# Sampling and sample size in B2B marketing

## Current practices and recommendations

Cabanelas, Pablo; Mora Cortez, Roberto; Pérez-Moure, Hugo; Lampón, Jesús F.

*Published in:*
Industrial Marketing Management

*DOI:*
10.1016/j.indmarman.2024.12.014

*Publication date:*
2025

*Document version:*
Final published version

Industrial Marketing Management 125 (2025) 71–86

Contents lists available at ScienceDirect

Industrial Marketing Management

journal homepage: www.elsevier.com/locate/indmarman

# Sampling and sample size in B2B marketing: Current practices and recommendations

Pablo Cabanelas [a,*], Roberto Mora Cortez [b,c], Hugo Pérez-Moure [d], Jesús F. Lampón [e]

[a] Department of Business Organization and Marketing, ECOBAS, University of Vigo, Vigo, Spain
[b] Department of Business Administration, Morehouse College, Atlanta, United States
[c] Department of Business and Sustainability, Southern Denmark University, Denmark
[d] Department of Business Economics, Universidad Rey Juan Carlos, Madrid, Spain
[e] Department of Business Organization and Marketing, University of Vigo, Vigo, Spain

ARTICLE INFO

*Keywords:*
Sampling
Sample size
Industrial marketing
Quantitative research
Systematic literature review
Methodology

ABSTRACT

Sampling procedures and sample size have the potential to improve the accuracy and efficiency of business-to-business (B2B) marketing research, as well as provide added statistical rigor to research. Therefore, justifying the rationale for sampling is useful in reducing uncertainty and accomplishing high standards. This paper aims to understand the sampling approaches applied in B2B marketing through a literature review of the three most reputable journals focused on this area in the 2013–2023 period. Furthermore, the paper also aims to develop a set of best practices. Results suggest that, although quantitative research is gaining presence in B2B marketing literature, there are different areas of improvement in terms of justification, explanation of the methodology, and the use of data. Achieving a minimum sample size along with the combination of primary and secondary data, and justifying the sampling, data collection, and methods used through statistical lenses, refraining from simplistic arguments, are not only valuable sources of detailed information, but can also increase confidence in quantitative research.

## 1. Introduction

Traditionally, business decision-making involves a trade-off between *bias* and *variance* (Wedel & Kannan, 2016). This dilemma could be translated into the scholarly field, as better academic outputs need improved models and/or more data (Mora Cortez & Johnston, 2017). For the former, researchers usually rely on basic assumptions that create an incomplete picture of reality (Rigdon, 2023). For the latter, the larger the volume of data, the better the representation of reality; but then complexity and management costs increase, and scholars may need to make compromises. That is why researchers resort to sampling and measurement error, with the consequent effects on *variance* (McShane et al., 2024; McShane & Bockenholt, 2016). Overall, while *bias* results from an incomplete representation of the true data-generating mechanism by a model because of simplifying assumptions, *variance* results from random variation in the data due to sampling and measurement error (Wedel & Kannan, 2016, p. 104). In this article, we focus on sampling (in general) and sample size (in specific) as a path to deal with *variance*.

The analysis of sampling procedures and sample size has long attracted the attention of B2B marketing researchers (McIntosh, 1975), and improvement in both issues can favor accuracy and efficiency. Moreover, sampling and sample size are a source of statistically biased standard errors. For instance, Rigdon (2023) has named sampling design features and sample size, alongside scatter of observed data values or the specific estimators, as sources of biased standard errors. Similarly, Rigdon and Sarstedt (2022) consider sampling a major challenge for social science researchers because the population and sampling are one out of six relevant factors to be further analyzed. Sampling design, jointly with the specific nature of a population, is a familiar component of uncertainty for researchers, and it usually “dominates calculation of standard errors” (Rigdon, 2023, p. 4).

Therefore, it is gainful to justify the rationale behind a selected sample size (McShane et al., 2024). While it is well known that a larger volume of data reduces the *variance*, a better understanding of current practices on sample size and sampling procedures in B2B marketing can

* Corresponding author.
*E-mail addresses:* pcabanelas@uvigo.es (P. Cabanelas), roberto.moracortez@morehouse.edu (R. Mora Cortez), perez.moure@urjc.es (H. Pérez-Moure), jesus.lampon@uvigo.es (J.F. Lampón).

https://doi.org/10.1016/j.indmarman.2024.12.014
Received 23 March 2024; Received in revised form 11 December 2024; Accepted 18 December 2024
Available online 29 December 2024

help to reduce uncertainty and identify whether journals are accomplishing high standards. Therefore, this paper aims to answer the following research questions: What are the sampling approaches utilized in B2B marketing? What are the sample sizes used and their conditionings? How does sample size influence the analysis and what recommendations researchers should follow? Hence, this study addresses an old marketing paradigm about what is the minimum amount of data required to make good decisions (Kelley, 1965). Particularly, we conduct an analysis of recent quantitative articles in the three most reputable journals focused on B2B marketing (i.e., IMM, JBIM, and JBBM) in the 2013–2023 period.

The selected journals publish a myriad of relevant topics for B2B marketers and editorials to guide authors and reviewers. However, to our knowledge, an exhaustive examination of the sampling and sample sizes being studied within these journals has not been conducted. Against this backdrop, our paper presents a systematic literature review in line with previous best practices in the marketing field (e.g., Cabanelas et al., 2023; Mora Cortez et al., 2021; Snyder, 2019). A systematic approach facilitates a comprehensive review to ensure understanding of the selected literature (Hulland & Houston, 2020), through an organized, transparent, and replicable step-by-step process (Palmatier et al., 2018). As a result, this article sheds light on what we know about samples being reported in the method sections of the literature on B2B marketing, as well as developing a discussion on what should be included (Rutherford et al., 2023).

Our study offers several contributions to the B2B marketing field. First, we provide a guide to sampling processes and sample size used in recent quantitative papers in the B2B marketing field, in a similar effort that was made for experimentation (Viglia et al., 2021). It suggests that non-probability methods are dominant due to the constraints of finding reliable databases with the whole population or to the very specific characteristics demanded by the sample. Second, the analytical approaches are also dependent on such specific characteristics of sampling. Structural Equation Modeling (SEM), both in the form of covariance-based SEM, and particularly Partial Least Squares (PLS-SEM or variance-based SEM), are among the most applied techniques in B2B marketing (Guenther et al., 2023). Also, the application of regression analysis is common in this field, and the variety of approaches offers the flexibility to apply the best possible one to the data available. Third, the in-depth scrutiny of quantitative research in the three most reputable B2B marketing journals can provide a series of good practices and recommendations regarding rigorous standards in B2B marketing research (Palmatier et al., 2018; Rutherford et al., 2023). These standards, based on a solid platform that includes the analysis of 1065 papers, serve as a guide for researchers conducting a quantitative B2B marketing study. In addition, we contribute to the "quantitative vs. qualitative debate" throughout the manuscript, since qualitative research and quantitative research have both advantages and limitations. Our findings also open avenues for future research based on inconsistencies and challenges.

## 2. Method

We follow a systematic approach to review the sampling procedure and sample size applied in quantitative research in three journals specialized in B2B marketing (e.g., Mora Cortez et al., 2021; Snyder, 2019). *A systematic* (rather than ad hoc) *approach helps to ensure that the body of literature reviewed is as comprehensive as possible* (Hulland & Houston, 2020, p. 28). Thus, we use valid and reliable procedures at each stage of the process (Palmatier et al., 2018). We adhere to recommendations for successful reviews involving: (1) design, (2) conduct, (3) analysis, and (4) writing the review (see Snyder, 2019). As an initial step, we assessed the usefulness of conducting a systematic review of the sampling and sample size endeavor with a panel of 10 experienced marketing scholars, obtaining a 4.35 average score on a five-point scale running from 1 (not at all) to 5 (totally).

Systematic reviews are categorized into (1) domain-based, (2) method-based, and (3) theory-based (Palmatier et al., 2018). This manuscript follows a method-based review focused on the sampling and sample size challenge for quantitative studies. Our goal is to scrutinize, summarize, and develop the body of literature on the sampling and sample size domain (Palmatier et al., 2018). The review process is guided by best practices intended to deliver an overview that enables amalgamation of the extant knowledge on sampling and sample size in the B2B marketing literature (Fig. 1). The selected approach responds to calls for *summarizing* and *revising* (MacInnis, 2011) and *reconciling*, and then *extending* prior research in a relevant, rigorous manner (Hulland & Houston, 2020).

### 2.1. Preparation and pre-selection

We targeted the most reputable, peer-reviewed B2B marketing journals: *Industrial Marketing Management* (IMM), *Journal of Business and Industrial Marketing* (JBIM), and *Journal of Business-to-Business Marketing* (JBBM). To validate the final list of B2B marketing outlets, we formed an expert discussion roundtable during a major marketing conference with four senior scholars and asked them to generate a list of the active, focalized B2B journals in the marketing field. Their conclusion was consistent with our journal selection (i.e., IMM, JBIM, and JBBM).

The study timeframe covers 11 years, surpassing the minimum threshold (10 years) to support the validity of our analyses as acknowledged in extant literature (see Paul & Criado, 2020; Rutherford et al., 2023). Therefore, the emerging sample lies within the 2013–2023 period, allowing exhaustive coverage of the focal domain. This procedure generated 2845 articles published online, whose bibliometric details were transferred to an Excel file. The identification of quantitative articles was open to both regular and special issue manuscripts. To conduct the *pre-selection*, we accessed all manuscripts in the selected journals.

### 2.2. Selection

Articles *selection* involved the four authors who initially analyzed (separately) the 2845 papers assessing the use of quantitative data. Following prior research, meta-analytic articles were discarded to avoid data duplication (Morgan et al., 2019). It is important to identify all empirical evidence that meets the established research-goal criteria (Snyder, 2019). For evaluation purposes, the authors coded the articles with 1 (quantitative study) or 0 (non-quantitative study). Those papers with a convergent score equal to 1 were included in the review. As customary, the few discrepancies were resolved via discussion (Shamsollahi et al., 2021). The inter-rater reliability analysis was assessed with the proportional reduction of loss method, reaching a satisfactory level of 0.98 (Rust & Cooil, 1994). The result was 1065 articles in the final sample for further analysis and review (see Web Appendix 1).

