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Conceptual structure and thematic evolution in partial least squares structural equation modeling research

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Abstract
Structural equation modeling (SEM) using partial least squares (PLS) has received considerable attention in recent years. We address the increasing fragmentation of PLS-SEM-related research across multiple fields of scientific inquiry by presenting a bibliometric analysis's results of $n = 9{,}150$ documents from the Web of Science database. We identify the main themes by using bibliometric content analysis to explore the PLS-SEM knowledge structure's definition, its main drivers, and the interplay between the methodology and the application themes over time. Furthermore, we document the dynamics of the PLS-SEM knowledge structure over four periods spanning 1995–2022, unveiling a surge in scientific production and connections among thematic areas due to topic evolution and hybridization. Finally, we investigate the driving forces behind these trends and the relationship between methodology and application themes, providing an integrative view and insights into PLS-SEM research across disciplines.

Keywords Partial least squares · Structural equation modeling · Bibliometric content analysis · Conceptual structure · Network analysis · Bibliometrix R package

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1 Introduction

Structural equation modeling (SEM) is a general framework for analyzing hypothesized cause-effect relationships between latent variables and the indicators used to measure them. Researchers can draw on a great number of SEM estimators, which can broadly be differentiated into factor-based and component-based (Cho et al. 2022; Sarstedt et al. 2024a). While factor-based SEM was long regarded as the standard estimator, component-based methods—particularly partial least squares (PLS)—have recently gained prominence in a variety of research fields (Cheah et al. 2019a, b; Ciavolino et al. 2015a, 2022b; Guenther et al. 2023; Hair et al. 2012b, 2017a; Memon et al. 2019).

PLS-SEM's development can be characterized in terms of three distinct but connected research directions. First, methodological research has made considerable progress by proposing new model evaluation metrics (e.g., Ringle et al. 2023; Sarstedt et al. 2023; Shmueli et al. 2016) and procedures (Hair et al. 2020; Hubona et al. 2021). Similarly, complementary techniques allow researchers to, for example, model more complex relationships (e.g., Cheah et al. 2021; Lamberti et al. 2024; Sarstedt et al. 2020), account for heterogeneous data structures (e.g., Fordellone and Vichi 2020; Sarstedt et al. 2022c) or external information about the data (Ciavolino et al. 2015b), and visualize and explore the model estimates (Hauff et al. 2024; Richter et al. 2020; Sarstedt et al. 2024b). Finally, methodological research has extended the standard PLS-SEM algorithm to accommodate common factor models (Dijkstra and Henseler 2015a, b), thereby allowing researchers to estimate mixed factor-composite models to align with their measurement-theoretic assumptions (Rigdon et al. 2017; Sarstedt et al. 2016).

The second research direction relates to software tools that facilitate PLS-SEM analyses, which come in two forms, namely software tools with graphical user interfaces, such as SmartPLS (Cheah et al. 2024; Ringle et al. 2022; Sarstedt and Cheah 2019) and WarpPLS (Kock 2022). In addition, researchers can benefit from packages for both proprietary and open source statistical software (Deer et al. 2024). The former includes Stata (Mehmetoglu and Venturini 2021; Venturini and Mehmetoglu 2019), while the latter includes packages for R (R Core Team 2022), such as csem (Rademaker and Schuberth 2020) and SEMinR (Hair et al. 2021; Ray et al. 2021), and semophy for Python (Igolkina and Meshcheryakov 2020).

The third research direction involves the method's application in various fields such as higher education (Ghasemy et al. 2020, 2022), knowledge management (Cepeda-Carrion et al. 2018), marketing (Guenther et al. 2023; Sarstedt et al. 2022a), human resource management (Ingusci et al. 2023, 2024; Ciavolino et al. 2024), operations management (Bayonne et al. 2020), quality management (Magno et al. 2024), software engineering (Russo and Stol 2021), and information systems (Sabol et al. 2023). Common reasons for preferring PLS-SEM over factor-based techniques include its ability to estimate complex models with relatively small sample sizes, the lack of distributional assumptions in model estimation, and the analyses' causal-predictive focus (e.g., Chin et al. 2020; Hair et al. 2023, 2024b; Wold 1982)—see Hair et al. (2024a, Ch. 1) for an overview.

Owing to PLS-SEM's rapid evolution and adoption, researchers have recognized the need for a deeper investigation of research activities' dynamics within the method's context. This need is noteworthy because it supports the identification of (1) common knowledge drivers, (2) the state of methodological consolidation in different application contexts, and (3) the collaboration networks that shape the field. Understanding

such structures is relevant for researchers wishing to understand the different research streams and knowledge clusters that extend the method's capabilities or reveal its limitations in specific research settings.

Ciavolino et al. (2022a) and Khan et al. (2019) investigated some of these aspects but focused on the *inputs* underlying relational structures' generation in the PLS-SEM research areas, namely authors' production, collaboration, and citation networks. Specifically, these studies addressed the contributions to the PLS-SEM domain's evolution by exploring knowledge creation and sharing through a citation network. Furthermore, they analyzed the historiographic, geographic, and institutional attributes extracted from the selected information sources. On the contrary, Hwang et al. (2020) explored the domain's concept structure but focused on the specific context of composite-based SEM methods.

While these studies offer valuable insights into the field's structure, they focus on the syntactic relationships; that is, on the connections between documents along multiple attribute layers (e.g., the authors and their collaborations, journals, affiliations, and countries). However, such analyses leave the PLS-SEM corpus' semantic content unexplored. Understanding such semantic relationships is important because they inform researchers about the conceptual constructs, associations, and themes that prompt research in the field. In other words, they affect scientific collaborations' development within the academic network by specifying the ways domain knowledge is represented and communicated based on different thematic interpretations (Angelelli et al. 2024).

We address this limitation of prior bibliometric analyses by offering a large-scale bibliometric study of the main themes covered in PLS-SEM research, which we regard as the research activities' outputs in terms of knowledge creation and its temporal evolution. In order to do so, we take advantage of our network representation by quantifying the co-occurrence of words as a means to distinguish thematic contributions and identify topics. The combination of both syntactic and semantic analysis provides us with a more complete picture of the PLS-SEM domain's status and trends. Extending prior research, we also consider the recent PLS-SEM research, thereby exploring the latest developments in the field.

The remainder of the paper is organized as follows: In the next section, we briefly introduce the methodology adopted for the document dataset's acquisition. We then present the results of our analyses, initially focusing on the period 1985–2020. In doing so, we first identify the PLS-SEM's domain main topics and their development over time, followed by an exploration of topic clusters. We then continue our analysis of topics and topic clusters, focusing on the period 2021–2022. We conclude with a summary and discussion of our findings, highlighting limitations, and deriving opportunities for future research.

2 Materials and methods

2.1 Selection criteria

We identified documents eligible for inclusion in our bibliometric analysis by first identifying relevant search terms. Similar to Ciavolino et al. (2022a), we aimed at identifying all PLS-SEM-related papers, book chapters, and reviews published in the Web of Science (Core Collection), but focused on the period 1985–2022. The list of search terms also accounted for different terminologies used to refer to the PLS-SEM method, such as SEM-PLS, PLS path modeling, or PLS-PM. Therefore, we used the following search query to identify the relevant documents:

"Database: Web of Science Core Collection". **TOPIC**: ("Partial Least Squares Structural Equation Model*") OR **TOPIC**: ("Partial Least Squares SEM") OR **TOPIC**: ("PLS-SEM") OR **TOPIC**: ("SEMPLS") OR **TOPIC**: ("PLS Structural Equation Model*") OR **TOPIC**: ("Partial Least Squares Path Model*") OR **TOPIC**: ("PLS Path Model*") OR **TOPIC**: ("PLS-PM") OR **TOPIC**: ("Structural Equation Model* PLS")

We distinguish between the periods 1985–2020 and 2021–2022 since the latter period is characterized by an exponential increase in scientific production, which should therefore be investigated separately. The query restricted to the period 1985–2020 yielded a total of 3,877 documents, while the query focused on the period 2021–2022 resulted in 6,228 documents, which we reduced to 5,219 by excluding 3 retracted articles and 1,006 early access documents published in 2023 or 2024. It is worth noting that, even with these selection criteria, the resulting number of documents in the period 2021–2022 range is higher than the combined document corpus for the entire period 1985–2020.

To identify additional seminal papers that may have not been covered by our initial WoS search query but are likely to have a significant impact on the formation of thematic clusters in the field, we considered other meaningful expressions in the PLS-SEM-related domain (e.g., *"Partial least squares"* and *"Variance-based approach"*). This additional analysis resulted in the integration of $n = 54$ additional out-of-collection documents, all of which were published in the earlier period (1985–2020). We subjected the collection of documents to a bibliometric analysis using the R package Bibliometrix (Aria and Cuccurullo 2017).

3 Results: research areas and trend topics

3.1 Data description

Based on the selection criteria specified in the previous section, we identified a total of 9,150 documents. Table 1 offers an overview of the relevant descriptive statistics.

3.2 Research areas

We started our investigation of the different PLS-SEM dissemination by exploring the selected documents' domain coverage. We found that the 3,931 documents were assigned to 100 research areas covering 92% of all the research areas in the entire collection and 40% of all the Web of Science research areas. Since there were no relevant documents published before the mid-1990s, we refer to 1995–2020 only. We discuss the results of period 2021–2022 separately in Sect. 5.

The main research area was *Business & Economics* (40%), followed by *Environmental Sciences & Ecology* (11%), *Social Sciences—other topics* (10%), *Computer Science* (8%), *Engineering* (8%), and *Science & Technology—other topics* (8%). The remaining areas were: *Information Science & Library Science* (5%), *Education & Educational Research* (4%), *Psychology* (4%), and *Mathematics* (2%), which also included documents devoted to

Table 1 Descriptive statistics

Description	Value (1985–2020)	Value (2021–2022)
Documents	3,931	5,219
Sources (journals, books, etc.)	1,198	1,224
Publication's annual growth rate	27.64%	55.83%
Document's average age	5.91	2.39
Average citations per document	54.51	11.77
Average citations per year per document	6.87	3.36
References	172,304	251,903
Author		
Number of authors	9,166	13,282
Authors' keywords	10,573	13,975
Average number of co-authors per document	3.35	3.74
Document type		
Articles	3,830	5,176
Book chapters	1	0
Data papers	8	10
Reviews	52	28
Notes	1	0
Proceedings	39	5

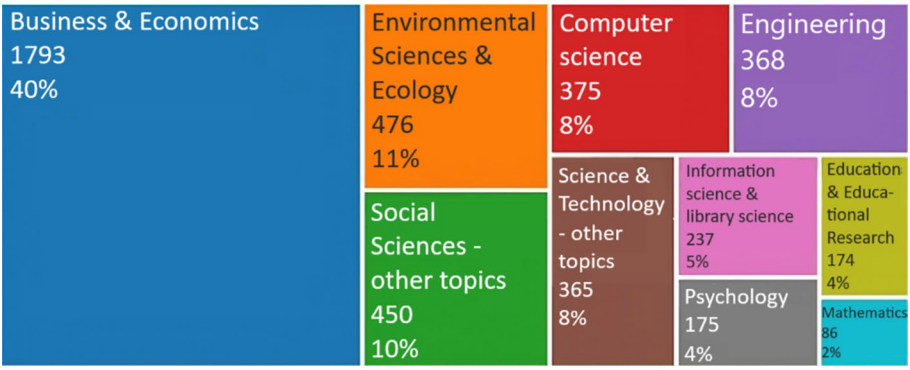


Fig. 1 Tree map of research areas (1995–2020)

mathematical and statistical developments. The tree map in Fig. 1 visualizes the research areas' distribution.[1]

[1] Note that a document can be assigned to multiple research areas.

