23% use techniques for evaluating reflective constructs; 38% evaluate the multicollinearity of the formative measurement items, for the most part using the	4% use techniques for evaluating reflective constructs; 76% evaluate the multicollinearity of the formative measurement items using the variance inflation factor (VIF);

Referring to	Peng and Lai (2012)	Kaufmann and -Gaeckler (2015)	Present research
	37% examine formative construct item weights; 16% of the articles that use formative constructs do not perform any analysis of their measurement properties; 16% examine discriminant validity.	variance inflation factor (VIF); 73% examine formative construct item weights and 19% report their sign and magnitude	96% examine formative construct item weights and 40% report their sign and magnitude
PLS software	62% of the articles report the PLS software used, with PLS-Graph the most popular (45%)	69% of the articles report the PLS software used, with SmartPLS the most popular (39%)	83% of the articles report the PLS software used, with SmartPLS the most popular (82%)
Resampling methods	52% of the articles report details of their bootstrapping procedures with a 100 to 1,500 generated bootstrap sample range. 500 is the most common resampling number (26%)	71% mention the use of resampling methods and 51% report the number of generated bootstrap samples	61% of the articles report details of their bootstrapping procedures with a 100 to 5000 generated bootstrap sample range. 5000 is the most common resampling number (55%)
Reporting of results	86% of the articles report the endogenous variables' R^2. However, other techniques for evaluating predictive validity are underused. 14% report the effect size (f^2) and 9% report predictive relevance (Q^2). 14% report effect size	95% of the articles report the endogenous variables' R^2. However, other techniques for evaluating predictive validity are underused. 11% report the effect size (f^2) and 10% report predictive relevance (Q^2). 11% report effect size. 93% report the item wording. 84% include the correlation matrix. 71% report scale means and standard deviation	80% of the articles report the endogenous variables' R^2. However, 20% report the effect size (f^2) and 30% report predictive relevance (Q^2). 4% report effect size. 82% report the item wording. 79% include the correlation matrix. 31% report scale means and standard deviation

Table 11. Most important characteristics and conclusions extracted from previous OM reviews

We find some significant improvements such as (i) the incorrect use of techniques to evaluate reflective constructs (a decrease from 26% to 4%); (ii) the evaluation of the multicollinearity of the formative measurement items using the variance inflation factor (VIF) (an increase from 36% to 76%); (iii) the examination of formative construct item weights and the reporting of their signs and magnitudes (an increase from 73%/19% to 96%/40%); (iv) articles reporting the software used (an increase from 69% to 83%); (v) the reporting of the f^2 effect size (an increase from 11% to 20%) and (vi) the reporting of Q^2 (an increase from 10% to 30%).

To the contrary, some important assessment aspects are being less reported: (i) articles reporting details of their bootstrapping procedures (a decrease from 71% to 61%); (ii) articles reporting the R^2 of the endogenous variables (a decrease from 95% to 80%); (iii) indicator wording (a decrease from 93% to 82%); (iv) q^2 effect size (a decrease from 11% to 4%) and (v) scale means and standard deviation (a decrease from 71% to 31%).

Although there has been some improvement in the reporting of some of the parameters, many still do not reach the desired level of reporting: R^2 (80%), f^2 (20%), Q^2 (30%), q^2 (4%), bootstrapping (61%), reasoning (80%), among others. Researchers need to be aware of the importance of providing the information required to follow and be able to replicate the research. Although it is likely that they will be required to reduce the length of their articles, some important, useful information about their research should not be left out.

Therefore, in answer to our third research question regarding the current validity of the results of previous reviews, based on a very limited set of journals and given that the reviews were published before substantial modifications were made to the PLS-based study reporting methods, we can argue that they are partially valid.

Our research has been conducted with a significant increase in the number of journals and articles reviewed and all of the latter are, on average, more than eight years more recent than previous reviews. Consequently, the modifications to the PLS-based study reporting method have been partially implemented since more reporting information has been provided, but further improvement is still required in aspects such as those stated in the previous paragraph.