### 2.3. Analysis

The final step is the *articles analysis,* which requires a protocol for coding, summarizing, and reviewing the papers. An Excel document was created to code (1) method used and its justification, (2) type of data (primary vs. secondary), (3) nature of data (subjective vs. objective), (4) sample size and response rate (and justification), (5) random vs. non-random procedure, (6) international vs. local sample, and (7) countries used as context. To ensure the trustworthiness of the revised protocol, a marketing researcher reviewed 10 randomly selected articles. The expert indicated high validity of the protocol.

The author team (separately) coded 1065 selected articles. As usual, the few coding disagreements were settled through discussion sessions. To enhance the trustworthiness of the coding, two independent B2B marketing scholars from an R1 U.S. university in the Carnegie Classification of Institutions of Higher Education coded the raw data of 10

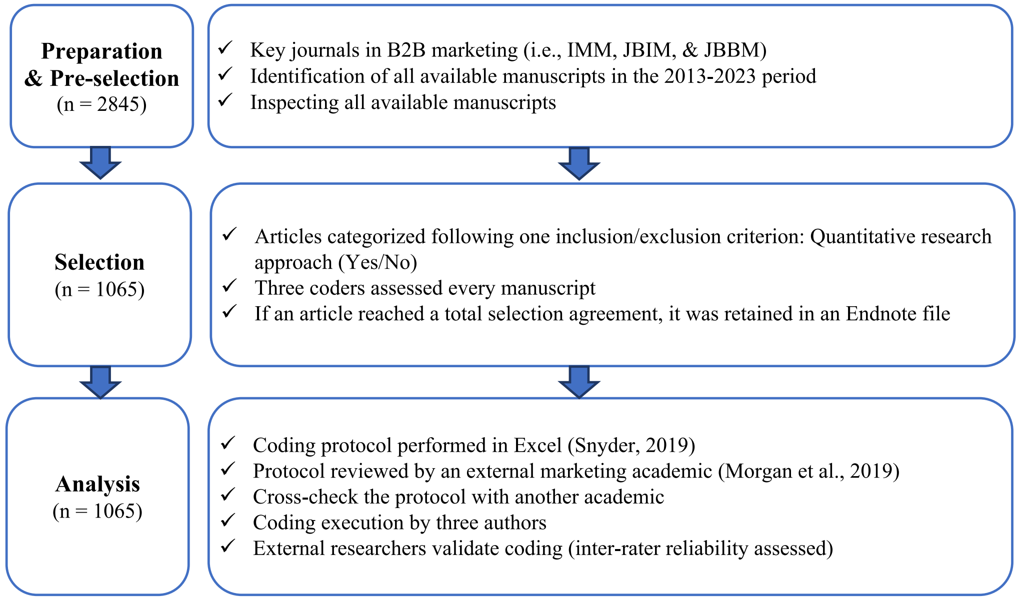



**Fig. 1.** Review process.

randomly selected articles, reaching an adequate inter-rater reliability (proportional reduction of loss method) of 0.96 (Rust & Cooil, 1994). The coding outcomes were like those of the authors, with just slight differences in method labeling. The final coding scheme, therefore, supports the validity and consistency of our results.

## 3. Descriptive analysis

### *3.1. Quantitative versus qualitative research*

This analysis starts with a comparison between the number of quantitative and qualitative articles published from 2013 to 2023, and the associated trends. As Fig. 2 suggests, the number of quantitative papers in B2B marketing journals is approaching the number of qualitative papers in absolute terms (see also the projection represented by a dashed line, which indicates convergence over time).

Regarding the differences among journals, they are to be found in the representativeness of quantitative papers. 42.89 % and 43.62 % of publications of JBIM and JBBM were respectively quantitative papers in the analyzed period, while IMM reached 31.68 %. A chi-square test (contingency table) comparing quantitative and qualitative papers by journal in the period of analysis shows a significant difference (chi-square = 32.94, $p < .05$) among journals (see Appendix I). Overall, IMM has favored more qualitative research than JBIM and JBBM.

Greater detail on the quantitative papers is presented in Table 1. Remarkably, there is some variability between years and journals. For instance, 2014 and 2021 saw the lowest number of quantitative articles published. Apart from 2021 (maybe due to the COVID-19 pandemic impact), the publication levels of quantitative articles have remained above average (40.18 %) since 2016, while qualitative articles remained below average (59.82 %). Thus, B2B marketing is starting to suffer from the quantitative bias previously identified in top-tier journals (see Crick, 2021).

Looking at the journals, JBIM publishes more quantitative articles, although this trend has slowed down in the last five years. Likewise, trends both by journal and by year show relatively low standard deviations. In general, the percentage of variance of quantitative articles is between 0.11 and 0.15 for the three journals, while for years it is between 0.04 and 0.2. JBBM reached its maximum percentage for quantitative research in 2022 (68.42 %), JBIM in 2019 (67.01 %), and IMM in 2020 (53.17 %). In any case, for the last two years quantitative articles have remained above the average percentage (JBBM and IMM) or very close to it (JBIM). There is a positive and significant correlation (Spearman's index = 0.87, $p$ = .000) between the total number of published articles and the number of published quantitative articles. These results indicate a growing trend of quantitative research in B2B marketing in the three journals analyzed.

### *3.2. Selected methods*

We further explore how data were analyzed in the quantitative articles. A large variety of quantitative methods are identified (see Web Appendix 2 for details). Particularly, Structural Equation Modeling (SEM) is the main analytical tool, accounting for 54.27 % (578) of total articles. This methodology can be divided into covariance-based SEM (also known as LISREL-SEM or simply SEM, with 372 papers) and PLS-SEM (also known as variance-based SEM with 206). This paper distinguishes both types of method because there are important differences both in the approach and sample sizes. On one hand, PLS-SEM usually employs a lower sample size than covariance-based SEM. Among papers resorting to primary data in the period analyzed, the sample mean is 209 for PLS-SEM, while 311 for covariance-based SEM. Adding the mixed methods articles and the secondary data articles, sample size rises to 285 for PLS-SEM, and 313 for covariance-based SEM. In this vein, prior research indicates that the tolerance for a small sample size is not adequate justification for the selection of PLS-SEM (e.g., see Goodhue et al., 2012). However, simulation studies indicate that if the sample size is large (e.g., more than 250 observations), covariance-based SEM has higher parameters of accuracy and consistency than PLS-SEM. When the sample size is small, in comparison with covariance-based SEM, PLS-SEM always has larger or equal statistical power (see Rigdon et al., 2017).

On the other hand, the approaches are different too. Covariance-based SEM is commonly used because it "allows for a combination of measurement and structural models" (Liu et al., 2023, p. 264), and "provides a platform for simultaneously estimating observable and latent constructs, measurement error, and relationships among constructs and indicators" (Rangarajan et al., 2021, p. 2131). Conversely, covariance-based SEM needs latent variables with reflective items, and it may not be robust enough if there is missing data or if it does not follow a normal distribution (Gölgeci & Kuivalainen, 2020). In this regard, PLS-SEM has a more exploratory nature, and it is applied when there is no

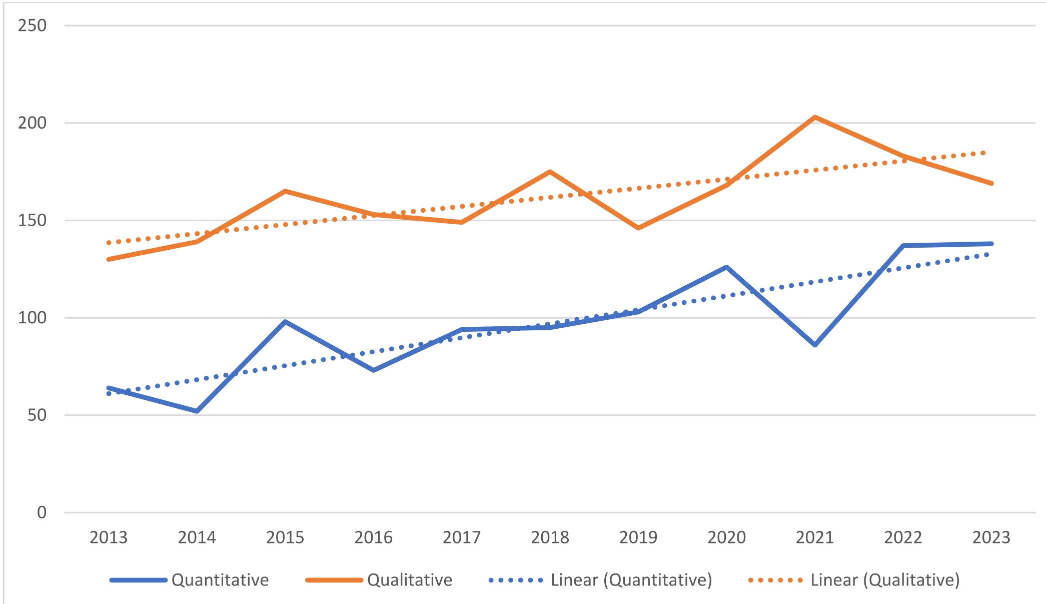



**Fig. 2.** Trend analysis comparing quantitative and qualitative papers 2013–2023.

established theory (Ranjan & Nayak, 2023). Furthermore, PLS-SEM can be more adequate to test interaction effects reaching a better power: "*While partial least squares modeling fits well for testing interaction effects (*Mitchell, Mitchell, & Smith, 2008*), the use of a multi-group structural model analysis approach may raise potential concerns regarding the power of the test and the validity of the findings when the model is applied to a small to medium sample size*" (Najafi-Tavani et al., 2015, p. 107).

Regression analysis ranked second, comprising 35.87 % (382) of the total articles. There are numerous regression-related approaches, the most used being hierarchical regression (25.91 %), multiple linear regression (23.04 %), and moderated regression (5.57 %). The regression type is not specified in 18.32 % of the cases, while the rest are another type of regression that is not representative enough (e.g., spline regression).

The analytical tools are highly dependent on the type of data. In the case of secondary sources (115, 10.08 %), the most frequently used methodology is some form of regression analysis (63.55 %), followed by SEM (12.15 %). In those papers using primary sources (950, 89.22 %), the data were collected mainly through questionnaires/surveys. Within this group, 84.68 % of the articles were subjective in nature, employing Likert scales to assess perceptions and opinions, while only 0.75 % utilized objective data, 2.54 % employed hybrid data (subjective and objective), and 2.26 % do not mention what kind of data are used. Only 0.85 % of the analyzed papers employed primary and secondary data. No discernible disparities were observed between journals or years.