3.3 Tree map analysis of keywords

In the next step, we analyzed the *Keyword Plus*®, which the Clarivate algorithm extracted from the cited references in the collection's documents. The use of these keywords generally improves the content information's acquisition (Zhang et al. 2016) compared to standard keywords. Moreover, we pre-processed the keywords by removing synonymous terms and stop words. The results of the Keywords Plus® tree map shown in Fig. 2 highlight two main themes: First, PLS-SEM was used primarily in business and information technology studies (keywords: "*Impact,*" "*Performance measurement,*" "*Management studies,*" "*Technology acceptance,*" "*Information technology,*" "*Innovation,*" "*Adoption*"), as well as in behavioral research (keywords: "*Satisfaction models,*" "*Behavioral research,*" "*Perceptions,*" "*Customer models,*" "*Work studies,*" "*Quality,*" and "*Trust*"). Second, keywords beyond those directly related to the methods (e.g., "*PLS-SEM,*" "*Partial least squares*") referred to modeling aspects or elements ("*Antecedents,*" "*Structural equation models,*" and "*Determinants*").

We also analyzed the evolution of the different names that researchers used when referring to the method. The results in Fig. 3 show that the early writings referred to "*PLS*" and "*SEM*." The publication of Tenenhaus et al.'s (2005b) seminal article on the method led to the appearance of a new term ("*PLS-PM*") in the literature, which was later complemented by "*PLS-SEM*." By 2020, the majority of publications referred to PLS-SEM.

3.4 Trend topics

In the next step, we extracted the dominant topics, using Keywords Plus® as input. Figure 4 visualizes the evolution of the dominant themes (*y*-axis) over time (*x*-axis). The circle sizes represent the word occurrences, and the gray line is bounded by the first and third quartiles.

The trend topic plot highlights 19 topics (authors' keywords) with a minimum absolute word frequency cutoff of 10. The results show that "*Covid-19,*" "*Leadership,*" and "*Artificial Intelligence*" dominated the last two years, while "*Satisfaction models,*" "*Sustainability*

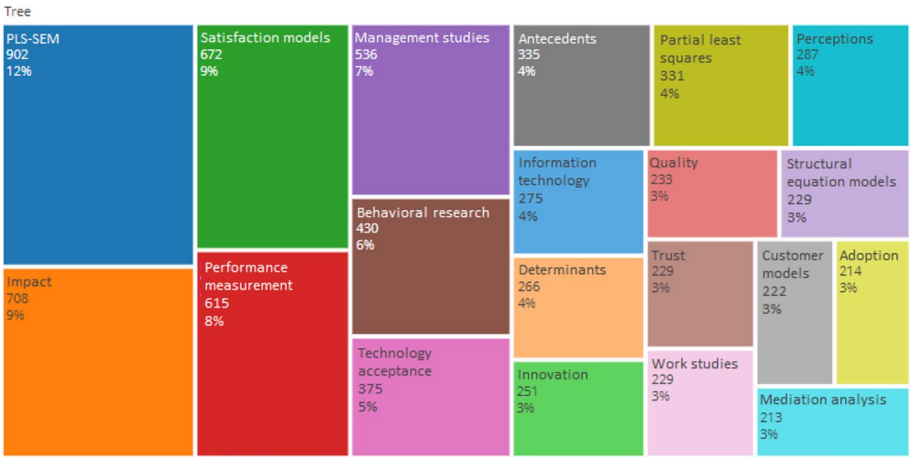


Fig. 2 Tree map of Keywords Plus.® (1995–2020)

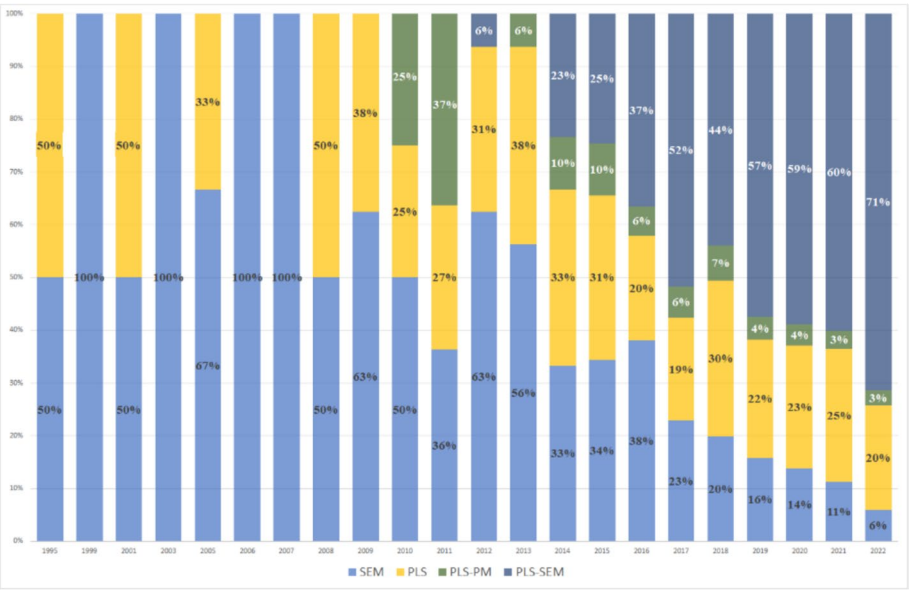


Fig. 3 Evolution of names extracted from authors' keywords

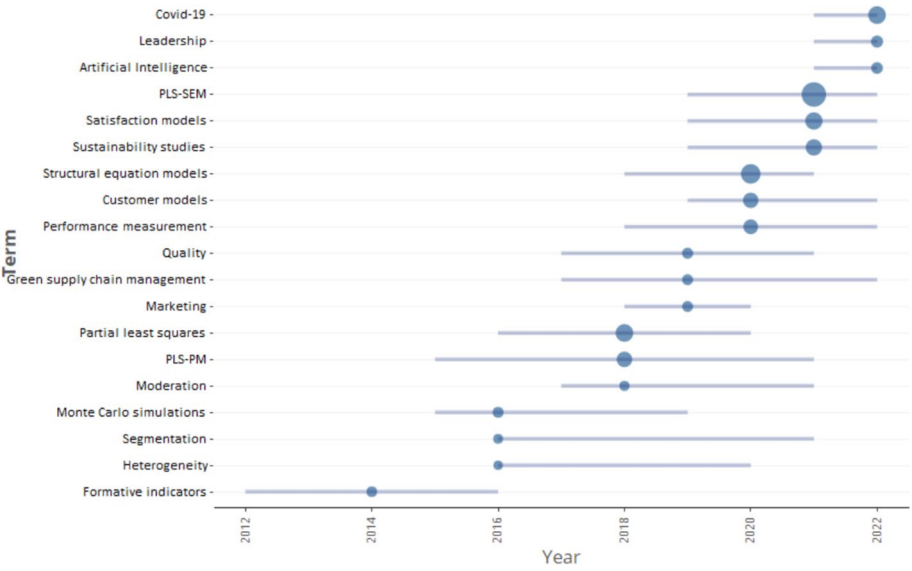


Fig. 4 Trend topics (1995–2022) extracted from authors' keywords

studies," "*Performance measurement*," "*Quality*," "*Green supply chain management*," and "*Marketing*" were particularly relevant application areas in the preceding years. The trend analysis also shows that the earlier periods were dominated by methodological topics, most notably those related to heterogeneity in PLS path models (i.e., "*Heterogeneity*,"

"*Moderation*," and "*Segmentation*") along with "*Formative indicators*" and "*Monte Carlo simulations*." Overall, these findings suggest methodological maturation of the field, which has led to PLS-SEM's increasing application in different business contexts.

4 Conceptual structure and thematic evolution results

4.1 Network analysis and community detection

Exploiting the insights derived in the previous section, we next deepen the evolution of the conceptual and thematic structures underlying the PLS-SEM framework by using network theory. We identified the PLS-SEM domain's conceptual structure and thematic evolution by undertaking a co-word network analysis (Meter et al. 2004; He 1999; Tijssen and Van Raan 1989; Leydesdroff 1989). This analysis draws on the authors' keywords to define a *co-occurrence network*, which is a graphical representation of the co-occurrence matrix. The latter is an instance of a weighted adjacency matrix. In other words, in the relevant network, each *node* is associated with a keyword, and the weight of the *edge* connecting the two nodes is proportional to the two keywords' co-occurrence frequency in the collection.

The main themes (or topics) emerge from the highly interconnected keywords identified by a community detection algorithm (Yang et al. 2016). For our analysis, we chose the Walktrap algorithm (Pons and Latapy 2006), which has been shown to perform well in respect of detecting a community structure (Signorelli and Cutillo 2022) and whose results are efficient and reproducible. The Walktrap algorithm operates by simulating random walks on a network, thereby leveraging their tendency to remain confined within clusters of interconnected nodes, thus helping with communities' detection and delineation. The Walktrap algorithm also shares conceptual analogies with spectral methods, which explore community structures based on the eigenvalues and eigenvectors of matrix representations of network properties. The algorithm proposed by Newman (2006) relies on a clustering score Q, which is formally defined as

$$Q = \frac{1}{W} \cdot \sum_{(ij)} \left[w_{ij} - \frac{W_i \cdot W_j}{W} \right] \cdot \delta(c_i - c_j) \tag{1}$$

where i, j belong to the set of nodes N in a graph with a set $\mathcal{E}$ of edges, w_{ij} is the weight of the edge or the (ij)-term of the adjacency matrix, $\delta(\cdot)$ is Kronecker's delta, c_i labels the cluster that contains the i-th node, and W_i corresponds to the i-th node's weighted degree with

$$W_i = \sum_{j:(ij)\in\mathcal{E}} w_{ij}, \; W = \sum_{i\in N} W_i \tag{2}$$

In the context of our analysis, the characteristic quantities of the network structure introduced in the previous equations also enable the graphical synthesis of the Walktrap algorithm's output as a *thematic map* (Cobo et al. 2011). Equations (1) and (2) allow the computation of the equivalence index (Callon et al. 1991)

$$e_{ij} = \frac{w_{ij}^2}{W_i \cdot W_j}, (ij) \in \mathcal{E} \tag{3}$$

In addition, for each cluster c identified by the community detection algorithm, we can compute Callon's centrality

$$C(c) = 10 \cdot \sum_{(ij):\, i \in c, j \notin c} e_{ij} \tag{4}$$

and Callon's density

$$D(c) = \frac{100}{\#c} \cdot \sum_{(ij):\, i,j \in c} e_{ij} \tag{5}$$

where $\#c$ is the cardinality of c. Similar to Eq. (1), the normalization takes into account that we are summing over actual edges rather than over node pairs in the network. Centrality refers to a theme's importance in the overall research field, and density refers to the measure of the theme's development.