5.3. Comparison with the Previous Research in other Disciplines

Table 12 presents a comparison of the main findings in a total of 11 assessments (the present assessment included) in a variety of areas such as OM (Kaufmann & Gaeckler, 2015; Peng & Lai, 2012), Hospitality and Tourism (Usakli & Kucukergin, 2018), Tourism (do Valle & Assaker, 2016), Hospitality Management (Ali ewt al., 2018), Human Resources Management (Ringle et al., 2018), Accounting (Nitzl, 2016), International Business (Richter, Sinkovics, Ringle & Schlägel, 2016), Information Systems (Hair, Hollingsworth, Randolph & Chong, 2017), Marketing (Hair, Sarstedt, Ringle et al., 2012) and Strategic Management (Hair, Sarstedt, Pieper et al., 2012).

Table 12 shows the 11 reviews in different areas carried out previously sorted by descending time-period of reviewed articles. This enables the evolution of PLS-SEM analysis reporting to be explored more easily. Some parameters have empty cells as the reviews do not explicitly mention their values.

	1	2	3	4	5	6	7	8	9	10	11
N of studies analyzed	102	206	29	82	77	44	37	43	75	42	37
Time-period covered	2014-18	2000-17	2001-15	2010-15	1985-14	2000-14	1980-13	1990-13	2002-13	2000-11	1981-10
Reasons for PLS-SEM											
Gives reasons	80.4%	66.0%	86.2%	85%	84.4%	95.5%	89.2%	90.7%	70.7%	71.4%	86.5%
Most cited reason											
small sample size	69.5%	20.4%	31.0%	34%	66.2%				36.0%	42.4%	53.1%
exploratory	28%	22.3%	24.1%	8.8%	26%				18.6%	33.3%	
formative constructs	22.0%	20.9%	17.2%	21.8%	19.5%				19.8%	24.2%	31.3%
non-normal data	41.5%	16.0%	31.0%	25.2%	42.9%			46.5%	25,6%		68.8%
Data characteristics											
Sample Size											
mean	186	425	332	333	142.5	487	138	354	274	246	154.9
median	177	341	382		145	321	105		168	126	83
range	(20;533)	(55; 2760)	(106; 1500)	(59; 1512)	(6;9623)		(18;359)	(38; 5191)	(35; 2465)	(35; 3926)	
under 100 observ.	12.8%	2.9%	0%	23.1%	33.3%	4,5%			17.3%	33.3%	
Gives response rate	65.7%										
resp. rate mean	40.6%										
resp. rate median	35.9%										
resp. rate range	(9%;85 %)										
Multiv. normal distrib.	11.8%										
Model characteristics											
Indicators											
give item wording	82.3%	94.6%		79.2%				76.7%	93.3%		
mean per variable	33.8	28.1	24.7	32	34.9	24.9			29.1		27

	1	2	3	4	5	6	7	8	9	10	11
median per variable	29.0	27	22		26	23			26.5		19
range per variable	(9;80)	(2;62)	(12;78)	(5;1064)	(7;161)	(8;65)			(9;70)		(7;114)
items mean & std.dev.	16.7%			58.5%					70.7%		
constructs only m & std.	31.4%										
Latent variables											
mean	7.7	7.8	7	7.3	7.8	6.0			7.0		7.5
median	6	7	7		7	6			6		6
range	(2;17)	(1;24)	(3;20)	(2;25)	(3;32)	(1;17)			(3;21)		(2;31)
Latent variables 1st order											
mean	7.1	7.3							7.1		
median	6	7							6		
range	(2;17)	(1;24)							(2;17)		
Latent variables 2nd order	30.4%				5.3%				35%		
range	(1;5)	(1;8)									
Latent variables 3rd order	3.9%										
range	(1)										
Reflective variables											
mean	6.9										
median	6										
range	(1;21)										
Formative variables											
mean	3										
median	2										
range	(1;7)										
Single-item variables	6.4%	18.4%	20.7%	20.7%	76.3%	13.6%	32.4%	46.5%	29.3%		67.9%
Only Reflective model	75.5%	62.6%	62.1%	87.8%	41.2%	61.4%	78.9%	60.5%	65.3%		10.7%
Only Formative model	2.9%	2.4%	0%	1.2%	0%	2.3%	0%	2.3%	0.0%		10.7%
Reflective + Formative	21.6%	29.6%	37.9%	22%	43%	36.4%	21.6%	34.9%	34.7%		50%
Consistent PLS (PLSc)	2.0%										
Mediating effects	46.1%										
Check for heterogeneity	7.8%				24.7%			32.5%			21.6%
FIMIX	2.9%			2%				2.3%			0%
POS	1.0%							0%			
Confirm. tetrad analysis	0%			0.7%	0%						
Import.-perform. matrix	3.9%										
PLSpredict	0%										
Outer model evaluation											
Outer model: Reflective											
Indicator loadings	83.8%	88.4%	93.1%	85.4%	76%	81.4%	48.7%	76%	84%		77.9%
Loadings data scheme	30.3%										
Composite reliability	88.8%	94.2%	79.3%	86.6%	69.8%	100%	86.5%	48.7%	79%		45.5%
Cronbach's alpha	78.8%	60.5%	48.3%	78%	45.8%		48.7%	26.8%	41%		30.8%
AVE Av. Variance Extracted	91.9%	96.8%	79.3%	89%	78.1%	97.7%	83.8%	80.4%	81%		42.7%
Fornell-Larcker criterion	53.5%	86.8%	79.3%	81.7%	59.4%	95.4%	89.2%		80%		19.1%
Cross-loadings	20.2%	34.7%	17.2%	28%	18.7%	21%	56.8%		75%		19.1%