With the intention of checking the potential differences among journals regarding the method applied, the Fisher exact test with a Monte Carlo approach was conducted (Tables 2 and 3). This technique demonstrated that there are significant differences among the journals. Thus, some disparities are observed. Covariance-based SEM is the analytical tool most applied in JBIM and JBBM, while IMM publications resort more to regression. PLS-SEM is the third method for the three journals, followed by other analytical techniques.[1]

A further trend analysis comparing year and method (Appendix II) shows an important projection growth for regressions and PLS-SEM, and also covariance-based SEM, which has a lower percentage growth. For instance, regressions surpassed SEM as the main methodology in 2023. The number of covariance-based SEM articles has a more moderate trend than regressions and PLS-SEM articles, having reached its maximum in 2017.

### 3.3. Sample size

The sample size requires special attention, since it is highly variable and relevant for the generalizability of a study. With this goal, it is important to distinguish that the sample size is highly dependent on the type of data, i.e., whether the article uses qualitative or quantitative data, or primary or secondary data. Regarding the sample size used in research with primary sources, the mean is 293 observations, with a maximum[2] of 16,062 and a minimum[3] of 19. However, as the mean may not correctly represent reality; if there is a large variation in the data, as in this case, it is recommended to use the median (272.5). 87.05 % (837) of papers use a sample $\leq$ than 400 observations (Fig. 3).

A cross tabulation of method (analytical tool) and journal for primary data indicates that the sample size is dependent on the methodology and journal (Table 4). For instance, the sample size is 30 % higher for IMM and JBBM than JBIM. Furthermore, the mixed methods (e.g., those combining covariance-based SEM and regression) are those with the largest sample size, while the lowest ranked methodologies are fuzzy-logic and PLS-SEM. The sample size was increasing over the period of analysis, but this growth trend seemingly decelerates over time (Appendix III). It is noticeable that the average sample size ranges between 200 and 400.

In addition, 89.98 % of the articles based on primary data are considered non-random. That is, they do not use any type of random sampling. As in the previous section, most of the articles using primary

[1] Analytical techniques are a category that includes those analytical tools that cannot be considered as methodologies per se, but that were used as the main method for quantitative papers. They include, among others, Confirmatory Factor Analysis (CFA), Exploratory Factor Analysis (EFA) or Mann-Withey *U* test.

[2] The sample comes from a binary logistic regression with primary sources and mixed data (objective and subjective), with a 76.54 % response rate and with a local scope.

[3] The sample is employed in a multiple regression methodology with primary, subjective data. In addition, there are four papers using a sample lower than 40, two employing primary data and two secondary data, and different methodologies like regressions and one-way ANOVA.

**Table 1**
Relative, absolute and variation rate of quantitative and qualitative papers per journals and year.

| | JBBM | | | | | | JBIM | | | | | | IMM | | | | | | ALL |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Quant | % | Variation | Qual | % | Variation | Quant | % | Variation | Qual | % | Variation | Quant | % | Variation | Qual | % | Variation | n |
| 2013 | 4 | 30.8 % | | 9 | 69.2 % | | 30 | 51.7 % | | 28 | 48.3 % | | 30 | 24.4 % | | 93 | 75.6 % | | 194 |
| 2014 | 3 | 23.1 % | −25.0 % | 10 | 76.9 % | 11.1 % | 21 | 38.2 % | −30.0 % | 34 | 61.8 % | 21.4 % | 28 | 22.8 % | −6.7 % | 95 | 77.2 % | 2.2 % | 191 |
| 2015 | 5 | 27.8 % | 66.7 % | 13 | 72.2 % | 30.0 % | 37 | 41.6 % | 76.2 % | 52 | 58.4 % | 52.9 % | 56 | 35.9 % | 100.0 % | 100 | 64.1 % | 5.3 % | 263 |
| 2016 | 7 | 43.8 % | 40.0 % | 9 | 56.2 % | −30.8 % | 44 | 51.8 % | 18.9 % | 41 | 48.2 % | −21.2 % | 22 | 17.6 % | −60.7 % | 103 | 82.4 % | 3.0 % | 226 |
| 2017 | 9 | 56.2 % | 28.6 % | 7 | 43.8 % | −22.2 % | 48 | 48.0 % | 9.1 % | 52 | 52.0 % | 26.8 % | 37 | 29.1 % | 68.2 % | 90 | 70.9 % | −12.6 % | 243 |
| 2018 | 9 | 56.2 % | 0.0 % | 7 | 43.8 % | 0.0 % | 49 | 35.2 % | 2.1 % | 90 | 64.8 % | 73.1 % | 37 | 32.2 % | 0.0 % | 78 | 67.8 % | −13.3 % | 270 |
| 2019 | 7 | 41.2 % | −22.2 % | 10 | 58.8 % | 42.9 % | 65 | 67.0 % | 32.6 % | 32 | 33.0 % | −64.4 % | 31 | 23.0 % | −16.2 % | 104 | 77.0 % | 33.3 % | 249 |
| 2020 | 9 | 56.2 % | 28.6 % | 7 | 43.8 % | −30.0 % | 50 | 32.9 % | −23.1 % | 102 | 67.1 % | 218.8 % | 67 | 53.2 % | 116.1 % | 59 | 46.8 % | −43.3 % | 294 |
| 2021 | 6 | 28.6 % | −33.3 % | 15 | 71.4 % | 114.3 % | 47 | 28.8 % | −6.0 % | 116 | 71.2 % | 13.7 % | 33 | 31.4 % | −50.8 % | 72 | 68.6 % | 22.0 % | 289 |
| 2022 | 13 | 68.4 % | 116.7 % | 6 | 31.6 % | −60.0 % | 75 | 42.4 % | 59.6 % | 102 | 57.6 % | −12.1 % | 49 | 39.5 % | 48.5 % | 75 | 60.5 % | 4.2 % | 320 |
| 2023 | 10 | 43.5 % | −23.1 % | 13 | 56.5 % | 116.7 % | 77 | 51.0 % | 2.7 % | 74 | 49.0 % | −27.4 % | 50 | 38.4 % | 4.1 % | 82 | 61.7 % | 9.3 % | 306 |
| Total | 82 | 43.62 % | 17.68 % | 106 | 56.38 % | 17.19 % | 543 | 42.89 % | 14.21 % | 723 | 57.11 % | 28.16 % | 440 | 31.68 % | 20.25 % | 951 | 68.32 % | 1.01 % | 2845 |

**Table 2**
Methods applied by journal for all type of data sources papers.

| Method | IMM | JBBM | JBIM | Total |
|---|---|---|---|---|
| Regression | 185 | 20 | 177 | 382 |
| Covariance-based SEM | 132 | 36 | 204 | 372 |
| PLS-SEM | 77 | 19 | 110 | 206 |
| Analytical techniques | 28 | 2 | 24 | 54 |
| Mixed | 7 | 3 | 16 | 26 |
| Descriptive analysis | 3 | 1 | 8 | 12 |
| Experiment | 3 | 1 | 1 | 5 |
| Hazard model | 2 | 0 | 2 | 4 |
| Fuzzy-logic methods | 2 | 0 | 1 | 3 |
| Other | 1 | 0 | 0 | 1 |
| Total | 440 | 82 | 543 | 1065 |

Fisher exact test with Monte Carlo approach $p = .01$.

**Table 3**
Methods applied by journal to papers with primary sources.

| Method | IMM | JBBM | JBIM | Total |
|---|---|---|---|---|
| Covariance-based SEM | 130 | 36 | 199 | 365 |
| Regression | 136 | 16 | 146 | 298 |
| PLS-SEM | 76 | 19 | 106 | 201 |
| Analytical techniques | 24 | 1 | 22 | 47 |
| Mixed | 5 | 3 | 13 | 21 |
| Descriptive analysis | 2 | 1 | 6 | 9 |
| Experiment | 3 | 1 | 1 | 5 |
| Fuzzy-logic methods | 2 | 0 | 0 | 2 |
| Hazard model | 0 | 0 | 1 | 1 |
| Other | 1 | 0 | 0 | 1 |
| Total | 379 | 77 | 494 | 950 |

Chi-square = 32.94, $\alpha = 0.05$, $p = 0.02$.

sources are unjustified, representing 79 % compared with 21 % with justification. An example of the explanation could be associated with the research field and context, like that of Ranjan and Nayak (2023): "*it is commensurate with prior empirical research on pricing* (Burkert, Ivens, Henneberg, & Schradi, 2017; Forman & Hunt, 2005; Jobber & Shipley, 2012) and *other survey-based research conducted in India* (Tripathy, Aich, Chakraborty, & Lee, 2016; Vashishth, Chakraborty, Gouda, & Gajanand, 2021)". Alternatively, it could be more concerned with the type of method, as that included by Bazyar et al. (2013): "*A sample size approaching 100 is often thought to be sufficient for structural equation analysis unless there are many indicators* (Loehlin, 1992)". Papers of this type have a mean in the response rate of 37.62 % while the median is 31.84 %. Thus, the response rate in 22.57 % of the articles is less than 20 %, 31.01 % between 20 % and 40 %, with 16 % with no information (Fig. 4). There were no significant differences by journal or by year at the $\alpha = 0.05$ level.

The sample size used in research with secondary data is greater in magnitude and breadth (Table 5). While the mean is 4470 observations (the minimum number of observations used is 13,[4] and the maximum is 119,050[5]), the median is 994 observations. Therefore, it is most common for the sample size to be below 1000 (50.46 %) and mostly at values between 100 and 200 (24.20 %). Thus, the sample size shows greater variation, and there are important differences among the methods applied; with regressions that resort to a higher sample size being among the most used (mean = 4547.2).

Regarding justification, only 10.28 % of the articles provide an explanation of the sample size. In the papers resorting to secondary data, the sample size is usually larger than in those using primary data. Therefore, the main concerns are two-fold. First, about how

[4] This sample is employed in a regression analysis based on secondary data with an international scope over more than 10 countries.

[5] This sample is applied for a multiple regression analysis based on secondary data with an international scope worldwide.