Following Cahlik (2000) and Cobo et al. (2011, 2015), the thematic map is obtained by placing Callon's centrality and density on, respectively, a Cartesian plane's x-axis and y-axis. The centrality index is a measure of the between-community connections that can be used for comparative purposes; given two communities c_1 and c_1 with $C\left(c_1\right) > C(c_2)$, from Eq. (3), we see that c_1 generates a higher cumulative weight of connections with the remaining clusters than c_2. Hence, c_1 mediates between communities to a greater extent compared to c_2 and is more central in this sense. While centrality is a measure of external connectivity, density is a quantification of internal connectivity and can be interpreted as a degree of cluster development in terms of mutual relationships' intensity. After plotting each thematic cluster on the centrality-density plane, this interpretation divides the region containing the clusters into four quadrants (Fig. 5).

1. Motor themes (first, upper-right quadrant): This quadrant includes themes that are "*both well developed and important for the structuring of a research field*" (Cobo et al. 2015, Sect. 4). These themes have both internal consistency (in terms of a high weight of internal connections in the co-occurrence network) and importance in relation to the other themes (due to their high centrality).
2. Niche themes (second, upper-left quadrant): This quadrant contains themes where internal connections are highly developed, but they have lower centrality indices compared to other clusters in the thematic map. Such reduced centrality makes these themes isolated in the co-occurrence network, configuring them as niche themes.
3. Emerging or declining themes (third, lower-left quadrant): These themes are considered neither developed nor important. Specifically, emerging themes are under development and not yet important, while declining themes are losing importance.
4. Basic themes (fourth, lower-right quadrant): The high centrality of these themes suggests that they serve as a common foundation for multiple themes; the low density may also indicate weak connections among the clusters' elements and, hence, the cluster's limited internal consistency.

The size of each circle is proportional to the number of cluster words.

The rationale for including both emerging and declining trends is that, in both cases, the lack of centrality is associated with a substantial misalignment with recent developments. The identification of such themes requires a longitudinal analysis, which is carried out through thematic evolution (Aria and Cuccurullo 2017). Splitting the timespan into different periods allows for identifying the trajectory: A development toward the top of the

map suggests an emerging trend, while a development toward the lower left quadrant identifies a declining trend.

The analyses of period 1995–2020 were undertaken by considering three different periods. As in Hwang et al. (2020), we defined the following periods 1995—2013, 2014–2017, and 2018–2020. We use $n = 600$ as the number of words involved in the analysis; due to the three periods' unbalanced production rates, we set the minimum cluster frequency (MCF) as mitigating the increasing number of published documents' potential effects over time and to achieve comparable cluster structures. Specifically, we set the MCF equal to 25% of the total documents in the first period, to 10% in the second period, and to 6% in the third period.

4.2 Time slice analysis: 1995–2013

The total number of documents in the first period is 190. These documents can be classified into three main themes and six minor clusters, two of which overlap (Fig. 5). Each cluster's label reflects the words with the highest frequency, and its size is proportional to the word cluster's frequencies. We denote the cluster frequency as *CF*, which we obtained from the occurrences of the keywords belonging to the specific cluster. In the following, we briefly discuss the cluster topics and identify their main papers.

Table 2 in the Appendix offers more detailed insights into the most cited articles within each cluster based on their CF. We denote the maximum CF in the period as *F* and use this reference quantity to select the most relevant articles for each period (Tables 3, 4, 5 in the Appendix). For clusters with a CF higher than or equal to *F*/10 (*high frequency*), we show five articles with the highest number of citations. For clusters with a CF between *F*/100 and *F*/10 (*medium frequency*), only the first two most cited articles are shown. Finally, for clusters with a CF less than *F*/100 (*low frequency*), we report the single most cited article.

The dominant *motor theme* in the first quadrant is "*Indicators*" (CF = 303). In this cluster, the main theme refers to structural equation models' use for performance measurement. The major papers apply these themes in various research areas, including strategic management (Hulland 1999; Hair et al. 2012a), marketing (Hair et al. 2012b), and information

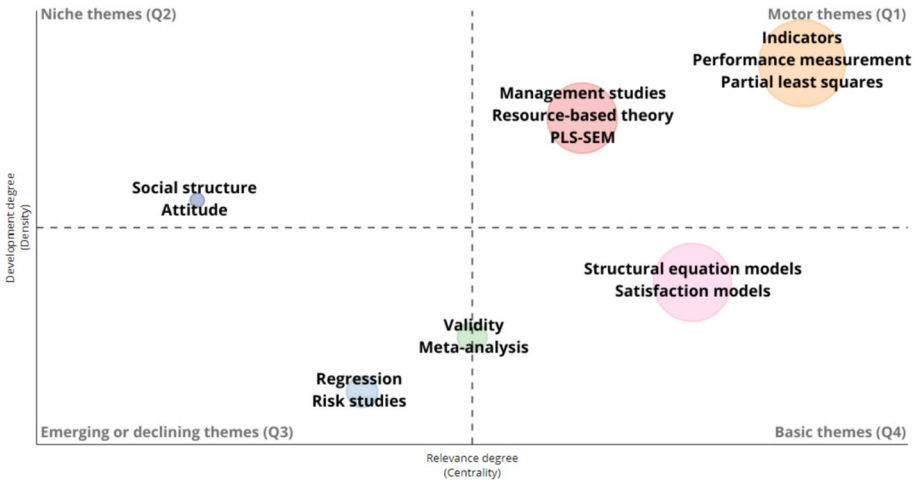


Fig. 5 Thematic map identified by the co-occurrence network (1995–2013)

systems (Petter et al. 2007; Kock and Lynn 2012). Chin et al. (2003) conduct simulations and empirical studies pertaining to information systems and technology adoption support. Wetzels et al. (2009) provide guidelines and an empirical demonstration of hierarchical models' use based on PLS-SEM in order to develop conceptual frameworks. This cluster includes one of three book reviews in the entire collection—Ketchen (2013) reviewed the first edition of Hair et al.'s (2017b) book. The cluster's medium-large size denotes considerable word cluster occurrences, and the position indicates that this theme has a high centrality level and good density values.

Similar considerations hold for the "*Management studies*" cluster (CF = 112) in the same quadrant, which also contains the keyword "*PLS-SEM*." This cluster has a slightly lower degree of development and relevance compared to the "*Indicators*" cluster, which indicates a substantial interest in PLS-SEM. However, the topics' centrality is still dominated by the "*Partial least squares*" and "*Structural equation models*" clusters, in line with the authors' keyword distribution depicted in Fig. 3. The main paper in this cluster discusses methodological aspects, estimation approaches, and recommendations regarding higher-order constructs with formative relationships (Becker et al. 2012). Other contributions investigate dynamic capabilities (Cepeda-Carrión and Vera 2007; Wilden et al. 2013), which are related to the "*Resource-based theory*" theme in the cluster. Other influential papers explore the combination of PLS-SEM and specific technologies, such as neuroimaging (Krishnan et al. 2011), or draw on Venkatesh et al.'s (2003) unified theory of acceptance and use of technology (UTAUT) model (Kijsanayotin et al. 2009).

In the fourth quadrant, "*Structural equation models*" (CF = 180) is a basic and transversal well-developed theme, with the main keywords also including "*antecedents*" and "*trust.*" This theme refers to the application of PLS-SEM to study the drivers of consumer attitudes and behaviors, such as customer satisfaction and loyalty. The papers associated with this cluster are mainly devoted to applications in marketing (Johnson et al. 2006) and business sectors, with particular emphasis on consumers' preferences (Albert et al. 2013) and the adoption of digital services (Akter et al. 2011; Tenenhaus et al. 2005a). Such works mainly relate to the "*Consumer behavior*," "*Consequences,*" and "*Trust*" keywords in the cluster. The circle's large size is due to this theme's application to different domains; its position reveals that this theme has a high centrality and low density. Methodological aspects are also discussed, such as the confirmatory tetrad analysis by Gudergan et al. (2008); along with an application to customer satisfaction, this work also shares a partial membership in the "*Indicators*" cluster. This phenomenon occurs because the documents' association with thematic clusters is not univocal but is defined by a membership degree to individual clusters, expressed as a percentage. Taking into account this uncertainty in the document-cluster association helps contextualize the thematic interpretation of some articles in the collection.

Beyond these major clusters, a smaller thematic cluster called "*Validity*" (CF = 10) lies between the third and fourth quadrants. The papers in this cluster analyze and validate different psychological models (Brunetto et al. 2012; Jacobs et al. 2011). In respect of the *emerging or declining theme* (third quadrant), which tends to have a low centrality and density, there is also a single cluster called "*Regression*" (CF = 11). The main papers in this group are Tenenhaus and Tenenhaus (2011) and Liu et al. (2011).

Finally, the second quadrant shows the *niche themes*, with two clusters called "*Social structure*" and "*Attitude"* with the lowest cluster frequency (CF = 4). These clusters coincide and have identical centralities, densities, and cluster frequencies. The papers in the "*Social structure*" cluster are authored by Lew and Sinkovics (2013) and Tashiro et al. (2012), while Rabl (2010) as well as Spielvogel and Terlutter (2013) contribute to the

"*Attitude*" cluster. The topics covered by these clusters are specific, with well-developed internal links (high density), but unimportant external links (low centrality). This means that, in the first period, they are of limited importance for the field.