	1	2	3	4	5	6	7	8	9	10	11
HTMT heterotrait - monotrait	13.2%	18.8%	0%								
Outer model: Formative											
Multicollinearity (VIF)	76.9%	68.2%	27.7%	88.2%	18.3%	64.7%	62.5%	50%	38%		1.5%
Indicator weights	96%	68.2%	18.2%	88.2%	18.4%	100%	62.5%	50%	73%		38.2%
Significance of weights	40%	51.5%	18.2%	3.7%	20.4%	82.4%	75%	25%	19%		4.4%
Redundancy analysis	24%										
Use reflective criteria	4%			17.1%	65.3%				23%		
Inner model evaluation											
R² (determination)	80.4%	96.1%	82.8%	94.1%	82.5%	97.6%	95%	95.3%	95%	85.7%	80.4%
Q² (Stone-Geisser value)	30.4%	44.8%	24.1%	16.5%	7%	33.3%	10.8%	27.5%	13%	9.5%	2.7%
f² (Cohen's effect size)	19.6%	15.3%	17.2%	27.1%	5.3%	11.9%	8.1%	4.7%	11%	14.3%	10.7%
q² (effect size)	3.9%	0.5%		5.9%	0%	0%	0%	0%	0%	0.0%	0%
Path coefficients (β)	91.2%	99%	95.6%	82.4%	100%		100%	95.3%	97%	100.0%	95.5%
Significance of paths	34.3%	99.5%	55.2%	91.8%	99.1%	100%	100%	95.3%	97%	100.0%	95.5%
Model fit	33.3%										
Tenenhaus GoF	9.8%	27.2%			7%	14.3%			5%		0%
SRMR	15.7%	2.9%			0%						
APC, ARS, AFVIF	9.8%										
Reporting of other aspects											
Statistical power	6.9%									4.8%	
Jackknifing					66.2%	15.9%	27%				
Bootstrapping	60.8%	80.1%	41.4%	70.1%	19.5%		81.1%		71%	52.4%	
sign change options, etc	9.8%			16.3%					51%		
100 samples	1.6%									4.5%	
≤500 samples	22.6%									72.7%	
1000 samples	14.5%									22.7%	
1500 samples	1.6%										
2000 samples	4.8%										
5000 samples	54.8%										
Software used	83.3%	65%	72.4%	67.1%	55.5%	81.8%5	67.6%		61%	61.9%	49.6%
SmartPLS	82.4%	63.1%	44.8%	39%	24.7%	56.8%	27%			14.3%	5.4%
WarpPLS	12.9%	4.4%	0%	0%	0%	2.3%	0%				
Adanco	1.2%										
G*Power	1.2%										
PLS-Graph		8.7%	20.6%	15.9%	26%	13.6%	40.5%		29%	45.2%	27%
XLSTAT-PLS		4.9%	3.4%	0%	1.3%	4.5%	0%				
R	2.4%										
Algorithm settings	6.9%	93.1%				4.5%					
Covaria./correlate. matrix	6%	1.5%		85.7%	88.3%						67.6%