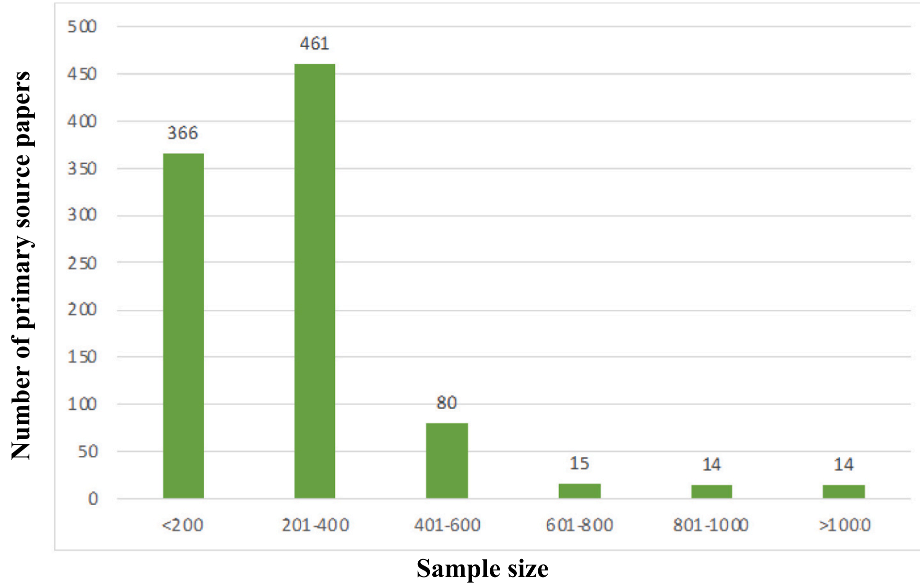



**Fig. 3.** Number of primary source papers classified by sample size.

**Table 4**
Sample Size for method and journal for primary data papers.

| Method | IMM | JBBM | JBIM | Total |
|---|---|---|---|---|
| Mixed | 218 | 1480 | 288 | 442 |
| Descriptive analysis | 139 | 666 | 377 | 356 |
| Analytical techniques | 361 | 1207 | 261 | 332 |
| Hazard model | NA | NA | 320 | 320 |
| Covariance-based SEM | 377 | 271 | 275 | 311 |
| Regression | 373 | 336 | 245 | 308 |
| Experiment | 249 | 157 | 280 | 237 |
| PLS-SEM | 207 | 198 | 213 | 209 |
| Fuzzy-logic methods | 114 | NA | NA | 115 |
| Other | 561 | NA | NA | 561 |
| Total | 336 | 330 | 254 | 293 |

generalizable the research is in relation to sample size, e.g., "*the sample size of the studied firms is relatively high, thus adding to the overall generalizability of the findings we report*" (Claro et al., 2023, p. 160). The second concern is about the origin of the data, e.g., "*the sample size for this study was 45 M&A deals from a wide range of US industries. The sample was drawn from the USA since it is the biggest market for M&A. The sample size was dictated by the need to obtain detailed data on both of the companies involved in each deal, which required extensive study of published records, and considerable manual data collection. This sample size is consistent with a number of previous studies (…) whose samples ranged from 36 to 80*" (Rahman & Lambkin, 2015, p. 29).

**Table 5**
Sample Size for method and journal for secondary data papers.

| Method | IMM | JBBM | JBIM | Total |
|---|---|---|---|---|
| Hazard model | 24,339 | NA | 5893 | 18,190 |
| Descriptive analysis | 2167 | NA | 21,243 | 14,884 |
| Regression | 2793 | 30,306 | 3621 | 4547 |
| Analytical techniques | 713 | 315 | 14,260 | 2904 |
| PLS-SEM | 4511 | NA | 1972 | 2818 |
| Covariance-based SEM | 186 | NA | 491 | 441 |
| Mixed | 310 | NA | 167 | 239 |
| Total | 3319 | 24,308 | 4084 | 4643 |

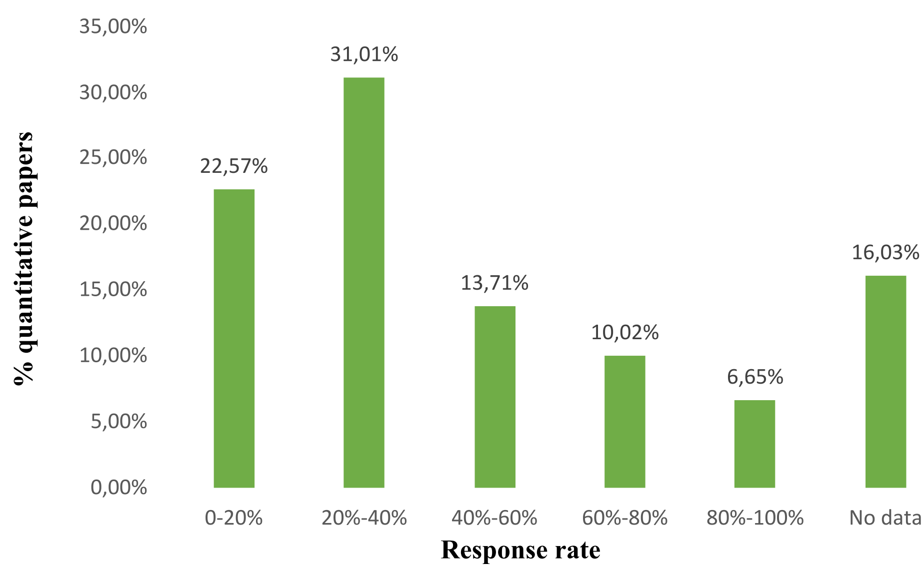



**Fig. 4.** Percentage of primary data source papers classified by response rate.

Finally, the Kruskal-Wallis test was employed to assess whether there are significant differences between journal and sample size differentiating papers using primary and secondary data, and journal and response rate for primary data source papers. For those papers using primary data sources, there is a non-significant difference between the different groups for a chi-square $= 3.72$, $p = .16$. Therefore, the differences in the sample size among journals is not statistically significant (Appendix IV-A). In terms of response rate, the application has achieved a similar result, indicating that there is a non-significant difference between the different groups for a chi-square $= 1.21$, $p = .55$ (Appendix IV-B). For those articles employing secondary data sources, the Kruskal-Wallis test does not find a significant difference among the different journals (chi-square $= 0.7$, $p = .70$, see Appendix IV-C).

### 3.4. Geographical analysis

The sample origin was also included in our analysis, as it influences the generalization of results. In this regard, 81.95 % (872) articles have a national focus, while 10.39 % (110) have an international focus. The remaining papers do not provide information on the origin, although they are usually signed by US-based authors. Fig. 5 notes those most represented countries (local samples) are China (27.64 %), followed by the US (14.33 %), Taiwan (6.88 %), India (5.39 %), and Spain (5.16 %). Altogether, these countries represent more than half of the articles with a local focus (59.40 %).

We highlight that only 192 papers have adopted an international approach. This means that 192 papers are collecting and analyzing data from at least two countries. In addition, among those papers only 52 are using this data for conducting any type of comparison. In this subset of manuscripts (international focus), only seven (6.3 %) consider China as part of the study location. Interestingly, the US is the country appearing in more publications (32.72 %).

From a local perspective, for IMM, the top 10 countries are China (32.56 %), the US (16.71 %), Germany (7.20 %), Taiwan (4.90 %), the UK (4.90 %), India (4.03 %), Australia (3.75 %), Finland (3.17 %), Spain (2.88 %), and Korea (2.02 %). For JBIM, they are China (24.46 %), the US (12.34 %), Taiwan (8.23 %), India (6.71 %), Spain (6.49 %), Brazil (2.81 %), South Korea (2.38 %), Australia (2.38 %), Finland (1.95 %), and Germany (1.73 %). Finally, for JBBM, they are China (23.81 %), the US (15.87 %), Taiwan (7.94 %), Spain (7.94 %), Germany (4.76 %), Israel (4.76 %), Korea (4.76 %), India (3.17 %), Turkey (3.17 %), and Norway (3.17 %). Furthermore, JBBM is the journal with the broadest diversity of countries.

Remarkably, an increasing tendency is seen in the case of China with an average growth from 2013 to 2023 of 36.41 %, and this is also true of the US with an average growth of 22.95 %. Taiwan presents a negative average growth rate, while both India and Spain are slightly positive. In the case of China, 142 articles use some type of regression as a method (58.92 %) and 94 (39 %) use some type of SEM (covariance-based SEM or PLS-SEM). In other words, practically 100 % of the methods applied are based on regression analysis or SEM. Particularly, in the US the most used method is SEM (48.41 %), while regression accounts for 38.10 %.

At 268, the average sample size is relatively low in China compared with countries using primary sources. That of the US is 332, that of Vietnam is 393 and that of Australia is 402. Finally, regarding the response rate, of the countries that most appear with a local approach, India has the highest response rate of 47.65 %, while China is second with 41.67 %. The US and Taiwan have a similar response rate with 34.60 %. Spain's is 28.95 %. We highlight that populations are generally sub-populations defined by the members of a business association or a panel registered with a market research agency. Depending on how authors define the scope of the selected population (even more critically for a sub-population), the validity of the response rate will fluctuate. Hence, editors and reviewers need to pay attention to this issue and request the use of sub-populations to be noted in the limitations due to potential self-selection bias (e.g., if a purchaser does not belong to a purchasing association, excluding them might bias the estimates).

## 4. Sampling and sample size in-depth analysis

The current paper provides a systematic literature review focused on those quantitative papers published in the most reputable B2B marketing journals (i.e., IMM, JBIM, and JBBM). The analysis of 1065 papers published in the last 11 years allows better understanding of the analytical methods employed, type of data, sample size and sampling process, response rate or the regional scope, and their related justifications. This method-based analysis contributes by identifying a series of trends, implications, conclusions, and recommendations to consider in future research.

### 4.1. The growing presence of quantitative papers in B2B marketing

Though not the main goal of this research, comparing the trends in quantitative and qualitative papers during the period of analysis, it was found that quantitative papers are gaining representativeness in the scrutinized journals. While qualitative articles have always had a superior share of articles in B2B marketing research, recently there is a change in the trend. We should pay attention to this trend, as it might imply a paradigm shift in how research is conducted in B2B marketing settings, probably no later than the upcoming decade (2030). This trend also conflicts with findings in other research areas like service marketing, where more qualitative-based research was expected for the near future (Valtakoski, 2020). One potential explanation could be that B2B marketing has built up new theory through qualitative research, and now it is time to perform conclusive research based on quantitative methods.