4.3 Time slice analysis: 2014–2017

The period 2014–2017 contains 885 documents, which can be classified into seven clusters (Fig. 6). Table 3 in the Appendix describes the primary papers that are relevant to each theme. The *motor themes* relate to "*Satisfaction models*" and "*PLS-SEM*." Taking the circles' positions into account suggests that the first motor theme has a slightly higher centrality and lower density than the second one, but that both of them are in a region that identifies developed and important themes for the research field. The "*PLS-SEM*" cluster (CF = 1,719) covers methodological developments in, for example, discriminant validity testing (Henseler et al. 2015) and PLS estimators' asymptotic properties (Dijkstra and Henseler 2015a). The same cluster also comprises applications, especially in business research (Sarstedt et al. 2014b; Akter et al. 2016) with links to other keywords in the clusters such as "*Impact*" and "*Performance*," and technology management (Hair et al. 2017a).

The most cited papers in the "*Satisfaction models*" cluster (CF = 1,473) cover several topics, ranging from collaborative consumption (Möhlmann 2015) to a comparison of PLS-SEM and factor-based SEM in theory development for family firm reputation and trustworthiness (Astrachan et al. 2014), and the effects social commerce constructs on trust and purchase intention (Hajli 2014, 2015). Nitzl et al.'s (2016) paper on mediation analysis appears in this cluster, as it relates to the keyword "*trust*" and the theme "*Fit indices*." This cluster absorbs a keyword that comprised the isolated "*Attitude*" cluster from the period 1995–2013 and includes the keywords "*Behavioral research,*" "*Antecedents,*" as well as other words relating to behavioral traits ("*Quality,*" "*Trust,*" and "*Perception*"). These topics also play a central role in technology adoption, which is reflected in the occurrence of papers that also belong to the "*Satisfaction models*" and "*Technology acceptance*" clusters (Ringle and Sarstedt 2016).

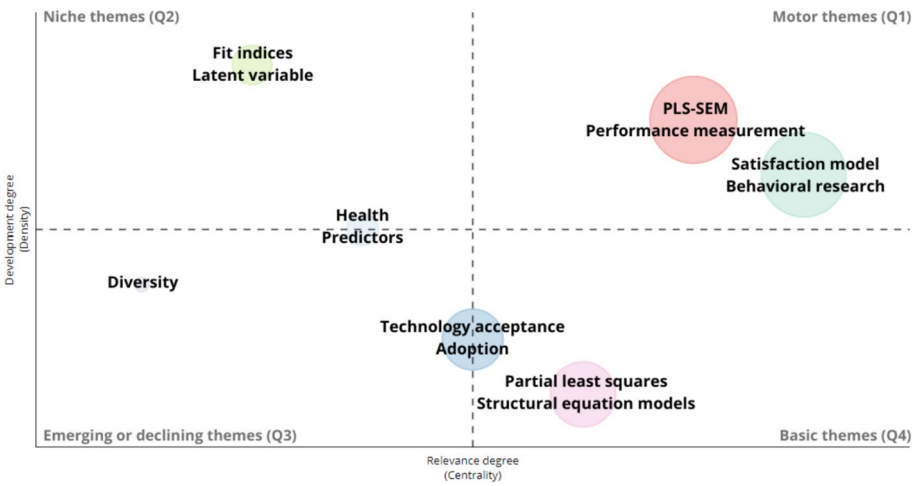


Fig. 6 Thematic map identified by the co-occurrence network (2014–2017)

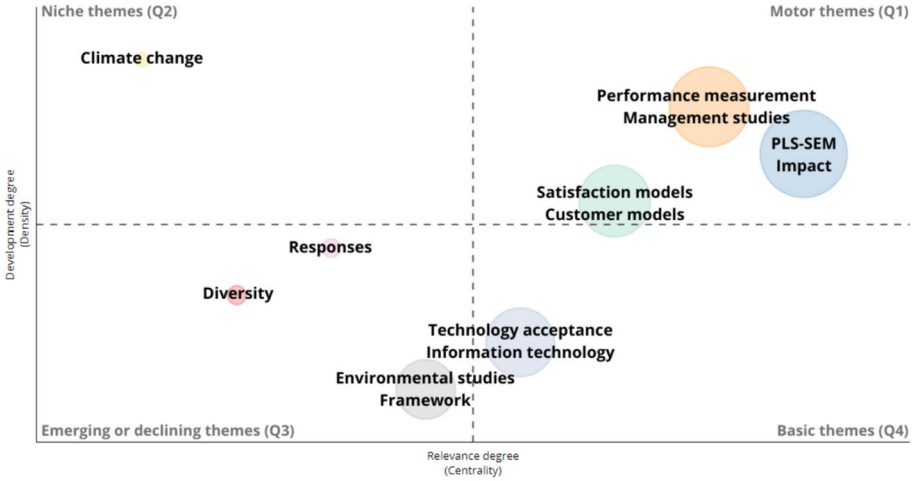


Fig. 7 Thematic map identified by the co-occurrence network (2018–2020)

The "*Partial least squares*" and "*Structural equation models*" themes combine into a single basic theme (CF = 375), which comprises methodological contributions including the analysis of the FIMIX-PLS method (Hair et al. 2016), moderating effects (Fassott et al. 2016), and measurement-theoretic aspects underlying the PLS-SEM method (Rigdon 2014). Applications in this cluster mainly focus on work studies, business research (Cepeda-Carrión et al. 2016), and management (Rasoolimanesh et al. 2015). The term "PLS-PM" appears frequently between 2014 and 2016 (see also Fig. 3).

Between the third and fourth quadrants, we find one cluster that covers PLS-SEM's applications in the context of "*Technology acceptance*" (CF = 273) or, more generally, the assessment of users' relationships with technology. Several papers investigate consumers' intentions regarding online purchases (Yeo et al. 2017; Amaro and Duarte 2015) or the adoption of new payment methods or mobile apps (Ooi and Tan 2016; Teo et al. 2015). Although this cluster's size is smaller than that of the motor themes, it is still medium to large in size; along with the cluster's average centrality, this reveals that this theme is becoming increasingly important for the domain.

Between the second and third quadrants lies the "*Health*" cluster (CF = 34), which concentrates on aspects such as satisfaction with healthcare services (Kasiri et al. 2017) and products (Price et al. 2015), nutrition, health risk factors, and mental well-being, including stress factors (Koay et al. 2017). Dupuis et al.'s (2017) membership degree to thematic clusters is equally distributed between the clusters "*Health*" and "*PLS-SEM*."

The theme "*Fit indices*" (CF = 59) belongs to the second quadrant, which is methodological in nature, as it also contains the "*Latent variables,*" "*Formative indicators,*" and "*Maximum likelihood*" keywords. The most cited articles in this cluster include guidelines (Henseler et al. 2016a), commentaries (Sarstedt et al. 2014a), and new estimation or testing techniques (Dijkstra and Henseler 2015b; Henseler et al. 2016b).

A minor cluster labeled "*Diversity*" (CF = 10) shows low density and centrality, configuring it as an emerging or declining theme. The documents in this cluster address different meanings of diversity, for example, in the ecological and biological domains (Kou et al. 2017) or in scientific networks (Guan et al. 2015).

4.4 Time slice analysis: 2018–2020

The third period 2018–2020 contains 2,856 documents, showing that the selection in this time window is much higher than in the other two periods. Figure 7 shows the seven main themes that emerged from our analysis.

With regard to the *motor themes*, the "*PLS-SEM*" cluster (CF = 6,564) further increases in its centrality while preserving its density. In the period 2018–2020, this cluster also includes "*Partial least squares*" and other keywords from other clusters in the previous period (e.g., "*Work studies*"), as well as "*Mediation analysis*" and "*Moderation analysis.*" The main documents in this cluster provide guidelines for model evaluation and results reporting (Hair et al. 2019, 2020), with Shmueli et al. (2019) focusing on predictive power assessment. Other topics of interest include higher-order constructs (Sarstedt et al. 2019) and reviews of PLS-SEM use in different research fields (Ali et al. 2018b; Ringle et al. 2020).

"*Performance measurement*" (CF = 3,603) is the second *motor theme*. The interpretation of "*Performance*" is manifold. On the one hand, the theme refers to methodological performance, such as the evaluation of PLS-SEM in terms of estimation accuracy and statistical power (Kock and Hadaya 2018). On the other hand, the theme relates to firms' competitive performance with applied research in business innovation, especially capabilities related to big data and information systems (Mikalef et al. 2019, 2020; Cenamor et al. 2019), and sustainable performance in green management (Zaid et al. 2018).

The last *motor theme* relates to "*Satisfaction models*" (CF = 1,867), whose centrality and density are slightly lower than those of the previous clusters. Several papers in this cluster focus on experience quality and perception in the tourism sector (Zatori et al. 2018; Ali et al. 2018a; Merli et al. 2019), while Cheah et al. (2018) present the results of an empirical study on service value; however, this paper's methodological focus on formative measurement model validation using redundancy analyses results in a small membership degree associated with the "*PLS-SEM*" cluster.

We find a single basic theme with a high centrality and a low labeled "*Technology acceptance*" (CF = 1,490). Among the main technologies explored in the most cited papers, we find e-learning technologies (Al-Fraihat et al. 2020; Salloum et al. 2019), telemedicine (Kamal et al. 2020), and relevant factors that strengthen the intention to continue using mobile apps (Tam et al. 2020). Different words relate to the semantic domain of "*Technology acceptance,*" while others refer to broader concepts; for example, "*Intention,*" in the same cluster (Zhang et al. 2018).

Among the *emerging or declining themes*, "*Environmental studies*" has the largest one (CF = 699). Its low level of development and average centrality may suggest the increasing attention paid to environmental research. The main papers focus on environmental performance (Seman et al. 2019) and pro-environmental behavior (Zhang et al. 2020), while other works link to projects' "*success factors*" in developing countries (Ahmadabadi and Heravi 2019; Yan and Zhang 2020).

Two smaller clusters in the third quadrant refer to "*Diversity*" (CF = 26) and "*Responses*" (CF = 25). The former uses PLS-SEM to investigate the factors influencing microbial communities or ecosystems and their dynamics (Ai et al. 2018); the latter comprises different interpretations of "*Responses,*" for example, organizations' responses to external pressure for sustainability (Wijethilake and Lama 2019).