Table 12. Comparison with reviews in other areas. 1: OM Present article; 2: Hosp&Tour (Usakli & Kucukergin, 2018); 3: Hospitality (Ali et al., 2018); 4: Inf. Systems (Hair, Hollingsworth, et al., 2017); 5: HRM (Ringle et al., 2018);6: Tourism (do Valle & Assaker, 2016); 7: Accounting (C Nitzl, 2018); 8: I. Business (Richter et al., 2016); 9: OM-SCM (Kaufmann & Gaeckler, 2015); 10: OM (Peng & Lai, 2012); 11: Strategic m. (Hair, Sarstedt, Pieper, et al., 2012)

It should be noted that the percentage of articles that justify the use of PLS-SEM has not improved over time but it has fluctuated. The maximum was reached in 2000-2014 (Tourism) and the minimum in 2000-2017 (Hosp. &

Tourism). Our value is in the range of the results for these reviews. Regarding the reasons given for using PLS, "small sample size" and for "non-normal data" are the reason most frequently referred to by articles over time.

The data and model characteristics produce similar statistics. The only differences presented are in sample size depending on the area of research, with a range from 154.9 (mean) / 83 (median) to 487 (mean) / 321 (median), which matches the OM sample size in this range.

We find that the trend in the reporting of outer and inner model evaluations has not improved over time. A better statistic can always be found for each of the assessed parameters in one of the article reviews from 2014 or before, the only exceptions being "using reflective criteria to assess formative constructs", which has fallen to 4%, and "model fit evaluation", with the number of articles in which it is reported rising to 33.3%.

Regarding the reporting of other aspects, the technical reporting is found not to have improved over time either, with the exception of the software used, which has increased slightly.

6. Conclusions

The use of PLS-SEM in OM has increased over time as it allows researchers to plan and assess complex hierarchical models with formative and reflective constructs while imposing few restrictions on the data. Our review has included the codification of 102 articles that applied the PLS-SEM approach and published in 45 journals related to OM indexed in Scopus and WOS during the 2014-2018 period. We have also compared our findings and results with previous reviews in OM and other disciplines.

Our review has demonstrated that PLS is gaining importance and is widely adopted in OM as the statistical analysis method of choice. However, OM researchers using PLS should be aware of the importance of correctly reasoning and justifying their choice and fully reporting the main parameters to enable other researchers to obtain useful information and reproduce the performed analysis.

CB-SEM and PLS-SEM are two different approaches to the same problem, so the reasoning behind PLS-SEM selection should be clearly explained. The arguments for the use of the PLS method focus mainly on the less stringent restrictions that the method imposes on the data. These arguments should not be those that determine the use of PLS in the investigation. Better argumentation can be found in recent publications on the subject (Becker, Hwa, Ringle, Sarstedt & Hair, 2019; Cepeda-Carrion, Cegarra-Navarro & Cillo, 2019; Hair et al., 2019; Khan et al., 2019; Lin, Lee, Liang, Chang, Huang, & Tsai, 2020; Marin-Garcia & Alfalla-Luque, 2019a). Besides, several authors (Hair, Sarstedt, Ringle et al, 2012) argue that using PLS-SEM with small samples can be problematic since it fails to capture heterogeneity in the population and can therefore result in a greater sampling error. It is advisable to use sample sizes above 100 (Hair, Hollingsworth et al., 2017; Reinartz et al., 2009).

Although all the reviewed publications include the sample size, the obtained response rate is not sufficiently reported and is not uniformly assessed, as some authors include samples that are subsequently discarded while others do not include them. Furthermore, although PLS-SEM is a non-parametric statistical method that does not require normal distribution of data, its verification is advisable (Baloglu & Usakli, 2017) and should be done by calculating its skewness and kurtosis, as very abnormally distributed data cause and magnify standard errors (Chernick, 2008).

Both the measurement and structural models lack some important information and parameters in many publications. Therefore, there is some room for improvement in terms of reporting and justification. OM researchers should take the latest developments in the assessment and reporting of PLS into consideration and their articles should indicate a clear trend toward compliance.

Declaration of Conflicting Interests

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