This tendency is expected to reach all journals, drawing authors and editors to deal with research more focused on quantitative methods. For instance, methodological richness is growing in quantitative research and sample size is increasingly higher as years go by in the analyzed timeframe. Therefore, a good balance in the journals between theory construction and theory testing is positive to advance the B2B marketing field. In addition, a better quantitative-qualitative balance favors answering *what* and *why* questions, and to overcome the idea that researchers usually rely on basic assumptions that create an incomplete picture of reality (Rigdon, 2023). Thus, editorial boards are urged to stress the importance of conducting both quantitative and qualitative research.

### 4.2. The lack of justification for quantitative research in B2B marketing

One surprising finding in the analysis was the scarce percentage of papers justifying either the selection of the method or the sample, an issue alerted to in previous research (Guenther et al., 2023). The lack of explanation of what methodology was used can convey an idea of irrelevance for the reader, when it is undoubtedly not the case. The selection of the method should be closely related to the goal of the paper, and it should fit the type of information collected; that is, be purposefully deployed for the research approach adopted. However, we usually found that those justifications are mostly instrumental. For example, for covariance-based SEM, the selection of the method is justified as it allows comparison between a proposed model and other "rivals" (Marquardt, 2013) or because it allows the identification of latent variables and relationships among constructs (Rangarajan et al., 2021). Hence, the selection of an analytical tool tends to be tautological (e.g., the selection of regression is sustained by its own characteristics).

Commonly, authors include justifications based on convenience sampling (Bazyar et al., 2013; Dowell et al., 2015) or the widespread popularity of the method (Haq & Huo, 2021; Mehdikhani & Valmohammadi, 2022). This implies that the method is chosen without specific justification but rather based on their own discretion or because it is widely employed in the scientific community. However, method

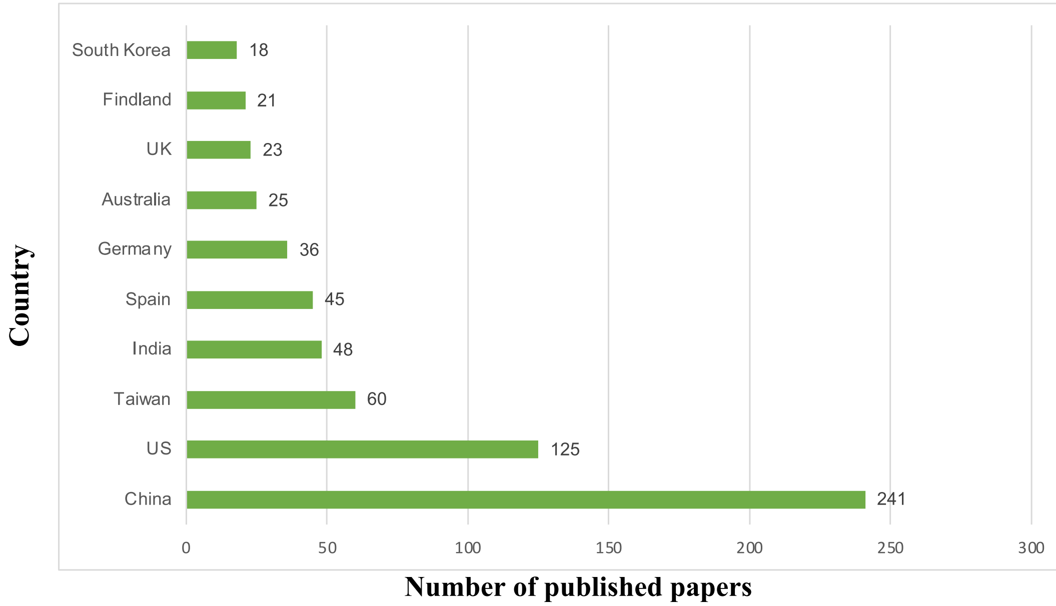



**Fig. 5.** Number of published papers with local approach per country.

selection can bias the results obtained. First, parametric-based methods assume a normal distribution and therefore do not provide reliable results in other cases. Second, although SEM is able to deal with latent variables, the omission of certain variables can lead to biased estimates and model misspecification, which in turn implies that the model might not be correctly identified. Third, although covariance-based SEM shows the relationships between variables, it cannot prove whether a relationship is causal. Finally, depending on the degree of complexity of the model, it will also imply a greater degree of complexity in the calculations, which may influence the search for a simplification of reality by reducing the number of variables or data to facilitate the analysis.

These problems are also reflected in PLS-SEM, whose main reasons for selection are the need for a lower sample size than covariance-based SEM (Cao & Weerawardena, 2023; Zhang & Li, 2019) and that it allows a check on the effect of interactions reaching a higher power (Najafi-Tavani et al., 2015; Ranjan & Nayak, 2023), as it does not affect the missing data and does not need a normal distribution. Although PLS-SEM has a more exploratory nature than covariance-based SEM (Ranjan & Nayak, 2023; Zhang & Li, 2019), one of the most repeated justifications is that it has become a popular methodology and because it is easy to use (Askariazad & Babakhani, 2015; Chang & Huang, 2022). However, some of the advantages are also their own limitations. For example, despite a normal distribution not being required, if there is a lot of variability in the data, PLS-SEM can generate unreliable estimates. A similar issue emerges if the sample is small ($< 90$) and there are many variables (Goodhue et al., 2012). Overall, both PLS-SEM and covariance-based SEM present challenges and opportunities (see Reinartz et al., 2009).

Both covariance-based SEM and PLS-SEM might be biased when sample size is too low (Rigdon, 2013). Hence, calculating an adequate sample size is highly important for researchers. On one hand, covariance-based SEM studies should acknowledge that a resulting sample size to achieve a certain level of power varies as a function of (a) number of variables/degrees of freedom, (b) relation among the variables, (c) choice of fit index, and (d) value of the fit index. In this vein, Kim (2005) indicates equations for the minimum sample size required to detect a difference between a model with perfect fit (e.g., CFI = 1 and RMSEA = 0.00) and models with less than perfect fit (e.g., CFI = 0.95 and RMSEA = 0.05; see p. 376). In addition, since Hu and Bentler (1999) suggested the use of at least two different classes of goodness-of-fit indices, to ensure power for both values of the fit indexes, the maximum proposed sample size from different fit indices must be used (Kim, 2005). If a researcher does not want to use fit indexes, the following methods are available: (1) Satorra-Saris, (2) bootstrap, and (3) Muthén-Muthén (see Kim, 2005 for a brief description of these methods). On the other hand, PLS-SEM studies have vastly used a simple heuristic suggestion that one might determine which of the many regressions within a PLS path model involves the largest number of independent variables and multiply that number by 10 (Rigdon, 2013, p. 106). However, more recent literature advocates for the usage of the inverse square root and gamma-exponential methods (Hair Jr et al., 2021). The inverse square root method builds on the expected minimum path coefficient in absolute value ($N$[6] $> (2.486/|\beta_{min}|)^2$, while the gamma-exponential method (which includes a correction for very small sample sizes, i.e., $1 < N < 10$) is represented by $|\beta_{min}|\sqrt{N}e^{(e|\beta_{min}|/\sqrt{N})} > 2.486$. Recent studies indicate that the gamma-exponential and inverse square root methods lead to relatively small and harmless over-estimations of the true minimum required sample size needed at power = 0.80 level (see Kock & Hadaya, 2018).

In spite of the large number of variants for regressions, the reason for selection seems to be clear. The type of regression is usually chosen either by the fit it has with the data or by the type of relationship between the variables. However, no study has justified the use of any type of regression to avoid overfitting, smooth out outliers, or avoid any of the assumptions in which regressions fall. Regarding analytical techniques, they are usually justified by the purpose of the technique (e.g., ANOVA is used to look for differences between groups). There are tremendous disparities in sample size recommendations. While the common rule of thumb is that the ratio of participants to independent variables be at least 10:1, prior research has recommended that with a moderate number of independent variables, sample sizes about 300 or 400 are sufficient in multiple regression (e.g., Nunnally, 1978). To bridge this gap, extant research emphasizes the role of assumed effect sizes. For example, there is an association between the number of independent variables ($p$) and the zero-order correlation among variables. In this vein, Maxwell (2000) indicates that in the complete absence of any theoretical expectations, a reasonable starting point is to assume that all zero-order correlations among variables are "medium." The

[6] N = sample size, $\beta_{min}$ = minimum path coefficient, and e is Euler's number (2.718)

author shows that a necessary sample size for power (β) equal to 0.8 is $N = 141$, 218, 311, 419, 543, 682, 838, 1009, and 1196 for the number independent variables fluctuating from 1 to 10, respectively.

Our results highlight the need for a comprehensive review of the methodology used in B2B marketing research to strengthen the justification of the methods applied. Moreover, it is important to encourage authors to carefully justify the selection of the method from different perspectives to increase confidence in the reader. It is crucial to recognize that the popularity of a methodology should not be reason enough for its selection. Instead, a few fundamental issues should be considered when selecting the appropriate methodology for a specific investigation.

Some recommendations can arise after these initial thoughts. First, it is essential to clearly define the objective of the research. Is it the aim to make a prediction, test a theory, or identify relationships between variables? This clarity of objectives will help guide the choice of the most appropriate methodology. Additionally, it is important to evaluate the advantages and disadvantages of each available methodology. What advantages does the chosen methodology offer compared with other available options? What are the drawbacks or limitations associated with its application? A complete understanding of these aspects will allow a more informed choice of methodology. Another crucial aspect to consider is the adequacy of the sample to the selected methodology. If the sample does not adequately fit the chosen methodology, is it more appropriate to change the methodology or adjust the sample? This question is essential to guarantee the validity and reliability of the results obtained.

### 4.3. Does the sample size really matter?

In general, the sampling-related problems are not exclusive to B2B marketing, and it is undeniable that a large number of biases in different disciplines are associated with it. Some examples are the selection of a specific area, self-selection bias, exclusion bias, and overfitting or survivorship bias (Berk, 1983; Cortes et al., 2008; Highhouse & Gillespie, 2009). If we focus on the sample size, it has several implications, although it is actually an ongoing discussion.