Among the *niche themes*, we find a unique small cluster labeled "*Climate change*" (CF = 18). This theme has a high density and low centrality, indicating the high

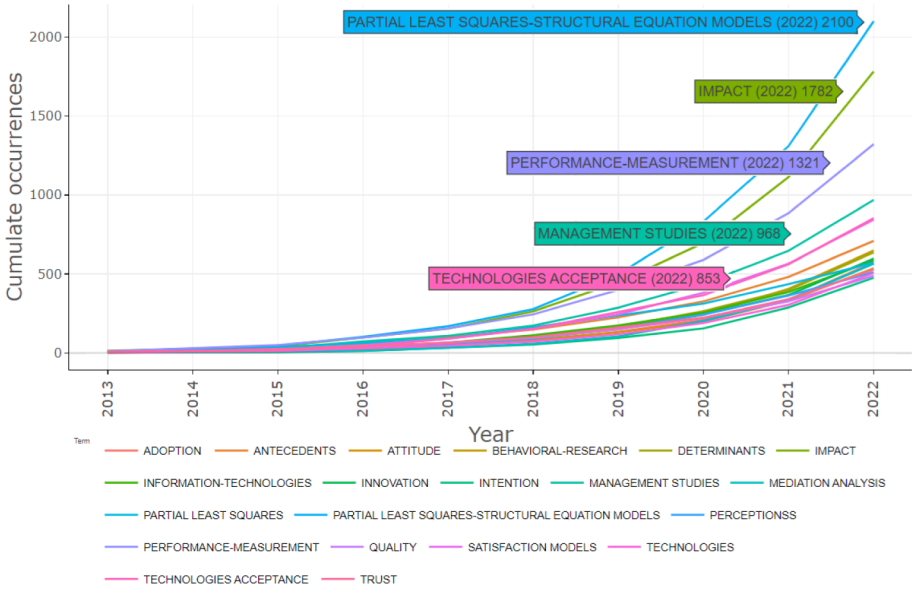
specificity and low connectivity with other nodes outside the cluster. The most cited paper in the "*Climate change*" cluster is by Soewarno et al. (2019), who used PLS-SEM to explore the antecedents and mediating effects linked to green innovation. In Table 4 (Appendix), we provide a summary of the most relevant papers with respect to this time window.

5 Beyond 2020: current exponential evolution

We extend the previous analysis to explore the more recent trends in knowledge creation within the PLS-SEM domain, focusing on the period 2021–2022. This period differs substantially from the previous ones, since a substantial increase in both the documents and word occurrences related to the PLS-SEM domain characterize it. The same query and filters described in Sect. 2.1 regarding the period 2021–2022 returned 5,219 documents from the WoS Core Collection. Analyzing the word frequency evolution (Fig. 8) and scientific production (Fig. 9) suggests an exponential growth of PLS-SEM-related research over time.

We report the results that the processing of Keywords Plus® generated in parallel to the analyses in the previous sections. Specifically, Fig. 10 reports the tree map generated by the selection in the period 2021–2022.

Finally, Fig. 11 summarizes the results of the co-occurrence analysis of the co-word network in the period 2021–2022, which provides us with a thematic map at a central density level. To improve comparability, we adopted the same parameters to run the



Note: The first five words with the highest frequency are highlighted

Fig. 8 Word frequency evolution over time.

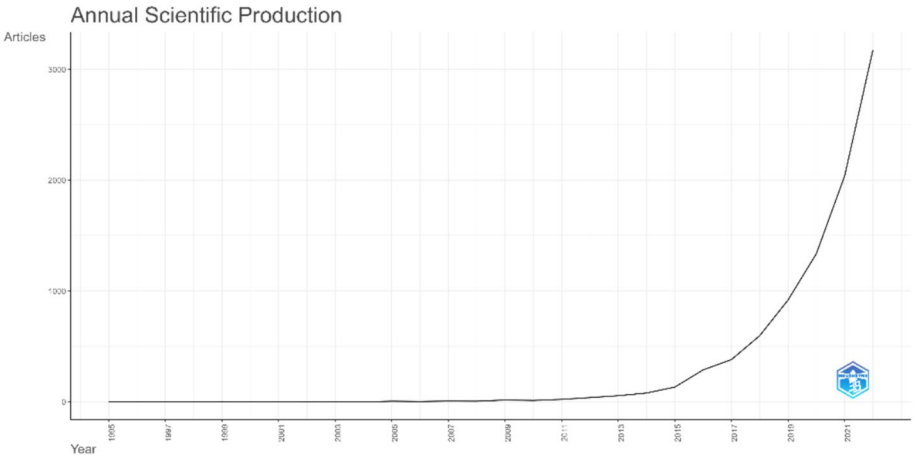


Fig. 9 Evolution of the annual scientific production, suggesting an exponential increase in words' occurrence over time

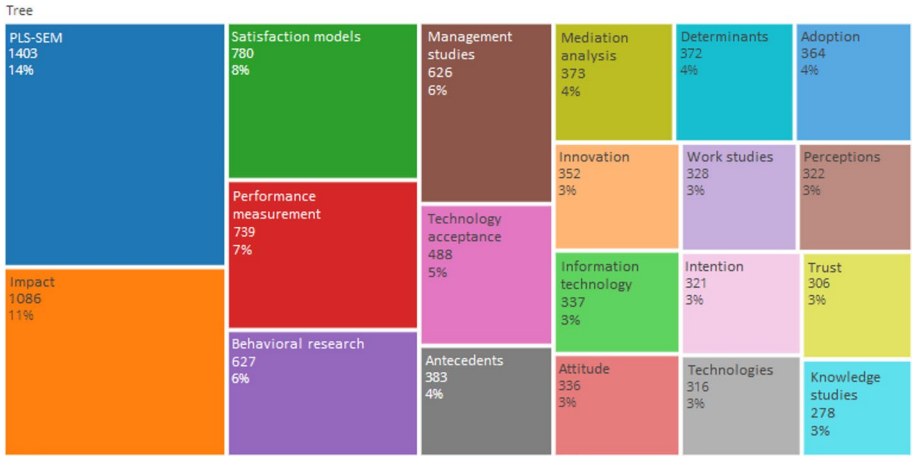


Fig. 10 Tree map of Keywords Plus.® (2021–2022)

Walktrap algorithm as in the previous periods, while setting the number of words to 800 and the MCF to 4%. We refer to Table 5 in the Appendix for more details on the most cited papers published in this time window.

The results show that "*PLS-SEM*" (CF = 14,744) has the highest centrality and an average density, positioning it between the first and fourth quadrants. In this period, PLS-SEM is used to investigate different behavioral aspects related to the COVID-19 pandemic. For example, Sánchez-Cañizares et al. (2021) analyze COVID-19's effects on travel intentions, while Rather (2021) focuses on revisit intention, and Soroya et al. (2021) study the psychological effects of health information conveyed through different media. These works are most strongly associated with the "*PLS-SEM*" cluster since it also contains the "*Impact*," "*Antecedents*," and "*Intention*" keywords. The cluster also

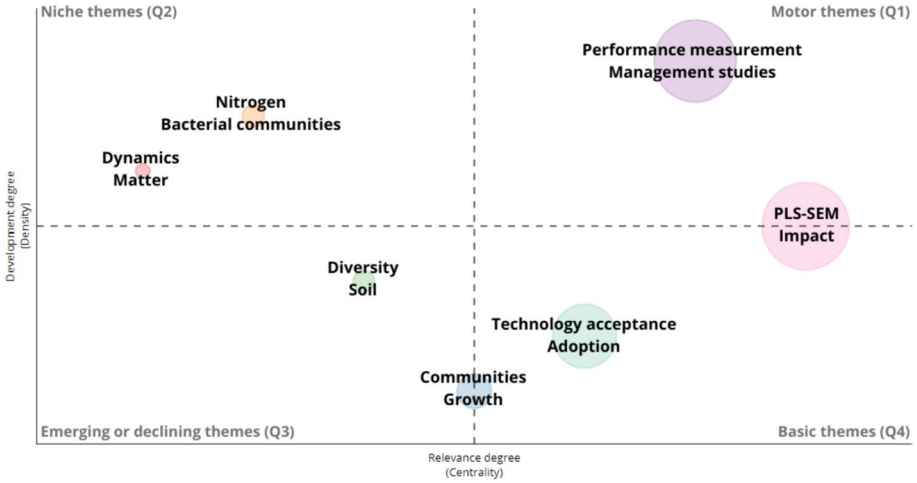


Fig. 11 Thematic map identified by the co-occurrence network (2021–2022)

comprises papers related to methodological advances (Dash and Paul 2021; Rasoolimanesh et al. 2021) and "*Satisfaction models*" (Fernandes and Oliveira 2021).

The "*Performance measurement*" cluster (CF = 9,962) is a *motor theme* and contains topics at the interface between social aspects, sustainability, and technology forecasting or emerging technologies. These topics characterize other clusters, but their performance measurement is the distinguished focus of this cluster. Main attention is paid to competitive advantage through big-data capabilities (Dubey et al. 2021; Ciampi et al. 2021), sustainability studies for the circular economy (Bag et al. 2021), critical success factors for resource planning projects in developing countries (Malik and Khan 2021), and updates and recommendations for PLS-SEM use in marketing research (Sarstedt et al. 2022a).

Emerging technologies are the core of the "*Technology acceptance*" *motor theme* (CF = 2,514). The most cited papers in this cluster explore the adoption of or experiences with emerging technologies, such as blockchain (Queiroz et al. 2021), personal intelligent agents (Moussawi et al. 2021), mobile apps (Akdim et al. 2022), and digital services (Troise et al. 2021), including healthcare services (Liu and Tao 2022).

The remaining four themes are of minor importance in terms of size. The "*Communities*" cluster (CF = 269) lies between the third and fourth quadrants and comprises contributions linked to green innovation and consumers' intentions towards renewable technologies (Jabeen et al. 2021) and applications of PLS-SEM in the context of sustainable agriculture (Sarkar et al. 2021). In this cluster, these works mainly relate to the keyword "*Climate change*." PLS-SEM is also used to analyze factors affecting ecosystems (Cui et al. 2021).

Finally, three minor themes indicate a reduced centrality in terms of word occurrences. In these three clusters—"*Nitrogen*" (CF = 107), "*Diversity*" (CF = 98), and "*Dynamics*" (CF = 59)—, PLS-SEM mainly serves as a practical tool to study the effects of substances, materials, and environmental variables on metabolic pathways and pollution in ecological systems. The first two *niche themes* concentrate on *microbial* communities (Zhao et al. 2021) and biodiversity and organic matter composition (Du et al. 2021), respectively. Different meanings of "*Dynamics*" contribute to the heterogeneity of this cluster in the third quadrant, with a significant contribution of environmental dynamics but also social

dynamics during the COVID-19 pandemic (Charoensukmongkol and Phungsoonthorn 2022).

6 Topic evolution

Next, we analyzed the persistence and evolution of selected clusters over time. Some themes turn out to be central during the entire period 1995–2022. In particular, we find that clusters relating to PLS-SEM have remained a basic or motor theme for more than 20 years. Not surprisingly, the "*PLS-SEM*" cluster's centrality remained high with a steady increase while its density fluctuated slightly. In other words, the topic's elevated importance in the overall collection has been constant, while the topic development has retained its medium–high values, with a few fluctuations over time. The interpretation of this behavior should also take the secondary keywords' variability in the cluster containing "*PLS-SEM*" into account. Indeed, the theme's development degree was higher when combined with "*Performance measurement*" (in the period 2014–2017). This form of theme combination is another factor that could contribute to the interactions' development between different research areas.