A common belief is that the larger the sample, the better. However, this is not always the case, since it can conflict with other principles such as control or costs (Levy & Varela, 2003). This research does not defend this principle in itself, but rather it identifies a potential improvement associated with the justification of methodologies and sample sizes, as well as the use of non-optimal sample sizes for the study (both due to excess and lack). In addition, a very large sample has the risk of oversensitivity such that even small effects can be shown as statistically significant.[7]

Although a small sample does not necessarily negatively affect the quality of the research (Highhouse & Gillespie, 2009), it can generate some problems. On one hand, a smaller sample than ideal can lead to not supporting a hypothesis when it should be supported (i.e., type I error). It can result in unreliable findings and a waste of resources and time, especially if the research is funded with public funds (Faber & Fonseca, 2014). Furthermore, small samples affect both the internal and external validity of the study. A low sample size usually implies low statistical power, which can negatively affect the representation of a real effect through statistical inference of the collected data (Button et al., 2013).

The sample size, usually when it tends to be small, is also the argument used to justify the application of certain methodologies instead of an alternative. For example, it is generally claimed that PLS-SEM works well with small sample sizes (Cao & Weerawardena, 2023; Zhang & Li, 2019). However, the statistical power of PLS-SEM with medium or small samples may be lower than that of regressions (Goodhue et al., 2006). The use of small samples is justified through methodologies that 'work' with small sizes rather than through power calculations. Another common justification is that this sample size is common in this type of studies (Nyadzayo et al., 2020). Nevertheless, even if the initial research achieved high statistical power, repeating the same sample size does not necessarily ensure the same result and, in fact, in many cases, it can be easily reduced by half (Button et al., 2013).

Finally, we acknowledge that other fields such as medicine, management, and sociology have discussed the validity of using small data (see Fahey, 2019; Hekler et al., 2019). For example, Kitchin and Lauriault (2015, p. 463) indicate that "*academic knowledge building has progressed for the past few centuries using small data studies characterized by sampled data generated to answer specific questions. It is a strategy that has been remarkably successful, enabling social sciences and humanities to advance in leaps and bounds. This approach is presently being challenged by the development of big data. Small data studies will however […] continue to be popular and valuable in the future because of their utility in answering targeted queries*."

### 4.4. Reflections on the sample size for quantitative research

The findings have shown certain elements of potential improvement in terms of methodology; however, in general there is consensus on which are the preferred approaches. Overall, the sample size is still a battlefield that should be considered, as the problems associated with its selection tend to be object of criticism (McShane et al., 2024; Rigdon & Sarstedt, 2022). In this regard, addressing concerns about sample size is of utmost importance for greater generalizing of results and for reaching greater academic rigor.

First, researchers do not usually support the sampling decision adequately. Our findings suggest that the majority of quantitative articles resort to primary sources, with subjective, non-probabilistic sampling, using Likert-scale questionnaires as the main source of data, regardless of the methodology selected (Hirshberg & Shoham, 2017; Minerbo et al., 2023; Moschko & Blažević, 2023). This can generate important biases, e.g., the generation of atypical data, not obtaining a representative sample, and difficulty to identify relationships or effects. Of course, it will depend on the population of study, but in general, the preference is for a broader picture with the combination of different types of sampling, and data collection methods. While it is more practical and simpler to develop a questionnaire, there are other techniques that can provide greater richness but are seldom used in the articles, such as observation, experiments, or even the application of interviews if the population is small.

Second, our findings indicate a high variability in the sample size and, usually, without a detailed explanation. Authors often justify the sample size or the response rate as similar to previous research (Karayanni, 2015; Nyadzayo et al., 2020) or that it is sufficiently representative (Jin, Shu, & Zhou, 2018; Hirshberg & Shoham, 2017; Hirunyawipada, Paswan, & Blankson, 2015) without providing any type of extra information to support it. Thus, there is a lack of a common framework to compare current research. That is, the fact that a sample is aligned with previous research does not necessarily mean that it is representative. However, there are some interesting efforts that justify the sample size by the application of specific methods to ensure their suitability. Some of these techniques are G*Power (Çolak & Kağnıcıoğlu, 2023; Hossain & Gilbert, 2021) or another mathematical formulation that calculates the power (β) to be able to identify an effect (Mwesiumo, Harun, & Hogset, 2023; Gnizy & Shoham, 2018). Through the application of such techniques, it is possible to provide additional information on the validity of the sample and its representativeness for the variables measured, so their use is highly recommended. In addition, the sample sizes should be close to the average shown in the analysis results and even improve on these data, as it would surpass the standard in terms of mean 293 or median 272.5. But this is intrinsically related to the population object of research, and for this circumstance it should be explained why the average size is not reached. By nature, B2B marketing has many different nuances to be considered in this regard. Furthermore,

[7] We thank an anonymous reviewer for this comment.

although the literature often indicates that a sufficient (minimum) size can exist for a methodology (Cao & Weerawardena, 2023; Wongsansukcharoen et al., 2015), it does not necessarily imply that it is rigorous or significantly representative.

Third, the response rate is not an indicator to determine the quality of a piece of research on its own, but it must be considered since low response rates directly impact the confidence intervals, hindering the possibility of subgroup analysis being carried out, and potentially increasing bias (Rutherford et al., 2023). Different researchers suggest as adequate a response rate higher than 20 % (Agyabeng-Mensah et al., 2023; Getele et al., 2022) or at least higher than 15 % (Navarro-García et al., 2016). Based on the descriptive analysis, and following previous contributions in B2B Marketing and other fields, we recommend as adequate a response rate between 20 % and 45 % (Rindfleisch & Antia, 2012).[8] Overall, the lower the response rate, the higher the likelihood of an inadequate sample size (Rindfleisch & Antia, 2012) and increased bias (Wilson, 1999).

Finally, our findings have shown how most of the articles have a local focus. Some research may require this narrowness, and it is not necessarily a negative characteristic of a study, but researchers should seek to expand the geographic scope since it would eliminate cultural biases, increase the sample size, and allow the results to be generalized. In fact, research with an international focus has higher sample sizes, and it is inherent for B2B firms, as they commonly sell abroad and manage a global offering (Mora Cortez & Lecaros, 2024).

### 4.5. *Quantitative vs. qualitative: An open debate*

This research does not only pertain to sampling and sample size, but it can also enrich the quantitative-qualitative debate (Bryman, 2017; Gelo et al., 2008; Lakshman et al., 2000). Certainly, there is not a best methodological approach. One may have advantages over the other depending on, e.g., the context and the objective of the research.

In qualitative research, the determination of sample size is contextual and partially dependent upon the scientific paradigm under which investigation is taking place. For instance, qualitative studies which are oriented towards positivism, require larger samples than constructivist studies do, so that an adequate representativeness of the whole population under review can be achieved (Boddy, 2016, p. 426). Moreover, *theoretical saturation* is particularly applied in Grounded Theory studies (Thomson, 2010). In this vein, researchers cannot make a judgment regarding sample size until they are conducting data collection and analyses (Glaser & Strauss, 1967). Indeed, researchers must allow the data to command the sample size; therefore, it is important to undertake data analysis during the data collection process (Thomson, 2010, p. 49).

While both quantitative and qualitative approaches to research seek validity (particularly through data collection; Eby et al., 2009), in quantitative studies this issue becomes more polarized. A few manuscripts calculate the minimum sample for adequate power, detail the characteristics of the sample, and describe the response rate and its justification. Nevertheless, most papers do not pay attention to these elements. Scholars should not forget that quantitative methodology is usually addressing the idea of generalization, without delving into a detailed description of each case under scrutiny (Holton & Burnett, 2006; Queirós et al., 2017). Thus, an adequate handling of the sample can help to mitigate this limitation. This information does not usually appear in the articles because it may be taken for granted, or because in the editors' and reviewers' view, this may not be deemed as attractive as the results or implications.

Finally, this methodological diversity implies that reviewers may not know all techniques and, therefore, assume that results are correct or less questionable (Queirós et al., 2017). Therefore, sometimes, quantitative methodologies may be less rigorous compared with qualitative methodologies due to the richness and the number of analyses, being especially noticeable in social science arenas such as B2B Marketing (Eby et al., 2009). Furthermore, quantitative methodologies cannot be used to address all possible research gaps.[9]

### 4.6. *Additional challenges influencing sampling and sample size*

To provide a more comprehensive analysis of factors relating to or influencing sampling and sample size, we explored external sources to the selected literature. First, the choice of outcome measures is identified as one such factor. It is well known that the usage of categorical dependent variables (e.g., dichotomized) results in loss of power (Auleley et al., 2004), which can be remedied by increasing the sample size. For example, to achieve similar power to multiple linear regression when utilizing logistic regression, larger sample sizes are required and recommended.[10]

Second, effect size (i.e., the magnitude of a result) is discussed as a factor indirectly related to sample size. Common effect size indices are Cohen's d, odds ratio (OR), and relative risk or risk ratio (RR). It is important to highlight that effect sizes are different for different analytical models. Unlike significance tests, effect size is independent of sample size. Statistical significance, on the other hand, depends upon both sample size and effect size (Sullivan & Feinn, 2012). Importantly, sample size relates to the cost of the data collection procedure (e.g., executing an experiment), and target effect size is often related to hoped-for cost savings due to process improvement (Lenth, 2001, p. 189). Overall, *the higher the magnitude of a coefficient at the population level, the higher is usually its effect size, and the greater is the likelihood that a true effect will be properly detected with a small sample* (Kock & Hadaya, 2018, p. 230).

Third, there is an ongoing concern about the low power of moderation models in both regression (Aguinis et al., 2001) and SEM (Irmer et al., 2024). Indeed, sample size and predictor-criterion relationships across moderator-based subgroups are identified as the two most influential factors on the observed effect size (e.g., Aguinis & Stone-Romero, 1997). In this vein, Aguinis et al. (2005) suggests that more attention to research design issues (e.g., sample size) can lead to a considerable payoff in terms of increasing the observed effect size, and consequently, the likelihood that population effects will be detected (p. 101).

Fourth, missing data are evidently detrimental for estimating unbiased parameter values. High-quality approaches to infer population information in the presence of missing data, such as full-information maximum likelihood (FIML) and multiple imputation (MI), increase power compared with traditional methods of handling missing data (e.g. listwise deletion, casewise deletion; Enders & Bandalos, 2001; Afghari et al., 2019). In relative terms, FIML performs better than with MI at smaller sample sizes (Jia et al., 2014).

Finally, longitudinal studies are often recommended as a solution to common-method variance (CMV) bias because temporal separation reduces the cognitive accessibility of responses to predictors collected at an earlier time in survey research (Rindfleisch et al., 2008). In addition, prior research indicates that longitudinal studies show greater power than cross-sectional studies (Yee & Niemeier, 1996). However, the selection of a longitudinal design versus a cross-sectional design is not directly associated with sample size. Indeed, Rindfleisch et al. (2008) argue that longitudinal data collection is most valuable when researchers are examining constructs, subjects, or contexts that display a substantial amount of method variance and when the correlations between predictors and outcomes are small (pp. 272–273).

[8] Further research could conduct simulations to assess the implications of different response rates in B2B research.

[9] Quantitative research tends to focus on "what" and "how" questions, while qualitative research tends to focus on "why" questions.

[10] We thank an anonymous reviewer for this comment.

To facilitate an adequate understanding and execution of sampling and sample size in B2B marketing research, we suggest standardizing some aspects of the analysis, as noted in the following section.

## 5. Best practices

The identification of best practices can guide future research with stronger empirical foundations. In this sense, our systematic literature review of the three most reputable journals in B2B marketing can shed light on what elements should be considered to describe the sampling process and the management of the data obtained. While there are good examples included in the previous sections, there are also opportunities to improve B2B marketing research. Particularly, four different focal points were identified: (A) data collection and sampling, (B) methodology applied, (C) response rate, and (D) geographical scope (see Table 6).

For the first element (A), there are potential areas of improvement in terms of the data used. That is, the combination of primary and secondary data would be welcome, and the joint efforts to develop databases useful for B2B marketing research that can include many companies and common challenges. The latter will drive the application of new sampling methods and the use of different types of data. In addition, the explanation of how the sample was achieved and a clear identification of the unit of analysis (and the process associated) are relevant for the reader. Also, the definition of the sampling frame applied, with a clear justification of the motivation, and the dates, sources, and type of contact within companies is always recommended. Moreover, a higher level of details for primary and secondary data is needed. At the same time, the incorporation of new approaches in sampling might emerge from other disciplines, and the adoption of specific tools to assess the pertinence of the sampling can add value to quantitative research.

From a methodological point of view (B), there are also some suggestions. For instance, the justification of the selected method should be required systematically, especially because of such a justification not currently being included in most articles. The selected method should be aligned with the objective of the paper and the type of data used in the research. In the Limitations section (of future articles), it is important to provide a statement on the sampling weaknesses potentially affecting the interpretation of results, as this can inspire future research and provide more transparency. In this regard, the application of mixed methods would be highly advisable, and part of this advancement can come from interdisciplinary teamwork.

The response rate (C) is another critical sampling element for B2B marketing research, and it is highly dependent on the type of population object of study, thus there could be some flexibility, but it needs detailed reflection by authors. A non-probability sampling is customary for the B2B field and thus the response rate is not inherently a statistical problem, but it should reach a minimum: a response rate ranging between 20 % and 45 % is a suggested threshold (Rindfleisch & Antia, 2012). And, as always, the more precise the information, the better. It is recommended to detail the recruiting process and outcomes at every step as this can increase confidence in the whole sampling process. In this regard, there are different contributions explaining factors that could positively influence the response rate, namely, sponsorship, interest in the topic, number of contacts, advance notice, follow-up, incentives (monetary or non-monetary), or anonymity, among others (Larson & Chow, 2003; Reid & Plank, 2004). Of course, it will depend on the type of respondent, but previous factors may help to reduce the nonresponse bias (Anseel et al., 2010).

Finally, the regional scope (D) is another area of interest. Given the nature of B2B commercialization, the international perspective provided by including multi-country research should be encouraged. At the same time, this effort would help to reduce cultural biases, increase the sample used and, finally, support the generalizability of results. Also, in this effort, researchers can include countries with similar characteristics (for example, emerging markets) and analyze similarities and differences. In addition, an article can be focused on a regional level, and the rationale for such an approach explained. In support of the urgency for multi-country studies, prior research indicates that cross-cultural studies have grown in terms of consumer attitudes and behavior and on promotion-related topics but not equivalently in terms of B2B topics/settings (Engelen & Brettel, 2011).

**Table 6**
Checklist for best practices in B2B marketing quantitative research.

| Focal Point | Recommendation |
|---|---|
| (A) Data collection and sampling | - The collective development of industrial marketing databases that can act as sample frames for probability methods<br>- Combination of primary and secondary data to strengthen analysis including objective and subjective data<br>- Detailed explanation of how the sample was reached and why it is adequate for the purpose of the study<br>- Clear identification of the unit of analysis and control processes to generate confidence in the sample used (i.e., type of company and industry, number of respondents by organization, descriptive data, among others)<br>- Details of the source of the data and, if the case, the way of contact<br>- Definition of the sampling frame (either non-probability – judgment, convenience, or snowball – or probability methods)<br>- Suggestions of novel approaches for sampling and research to overcome limitations<br>- For secondary data, explanation of the protocols used in the database<br>- Although the median sample for the analysis in the period was 272, the inclusion of specific methods to justify the adequacy of the sample size (e.g., G*Power or similar) would be welcome |
| (B) Method (analytical tool) applied | - Provide justification for the method selected and its connection with the aim of the paper<br>- Include an explanation on how the method is adequate for the type of data managed<br>- Specify the limitations of the method, and how it can affect the interpretation of results<br>- Encourage the application of mixed methods<br>- Explore new methods through interdisciplinary research teams |
| (C) Response rate | - Highly dependent on the universe object of study, it could justify different behaviors in the response rate<br>- Non-probability sampling is the most used sampling method, the response rate is not a problem<br>- Detail the contact process and results by each contact step<br>- The response rate should not be lower than 20 % to reach good standards |
| (D) Geographical scope | - Foster multi-country research due to the international nature of industrial firms, the reduction of cultural biases, greater sample size, and generalization<br>- Include countries with common characteristics from certain geographic areas (e.g., emerging markets)<br>- The geographical scope should be justified (e.g., because it has certain specific characteristics of interest or also due to generalization in similar areas) |

## 6. Limitations and conclusions

While we investigated a critical issue for the B2B marketing field, this study has limitations to consider. First, this research has focused on the three most reputable B2B marketing journals for a period of 11 years. This systematic review does not claim to include all publications on the field, as there are other marketing journals that also publish research based on B2B settings. Additionally, the timeframe could limit or affect the conclusions. Of course, the final sample of papers analyzed is relevant and more information is always useful. Hence, future research could add more journals or years and compare the characteristics among selected sampling processes and sample size.

Second, the aim of this research is to better understand the sampling and sample size (focusing on a series of associated decisions, e.g., type of analysis applied, kind of data used, sampling process and scope). Therefore, there are other pieces of information in an article that were not considered (theoretical section, results, or conclusions). Thus, our findings could be complemented with additional analyses of concepts, theories, or type of industry, which could provide new insights into the scientific approach and the specificity of the data used. It would be particularly interesting to address the contextual factors in future research to refine the analysis. Future research could also include the number of latent variables, indicators per variable and the number of degrees of freedom. These elements could be highly valuable to consider the generalizability of results, but they also require a greater focus because of the very specific elements to consider.

Third, though the process is systematic (rather than ad-hoc), it is also subjective with different scholars involved in the review. Despite the coordination efforts of the authors, some bias could appear in the analysis of the selected sample of articles. This is a circumstance that should be acknowledged in further studies and compared in terms of results. However, this research follows best practices for systematic reviews (e.g., Snyder, 2019), providing adequate validity and reliability to our findings and recommendations.

Fourth, we list an extensive typology of methods and a count of their use (Web Appendix 2). However, we do not map the methods in relation to specific features of the sample. Further research might granularly describe the associations between a method and the deployment of research in terms of sample characteristics (e.g., gender, hierarchy). In addition, the nuances of a method might have severe implications on sampling and sample size (e.g., logistic regression vs. linear regression; cross-sectional design vs. longitudinal design; Yee & Niemeier, 1996). Similarly, different underlying choices for use of mathematical algorithms in model operationalization can also affect sampling and sample size.[11] Future studies could thoroughly explore such method nuances and computational choices to provide more detailed help to B2B researchers. Moreover, there might be links between a method and certain countries/regions or journals in the sample frame. Such preferences or biases could be explored in forthcoming studies. Editors and reviewers would benefit from the emerging findings.

We conclude that quantitative research has been gaining presence in the most reputable B2B marketing journals during the last decade. Over time, it is possible to observe a growing interest in methods (analytical tools), approaches, sampling procedures and sizes. However, in parallel, there are important areas of improvement that should be studied. The first is to reach a minimum sample size—the median identified is 272.5—and this is an evidence-based reference for the field. Importantly, an explanation of the reason why a sample size is adequate is needed. Also, the use of power analyses or simulations should be encouraged. Of course, there could be differences in sample sizes, but the number achieved should be supported by a specific explanation. *Assuming that other situational characteristics are equal, the more heterogeneous the population, the larger the sample size needed to achieve an acceptable accuracy* (Hair Jr et al., 2021, p. 15).

The combination of primary and secondary data and the use of mixed methodologies can also strengthen B2B research in general and quantitative research specifically. It is ambitious, but sampling and sample size can be enhanced, and our article helps to develop a pertinent approach. Researchers should demonstrate, through justification, the adequacy of the method for the sample and type of data. All the processes conducted to obtain the data must be detailed (e.g., in a Web Appendix if space constraints exist). This transparency increases confidence and inspires future research and new approaches to these problems. Finally, it is highly beneficial to explore new sampling processes and methods from collaborative efforts with researchers from other areas (e.g., management). This initiative could adjust mental models and can foster creativity among B2B marketing researchers.

## CRediT authorship contribution statement

**Pablo Cabanelas:** Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization. **Roberto Mora Cortez:** Writing – review & editing, Validation, Supervision, Methodology, Formal analysis, Conceptualization. **Hugo Pérez-Moure:** Writing – original draft, Validation, Investigation, Formal analysis, Data curation. **Jesús F. Lampón:** Supervision, Formal analysis, Data curation.

## Data availability

Data will be made available on request.

## Acknowledgements

Recognition to the project funding by GPC-ED431B 2022/10 from Xunta de Galicia. Funding for open access charge: Universidade de Vigo, and CRUE-CISUG.