Further, "*Satisfaction models*" started as a *basic theme* in the first period, becoming a *motor theme* since the second one. Its centrality maintains its high values across all periods. The third cluster to maintain its position in terms of density while increasing its centrality is "*Technology acceptance,*" where techniques to assess technology adoption and perception evolve along with the emerging technologies.

A second class of thematic clusters comprises themes with low centrality. As in the first period, most of these clusters represent themes with low centrality, frequency, and word occurrences. Furthermore, the separation of documents defined by their inclusion in different clusters is less clear-cut than themes with a higher centrality. This behavior is quantified by the community detection algorithm's cluster assignment weights. Taking common research drivers related to environmental studies into account also allows users to interpret these thematic similarities; in this case, the underlying research field generates distinct topics with a high specificity.

Figure 12 visualizes the thematic clusters' evolution over time, thereby providing a global view of the main themes in the PLS-SEM domain's dynamics. The time slicing and the identification of the conceptual keyword clusters discussed in the previous sections, allow us to quantify their evolution and the convergence of keywords from one period to the next. Following Cobo et al. (2011), our analysis connects pairs of thematic clusters in subsequent periods, with edges representing the keywords occurring in both of the pair's clusters. The differences in the quantity of scientific production between the periods require careful use of community detection algorithms and parameter choices. We chose to examine pairwise comparisons between adjacent periods in order to mitigate the differences in scientific productions and to enhance content analyses' comparability over time. These analyses' results are depicted in Fig. 13, which complements the qualitative representation of the thematic evolution presented in Fig. 12 derived from Figs. 5, 6, 7 and Fig. 11. Each of these thematic maps seeks to balance the cluster's representativeness (avoiding a unique cluster) and their interpretability (avoiding many clusters of few words). This required tuning the parameters for each period. Note that the thematic evolution algorithm requires the same parameters for all the periods, so different fine-tuning was carried out to generate Fig. 13 based on this constraint.

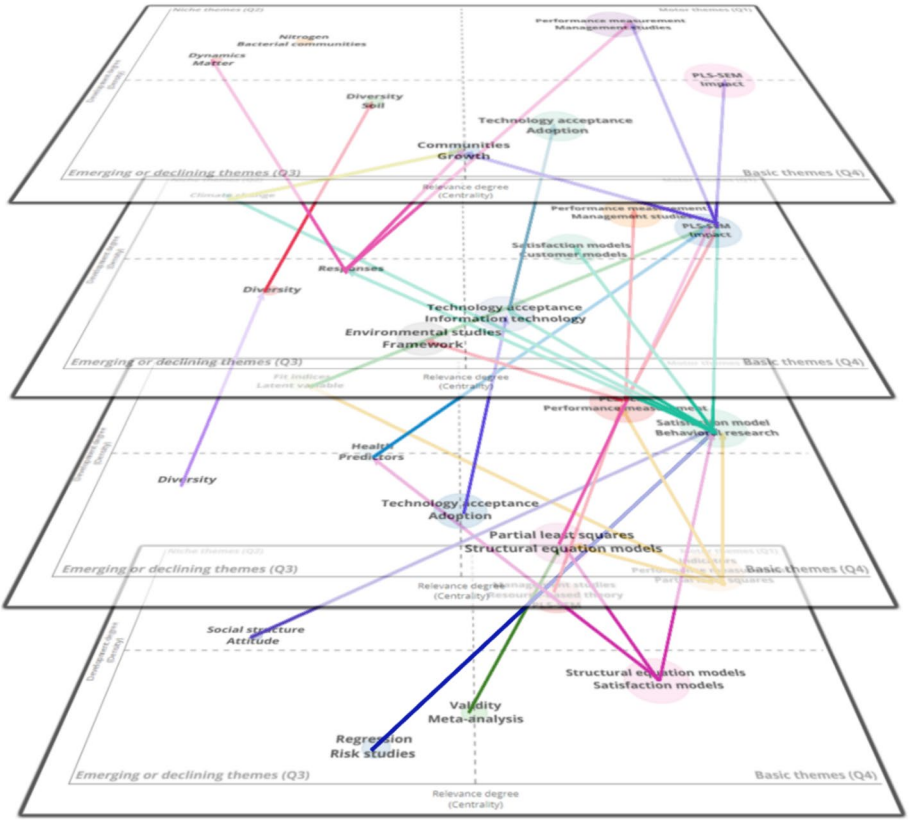
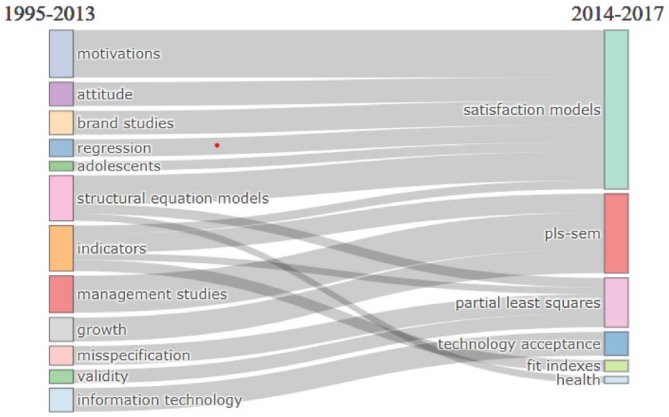


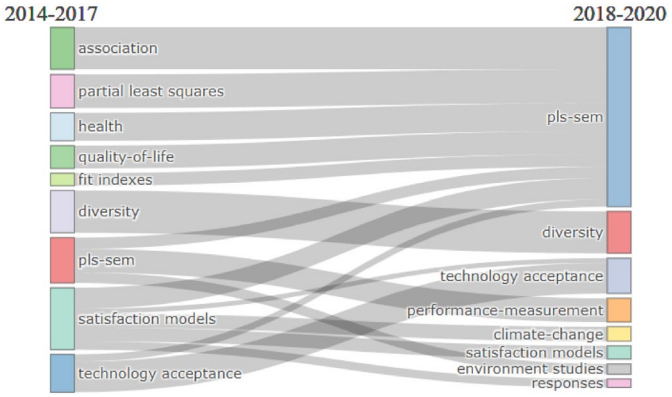
Fig. 12 Evolution of the thematic clusters across the four periods (1995–2013, 2014–2017, 2018–2020, and 2021–2022)

The visualization of the evolution derived from the Walktrap community detection algorithm highlights the temporal connections generated by the keyword flow, which also informs us of the specific topics' contribution to the thematic clusters' evolution. This creates both "conglomeration" and "fragmentation" effects in terms of topic structure and word occurrence from one period to the next.

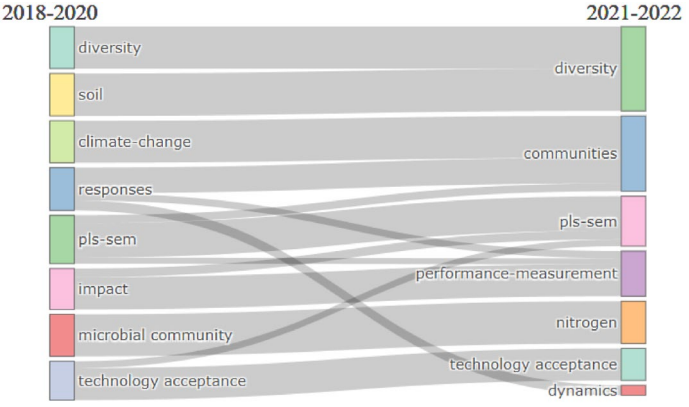
These effects could also depend on the unbalanced production rates at different periods. Our analysis also confirms that some topics are preserved over time, specifically "*PLS-SEM,*" "*Performance measurement,*" "*Satisfaction models,*" and "*Technology acceptance*." In addition, we observe that the first three themes receive multiple contributions from a variety of topics, which the incoming flows in Fig. 13a demonstrate. At the same time, "*Technology acceptance*" and themes related to environmental studies receive contributions from a more circumscribed set of topics in the subsequent periods, emphasizing their broader focus over time.



(a) 1995–2017, n. words = 600, MCF = 10‰



(b) 2014–2020, n. words = 600, MCF = 6‰



(c) 2018–2022, n. words = 800, MCF = 4‰

Fig. 13 Evolution of thematic clusters across the four periods

7 Discussion and conclusions

This work contributes to a better understanding of the way PLS-SEM supports knowledge advances across multiple scientific fields. In particular, the analysis revealed the role that PLS-SEM plays in knowledge transfer, portraying it as an integrative framework and a common methodological basis that connects distinct semantic fields. Our results inform researchers about the potential links and the impact that their studies can have on different domains.

Our research extends Ciavolino et al. (2022a) regarding the scientific relational structures' network analysis in PLS-SEM research. These authors focused mainly on PLS-SEM's "syntactic" aspects and on the inputs contributing to PLS-SEM research networks' generation. The present paper, however, addresses the "semantic" aspects, namely the emerging concepts and topics within the knowledge creation process, which can be examined through the keywords' associations and mutual relationships.

After identifying the main conceptual clusters that emerged from the Walktrap algorithm, we assessed their impact using Callon's centrality and density indices. Subsequently, we exploited their mutual position and the topics' evolution during the four main periods, covering 38 years (from January 1985 to December 2022). In addition, we highlighted that the most recent period showed an exponential increase in scientific production. The latter suggested substantial differences regarding the first "PLS-SEM era."

Our co-word network analysis of documents published in the four periods disclosed distinct themes and trends:

- The first period (1995–2013) is characterized by the prevalence of "*Indicators/Partial least squares*" and "*Management studies*" as highly important and developed motor trends compared to other consolidated, but less developed, themes ("*Structural equation models/Satisfaction models*"). In addition, we noted that "*Social structure*" was at a highly developed level compared to other themes' lower (or potentially slower) development ("*Regression/Risk studies" and "Validity*"). This could be interpreted as a significant driver provided by the motor theme, which prompted the development of a structured set of methods and techniques for niche or emerging applications.
- In the second period (2014–2017), "*PLS-SEM*" and "*Satisfaction models*" served as motor themes, while the individual topics "*Partial least squares*" and "*Structural equation models*" acted as basic themes. This positioning could relate to the thematic evolution, in particular to the coalescence of declining or emerging themes in the period 1995–2013 (e.g., "*Validity*") into the "*Partial least squares*" cluster. This behavior also suggests a synergic effect of PLS and SEM when they give rise to the "*PLS-SEM*" concept as a whole, which is in line with the dynamics of authors' keywords presented in Fig. 3. The "*Technology acceptance*" theme emerged with an average centrality but is not yet developed internally. Smaller clusters (in terms of word occurrence) with a low centrality included methodological aspects ("*Predictors,*" "*Fit indices*"), but applications in the health and ecological fields also emerged.
- In the third period (2018–2020), "*PLS-SEM*" and "*Performance measurement*" decoupled into two thematic clusters with high centrality and a high degree of development. "*Satisfaction models*" also became a motor theme, while "*Technology acceptance*" became a basic theme. Different thematic clusters related to environmental studies emerged as niche, emerging, or declining topics. In fact, this period showed PLS-SEM approaches extending beyond their original research fields (sta-

tistics, strategic management, business, psychometry, etc.) and entering the study of communities, soils, and ecosystems, where the method supports impact analyses and the study of metabolic pathways.

- The last period (2021–2022) continued the increasing trend of scientific productivity. The "*PLS-SEM*" cluster returned as a central theme supporting the investigation of new problems and research questions posed by the pandemic. This should be compared with more vertical themes of "*Performance measurement*" and "*Technology acceptance,*" which maintained their internal development degree by contributing to specific subjects related, for example, to sustainability performance and the role of emerging technologies during the pandemic. Similar to the previous period, several smaller clusters addressed environmental science's specific aspects, of which only one has a high centrality ("*Communities/Climate change*"), while the remaining clusters were configured as niche, emerging, or declining themes.

To summarize these outcomes, we linked the four periods to assess the themes' behavior over the years. A qualitative view of the clusters in Fig. 12 shows their "group dynamics," which the quantitative view in the thematic maps complements (Fig. 13), thereby representing the "internal dynamics," or the between-group (incoming or outgoing) flows. These two views provide different information on the themes' evolution in the centrality-density plane. On the one hand, the results point to the "*PLS-SEM*" cluster's stationary behavior as a relevant and generally well-developed theme. On the other hand, we find that the different themes in the period 1995–2013 merge into the "*PLS-SEM*" thematic cluster in the period 2014–2017. Analogous considerations also hold for other central topics, such as "*Satisfaction models.*" As anticipated, other clusters in the subsequent period absorbed themes with low development. Examples are "*Attitude*" moving into the "*Satisfaction models*" cluster in the period 2014–2017, and "*Fit indices*" and "*Health/Predictors*" entering the larger "*PLS-SEM*" cluster in the period 2018–2020.

This dynamic behavior should be compared with environmental themes, which, once generated, tend to acquire contributions from a narrow range of themes in the PLS-SEM domain. This factor could affect their specificity and centrality over time.

The themes' mutual interactions and their contribution to the creation and evolution of larger clusters suggest that the themes in the PLS-SEM field's group dynamics should be integrated into the exploration of their internal dynamics. This investigation provides a global–local view of the PLS-SEM domain, highlighting the common foundations or research directions prompting PLS-SEM developments' persistence in terms of their methodology, guidelines, and applications, as well as their diffusion into new fields.

In conclusion, our analysis underscores the evolution of themes within PLS-SEM research over several periods, shedding light on both their individual trajectories and their collective dynamics. The shift from focusing on syntactic aspects to semantic aspects reveals maturation in understanding and exploring the field's conceptual nuances. Key findings indicate the emergence of new themes, such as the expansion of PLS-SEM into diverse domains like environmental science, suggesting a broadening of its applicability and impact. Moreover, the observed clustering and absorption of themes over time suggest a dynamic interplay within the field, wherein certain concepts amalgamate into larger clusters while others emerge or decline. This fluidity not only reflects the adaptability of PLS-SEM methods but also highlights the interconnectedness of research themes. Furthermore, the integration of environmental themes into the PLS-SEM domain indicates a potential shift in focus and interdisciplinary collaboration, potentially enriching both fields.

However, it also poses challenges in maintaining the specificity and centrality of environmental themes within the broader context of PLS-SEM research.

The analysis also suggests that the topics' specificity may influence their persistence or adaptation over time. More transversal themes or keywords may give rise to ambiguity, which is reflected in the documents' cluster membership degree. However, such a form of ambiguity could be seen as a knowledge resource that fosters the adaptation capability of the topic over time, as it can relate to multiple research directions and is less dependent on their emergence or decline over time.

Finally, our analyses emphasize the importance of considering both the internal and external dynamics of thematic evolution within the PLS-SEM domain. Understanding these dynamics not only provides insights into the field's development, but also informs future research directions and interdisciplinary collaborations, thereby facilitating continued innovation and growth.

8 Limitations and further research

The emergence of periods characterized by substantial differences in their scientific production suggests that the present investigation should be refined by including suitable normalization criteria or comparative analyses. These two approaches could enhance a comparison of the thematic evolution's studies.

Two additional aspects need further consideration and investigation in future research. First, future studies should include new databases and documentation, such as reports and, if appropriate, grey literature on PLS-SEM. Such an extension would facilitate the identification of further themes and conceptual structures related to PLS-SEM in a less structured knowledge space (i.e., with reduced indexing and keyword identification). Simultaneously, a less formalized environment requires appropriate tools for its exploration, which would allow us to discover new relationships with other themes.

Second, future research should complement our analysis by assuming an information-theoretic perspective. Specifically, entropy-based methods could be useful regarding quantifying the divergence and mutual information that themes share in terms of word occurrences and cluster frequencies. The study of information-theoretic quantities has already proven useful in terms of analyzing latent semantics (Corallo et al. 2020), as well as membership functions (Ciavolino et al. 2014) and knowledge representations (Angelelli et al. 2024), which can support the exploration of the documents' associations with different thematic clusters. Furthermore, future studies should consider using geometric representations (Angelelli and Konopelchenko 2021) and algorithms (Angelelli et al. 2020) to explore the temporal dimension and investigate thematic information's evolution over time.

Appendix: Publications for each period (1995–2022)

See Tables 2, 3, 4, 5.

Table 2 Main documents in the period 1995–2013

Group	Authors & Year	Title	Source	Total citations
Indicators, performance measurement, partial least squares	Hulland (1999)	Use of partial least squares (PLS) in strategic management research: A review of four recent studies	Strategic Management Journal	4039
	Hair et al. (2012b)	An assessment of the use of partial least squares structural equation modeling in marketing research	Journal of the Academy of Marketing Science	3917
	Chin et al. (2003)	A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study	Information Systems Research	3712
	Wetzels et al. (2009)	Using PLS path modeling for assessing hierarchical construct models: guidelines and empirical illustration	MIS Quarterly	2632
	Petter et al. (2007)	Specifying formative constructs in information systems research	MIS Quarterly	1986
Structural equation models, satisfaction models, antecedents	Johnson et al. (2006)	The evolution of loyalty intentions	Journl of Marketing	433
	Gudergan et al. (2008)	Confirmatory tetrad analysis in PLS path modeling	Journal of Business Research	389
	Akter et al. (2011)	Trustworthiness in mHealth information services: an assessment of a hierarchical model with mediating and moderating effects using partial least squares (PLS)	Journal of the American Society for Information Science and Technology	232
	Albert et al. (2013)	Brand passion: Antecedents and consequences	Journal of Business Research	182
	Tenenhaus et al. (2005a)	PLS methodology to study relationships between hedonic judgements and product characteristics	Food Quality and Preference	177

Table 2 (continued)

Group	Authors & Year	Title	Source	Total citations
Management studies, resource-based theory, PLS-SEM	Becker et al. (2012)	Hierarchical latent variable models in PLS-SEM: guidelines for using reflective-formative type models	Long Range Planning	1140
	Krishnan et al. (2011)	Partial least squares (PLS) methods for neuroimaging: a tutorial and review	Neuroimage	800
	Cepeda and Vera (2007)	Dynamic capabilities and operational capabilities: A knowledge management perspective	Journal of Business Research	402
	Wilden et al. (2013)	Dynamic capabilities and performance: strategy, structure and environment	Long Range Planning	402
	Kijsanayotin et al. (2009)	Factors influencing health information technology adoption in Thailand's community health centers: Applying the UTAUT model	International Journal of Medical Informatics	369
Regression, risk studies	Tenenhaus and Tenenhaus (2011)	Regularized generalized canonical correlation analysis	Psychometrika	206
	Liu et al. (2011)	Spatial epidemiology and spatial ecology study of worldwide drug-resistant tuberculosis	International Journal of Health Geographics	31
Validity, meta-analysis	Brunetto et al. (2012)	Emotional intelligence, job satisfaction, well-being and engagement: explaining organisational commitment and turnover intentions in policing	Human Resource Management Journal	234
	Jacobs et al. (2011)	Testing an integrated model of the theory of planned behaviour and self-determination theory for different energy balance-related behaviours and intervention intensities	British Journal of Health Psychology	59

Table 2 (continued)

Group	Authors & Year	Title	Source	Total citations
Social structure	Lew and Sinkovics (2013)	Crossing borders and industry sectors: behavioral governance in strategic alliances and product innovation for competitive advantage	Long Range Planning	63
	Tashiro et al.(2012)	E-mail networks and leadership performance	Journal of the American Society for Information Science and Technology	4
Attitude	Rabl (2010)	Age, discrimination, and achievement motives: A study of German employees	Personnel Review	36
	Spielvogel and Terlutter (2013)	Development of TV advertising literacy in children: Do physical appearance and eating habits matter?	International Journal of Advertising	15

Table 3 Main documents in the period 2014–2017

Group	Authors & Year	Title	Source	Total citations
PLS-SEM, performance measurement, impact	Henseler et al. (2015)	A new criterion for assessing discriminant validity in variance-based structural equation modeling	Journal of the Academy of Marketing Science	12,422
	Hair et al. (2017a)	An updated and expanded assessment of PLS-SEM in information systems research	Industrial Management & Data Systems	1412
	Sarstedt et al. (2014b)	Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers	Journal of Family Business Strategy	882
	Akter et al. (2016)	How to improve firm performance using big data analytics capability and business strategy alignment?	International Journal of Production Economics	636
	Dijkstra and Henseler (2015a)	Consistent and asymptotically normal PLS estimators for linear structural equations	Computational Statistics & Data Analysis	591
Satisfaction models, behavioral research, antecedents	Nitzl et al. (2016)	Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models	Industrial Management & Data Systems	1167
	Möhlmann (2015)	Collaborative consumption: determinants of satisfaction and the likelihood of using a sharing economy option again	Journal of Consumer Behaviour	710
	Astrachan et al. (2014)	A comparative study of CB-SEM and PLS-SEM for theory development in family firm research	Journal of Family Business Strategy	402
	Hajli (2015)	Social commerce constructs and consumer's intention to buy	International journal of Information Management	390
	Hajli (2014)	A study of the impact of social media on consumers	International Journal of Market Research	314

Table 3 (continued)

Group	Authors & Year	Title	Source	Total citations
Partial least squares, structural equation models, work studies	Hair et al. (2016)	Identifying and treating unobserved heterogeneity with FIMIX-PLS: part I–method	European Business Review	535
	Rasoolimanesh et al. (2015)	A revised framework of social exchange theory to investigate the factors influencing residents' perceptions	Tourism Management Perspectives	192
	Cepeda-Carrión et al. (2016)	Prediction-oriented modeling in business research by means of PLS path modeling: introduction to a JBR special section	Journal of Business Research	138
	Fassott et al. (2016)	Testing moderating effects in PLS path models with composite variables	Industrial Management & Data Systems	128
	Rigdon (2014)	Rethinking partial least squares path modeling: breaking chains and forging ahead	Long Range Planning	127
Technology acceptance, adoption, intentions	Yeo et al. (2017)	Consumer experiences, attitude and behavioral intention toward online food delivery (OFD) services	Journal of Retailing and Consumer Services	362
	Amaro and Duarte (2015)	An integrative model of consumers' intentions to purchase travel online	Tourism Management	306
	Ooi and Tan (2016)	Mobile technology acceptance model: An investigation using mobile users to explore smartphone credit card	Expert Systems with Applications	259
	Teo et al. (2015)	The effects of convenience and speed in m-payment	Industrial Management & Data Systems	233
	Hew et al. (2015)	What catalyses mobile apps usage intention: an empirical analysis	Industrial Management & Data Systems	213

Table 3 (continued)

Group	Authors & Year	Title	Source	Total citations
Fit indices, latent variables	Henseler et al. (2016a)	Using PLS path modeling in new technology research: updated guidelines	Industrial Management & Data Systems	3062
	Henseler et al. (2014)	Common beliefs and reality about PLS: Comments on Rnnkkö and Evermann (2013)	Organizational Research Methods	1831
	Kasiri et al. (2017)	Integration of standardization and customization: Impact on service quality, customer satisfaction, and loyalty	Journal of Retailing and Consumer Services	186
Health, predictors	Price et al. (2015)	Establishing the relationship of inhaler satisfaction, treatment adherence, and patient outcomes: a prospective, real-world, cross-sectional survey of US adult asthma patients and physicians	World Allergy Organization Journal	43
Diversity	Kou et al. (2017)	Scale-dependent key drivers controlling methane oxidation potential in Chinese grassland soils	Soil Biology & Biochemistry	69

Table 4 Main documents in the period 2018–2020

Group	Authors & Year	Title	Source	Total citations
PLS-SEM, impact, behavioral research	Hair et al. (2019)	When to use and how to report the results of PLS-SEM	European Business Review	6686
	Hair et al. (2020)	Assessing measurement model quality in PLS-SEM using confirmatory composite analysis	Journal of Business Research	1423
	Shmueli et al. (2019)	Predictive model assessment in PLS-SEM: guidelines for using PLSpredict	European Journal of Marketing	1103
	Sarstedt et al. (2019)	How to specify, estimate, and validate higher-order constructs in PLS-SEM	Australasian Marketing Journal	931
	Ringle et al. (2020)	Partial least squares structural equation modeling in HRM research	International Journal of Human Resource Management	699
Performance measurement, management studies, innovation	Kock and Hadaya (2018)	Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods	Information Systems Journal	660
	Mikalef et al. (2020)	Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities	Information & Management	365
	Zaid et al. (2018)	The impact of green human resource management and green supply chain management practices on sustainable performance: An empirical study	Journal of Cleaner Production	330
	Mikalef et al. (2019)	Big data analytics capabilities and innovation: the mediating role of dynamic capabilities and moderating effect of the environment	British Journal of Management	317
	Cenamor et al. (2019)	How entrepreneurial SMEs compete through digital platforms: The roles of digital platform capability, network capability and ambidexterity	Journal of Business Research	276

Table 4 (continued)

Group	Authors & Year	Title	Source	Total citations
Satisfaction models, customer models, tourism studies	Cheah et al. (2018)	Convergent validity assessment of formatively measured constructs in PLS-SEM: On using single-item versus multi-item measures in redundancy analyses	International Journal of Contemporary Hospitality Management	205
	Gan and Li (2018)	Understanding the effects of gratifications on the continuance intention to use WeChat in China: A perspective on uses and gratifications	Computers in Human Behavior	185
	Zatori et al. (2018)	Experience-involvement, memorability and authenticity: The service provider's effect on tourist experience	Tourism Management	174
	Ali et al. (2018a)	Make it delightful: Customers' experience, satisfaction and loyalty in Malaysian theme parks	Journal of Destination Marketing & Management	143
	Merli et al. (2019)	Why should hotels go green? Insights from guests experience in green hotels	International Journal of Hospitality Management	138

Table 4 (continued)

Group	Authors & Year	Title	Source	Total citations
Technology acceptance, information technology, adoption	Al-Fraihat et al. (2020)	Evaluating E-learning systems success: An empirical study	Computers in Human Behavior	370
	Zhang et al. (2018)	A model of perceived image, memorable tourism experiences and revisit intention	Journal of Destination Marketing & Management	330
	Kamal et al. (2020)	Investigating acceptance of telemedicine services through an extended technology acceptance model (TAM)	Technology in Society	295
	Tam et al. (2020)	Exploring the influential factors of continuance intention to use mobile apps: Extending the expectation confirmation model	Information Systems Frontiers	226
	Salloum et al. (2019)	Exploring students' acceptance of e-learning through the development of a comprehensive technology acceptance model	IEEE Access	205
	Seman et al. (2019)	The mediating effect of green innovation on the relationship between green supply chain management and environmental performance	Journal of Cleaner Production	246

Table 4 (continued)

Group	Authors & Year	Title	Source	Total citations
Environmental studies, framework, scale	Zhang et al. (2020)	Predicting climate change mitigation and adaptation behaviors in agricultural production: A comparison of the theory of planned behavior and the Value-Belief-Norm Theory	Journal of Environmental Psychology	107
	Durdyev et al. (2018)	A partial least squares structural equation modeling (PLS-SEM) of barriers to sustainable construction in Malaysia	Journal of Cleaner Production	102
	Ahmadabadi and Heravi (2019)	The effect of critical success factors on project success in Public–Private Partnership projects: A case study of highway projects in Iran	Transport Policy	83
	Yan and Zhang (2020)	Interplay of contractual governance and trust in improving construction project performance: Dynamic perspective	Journal of Management in Engineering	66
Diversity	Ai et al. (2018)	Distinct responses of soil bacterial and fungal communities to changes in fertilization regime and crop rotation	Geoderma	188
Responses	Wijethilake and Lama (2019)	Sustainability core values and sustainability risk management: Moderating effects of top management commitment and stakeholder pressure	Business Strategy and the Environment	97
Climate change	Soewarno et al. (2019)	Green innovation strategy and green innovation: The roles of green organizational identity and environmental organizational legitimacy	Management Decision	144

Table 5 Main documents in the period 2021–2022

Group	Authors & Year	Title	Source	Total citations
PLS-SEM, impact, satisfaction models	Dash and Paul (2021)	CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting	Technological Forecasting and Social Change	468
	Soroya et al. (2021)	From information seeking to information avoidance: Understanding the health information behavior during a global health crisis	Information Processing & Management	215
	Sánchez-Cañizares et al. (2021)	Impact of the perceived risk from Covid-19 on intention to travel	Current Issues in Tourism	208
	Fernandes and Oliveira (2021)	Understanding consumers' acceptance of automated technologies in service encounters: Drivers of digital voice assistants adoption	Journal of Business Research	203
	Rather (2021)	Demystifying the effects of perceived risk and fear on customer engagement, co-creation and revisit intention during COVID-19: A protection motivation theory approach	Journal of Destination Marketing & Management	146

Table 5 (continued)

Group	Authors & Year	Title	Source	Total citations
Performance measurement, management studies, mediation analysis	Dubey et al. (2021)	Empirical investigation of data analytics capability and organizational flexibility as complements to supply chain resilience	International Journal of Production Research	366
	Malik and Khan (2021)	Analysis of ERP implementation to develop a strategy for its success in developing countries	Production Planning & Control	270
	Ciampi et al. (2021)	Exploring the impact of big data analytics capabilities on business model innovation: The mediating role of entrepreneurial orientation	Journal of Business Research	195
	Sarstedt et al. (2022a)	Progress in partial least squares structural equation modeling use in marketing research in the last decade	Psychology & Marketing	180
	Bag et al. (2021)	Key resources for industry 4.0 adoption and its effect on sustainable production and circular economy: An empirical study	Journal of Cleaner Production	174
Technology acceptance, adoption, information technology	Queiroz et al. (2021)	Blockchain adoption in operations and supply chain management: empirical evidence from an emerging economy	International Journal of Production Research	143

Table 5 (continued)

Group	Authors & Year	Title	Source	Total citations
	Troise et al. (2021)	Online food delivery services and behavioural intention—a test of an integrated TAM and TPB framework	British Food Journal	104
	Moussawi et al. (2021)	How perceptions of intelligence and anthropomorphism affect adoption of personal intelligent agents	Electronic Markets	98
	Liu and Tao (2022)	The roles of trust, personalization, loss of privacy, and anthropomorphism in public acceptance of smart healthcare services	Computers in human behavior	95
	Akdim et al. (2022)	The role of utilitarian and hedonic aspects in the continuance intention to use social mobile apps	Journal of Retailing and Consumer Services	87
Communities, climate change	Cui et al. (2021)	Extracellular enzyme stoichiometry reveals the carbon and phosphorus limitations of microbial metabolisms in the rhizosphere and bulk soils in alpine ecosystems	Plant and Soil	97
	Jabeen et al. (2021)	Perceived critical factors affecting consumers' intention to purchase renewable generation technologies: rural–urban heterogeneity	Energy	73
Nitrogen	Zhao et al. (2021)	Deciphering the transfers of antibiotic resistance genes under antibiotic exposure conditions: driven by functional modules and bacterial community	Water Research	65
Diversity	Du et al. (2021)	Direct versus indirect effects of human activities on dissolved organic matter in highly impacted lakes	Science of the Total Environment	46

Table 5 (continued)

Group	Authors & Year	Title	Source	Total citations
Dynamics	Charoensukmongkol and Phungsoonthorn (2022)	The interaction effect of crisis communication and social support on the emotional exhaustion of university employees during the COVID-19 crisis	International Journal of Business Communication	45

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Declarations

Conflict of interest Even though this research does not use the statistical software SmartPLS (https://www.smartpls.com), Christian M. Ringle acknowledges a financial interest in SmartPLS.

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