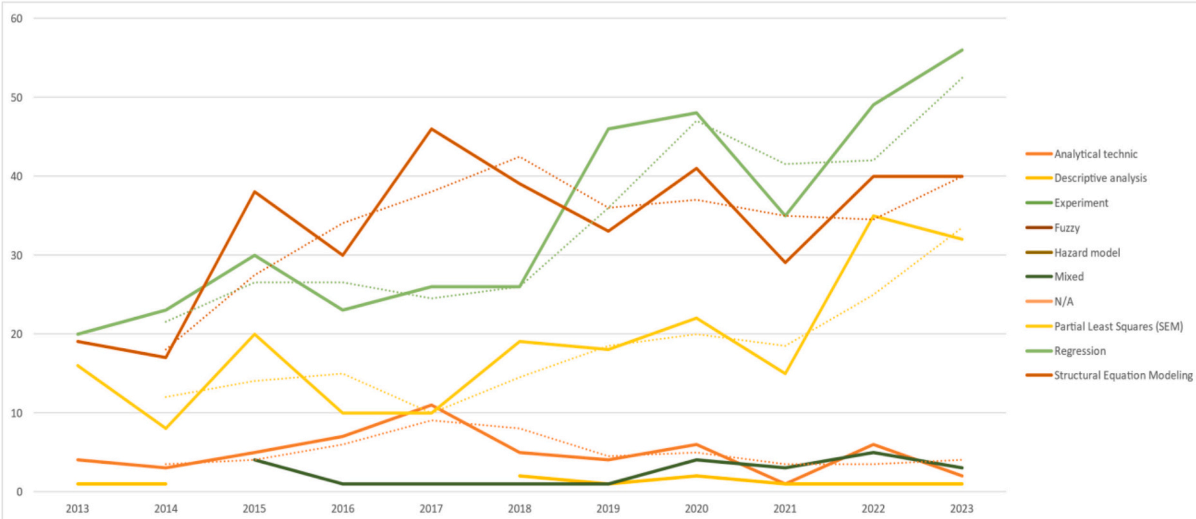
## Appendix A. Appendix

**Appendix I**
Contingency table qualitative/quantitative paper by journal.

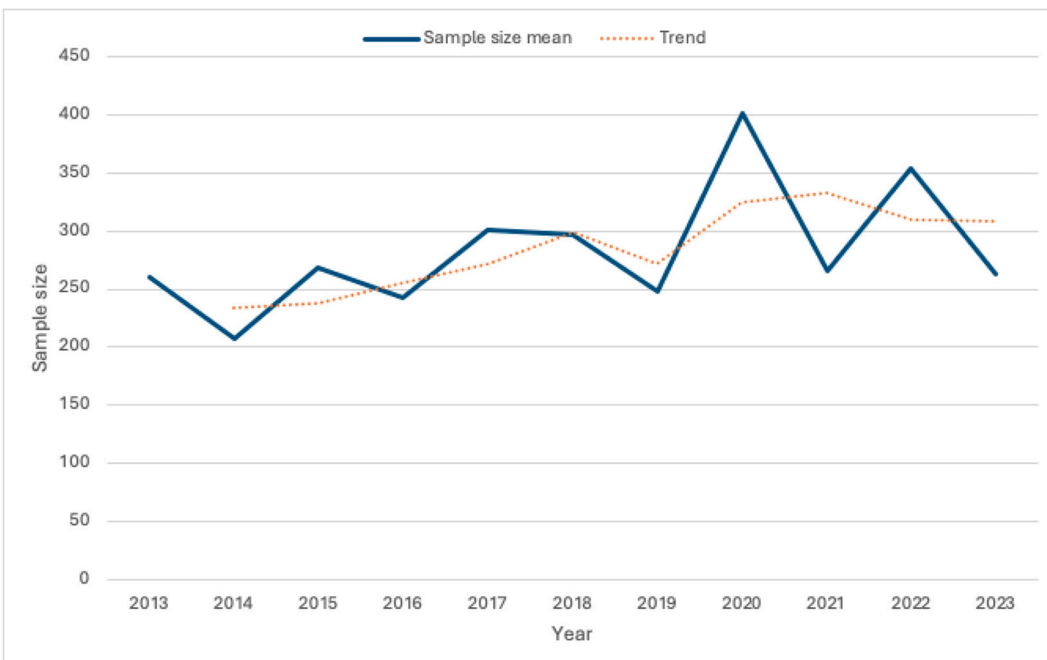
| | JBBM | | JBIM | | IMM | | Total | |
|---|---|---|---|---|---|---|---|---|
| Quantitative | 82 | 2,9 % | 543 | 19,1 % | 440 | 15,5 % | 1065 | 37,4 % |
| Qualitative | 106 | 3,7 % | 723 | 25,4 % | 951 | 33,4 % | 1780 | 62,6 % |
| Total | 188 | 6,6 % | 1266 | 44,5 % | 1391 | 48,9 % | 2845 | 100.0 % |

Chi-square = 32.94; $p < .01$.

[11] We thank an anonymous reviewer for this comment.




**Appendix II.** Trend analysis of the methodologies used.




**Appendix III.** Trend analysis of the sample size in the period analyzed.

a. Sample size by journal for primary data papers

| Groups: | IMM | JBBM | JBIM |
|---|---|---|---|
| Skewness: | 15.0956 | 5.4902 | 2.7717 |
| Skewness Shape: | **Asymmetrical**, right/positive | | **Asymmetrical**, |
| Excess kurtosis: | 250.4237 | 37.4565 | 11.7061 |
| Tails Shape: | **Leptokurtic**, long heavy tails | | **Leptokurtic**, long heavy |
| Normality | 0 | 4.774e-15 | 0 |
| Outliers: | 16062, 7023, 1769, 1762, 1692, 1386, 944, 893, 880, 872, 816, 786, 764, 709, 706, 658, 628, 585, 562, 561, 561, 544, 543 | 3250, 1207, 971, 951, 929, 666, 657 | 1399, 1200, 1032, 1010, 1006, 952, 948, 846, 840, 837, 802, 788, 676, 647, 632, 627, 611, 564, 561, 561, 550, 547, 539, 530, 530, 520 |
| Median: | 228 | 216.5 | 218 |
| Sample size (n): | 377 | 76 | 493 |
| Rank sum (R): | 185383.5 | 37195.5 | 225352 |
| $R^2/n$: | 91159262.79 | 18204016.06 | 103009176.3 |

b. Response-rate by journal

| Groups: | IMM | JBBM | JBIM |
|---|---|---|---|
| Skewness: | 0.8628 | 0.4402 | 0.7493 |
| Skewness Shape: | **Asymmetrical**, | Potentially | **Asymmetrical**, |
| Excess kurtosis: | 0.09894 | -1.1541 | -0.4245 |
| Tails Shape: | Potentially | Potentially | Potentially |
| Normality | 2.583e-11 | 0.0004002 | 2.486e-13 |
| Outliers: | 0.955, 0.99, 1, 1, 1, 1, 1 | | |
| Median: | 0.3182 | 0.348 | 0.3053 |
| Sample size (n): | 338 | 61 | 397 |
| Rank sum (R): | 132494 | 26044 | 158668 |
| $R^2/n$: | 51936864.01 | 11119507.15 | 63414443.89 |

c. Sample size and journal for secondary data papers

| Groups: | IMM | JBBM | JBIM |
|---|---|---|---|
| Skewness: | 4.8022 | 0.8923 | 3.4731 |
| Skewness Shape: | **Asymmetrical**, | Potentially **Symmetrical** | **Asymmetrical**, |
| Excess kurtosis: | 26.5682 | 1.0826 | 14.5646 |
| Tails Shape: | **Leptokurtic**, long | Potentially **Mesokurtic**, | **Leptokurtic**, long |
| Normality | 1.925e-13 | 0.975 | 9.598e-10 |
| Outliers: | 47875, 25374, 12701, 11021, 8876, 6981 | | 42190, 22352 |
| Median: | 1040 | 572 | 500 |
| Sample size (n): | 57 | 4 | 41 |
| Rank sum (R): | 3048.5 | 176 | 2028.5 |
| $R^2/n$: | 163041.2675 | 7744 | 100361.2744 |

**Appendix IV.** Kruskal-Wallis results.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.indmarman.2024.12.014.

## References


Afghari, A. P., Washington, S., Prato, C., & Haque, M. M. (2019). Contrasting case-wise deletion with multiple imputation and latent variable approaches to dealing with missing observations in count regression models. *Analytic Methods in Accident Research., 24*, Article 100104.

Aguinis, H., Beaty, J. C., Boik, R. J., & Pierce, C. A. (2005). Effect size and power in assessing moderating effects of categorical variables using multiple regression: A 30-year review. *Journal of Applied Psychology, 90*(1), 94.

Aguinis, H., Boik, R. J., & Pierce, C. A. (2001). A generalized solution for approximating the power to detect effects of categorical moderator variables using multiple regression. *Organizational Research Methods, 4*(4), 291–323.

Aguinis, H., & Stone-Romero, E. F. (1997). Methodological artifacts in moderated multiple regression and their effects on statistical power. *Journal of Applied Psychology, 82*(1), 192.

Agyabeng-Mensah, Y., Afum, E., Acquah, I. S. K., & Baah, C. (2023). How does supply chain knowledge enhance green innovation? The mediation mechanisms of corporate reputation and non-supply chain learning. *Journal of Business & Industrial Marketing, 38*(4), 852–868.

Anseel, F., Lievens, F., Schollaert, E., & Choragwicka, B. (2010). Response rates in organizational science, 1995–2008. A Meta-analytic review and guidelines for survey researchers. *Journal of Business Psychology, 25*, 335–349.

Askariazad, M. H., & Babakhani, N. (2015). An application of European customer satisfaction index (ECSI) in business to business (B2B) context. *Journal of Business & Industrial Marketing, 30*(1), 17–31.

Auleley, G. R., Giraudeau, B., Baron, G., Maillefert, J. F., Dougados, M., & Ravaud, P. (2004). The methods for handling missing data in clinical trials influence sample size requirements. *Journal of Clinical Epidemiology, 57*(5), 447–453.

Bazyar, A., Teimoury, E., Fesharaki, M., Moini, A., & Mohammadi, S. (2013). Linking power, risk, and governance: A survey research in new product development relationships. *The Journal of Business and Industrial Marketing, 8*(5), 375.

Berk, R. A. (1983). An introduction to sample selection Bias in sociological data. *American Sociological Review, 48*(3).

Boddy, C. R. (2016). Sample size for qualitative research. *Qualitative Market Research: An International Journal, 19*(4), 426–432.

Bryman, A. (2017). Quantitative and qualitative research: Further reflections on their integration. In J. Brannen (Ed.), *Mixing methods: Qualitative and quantitative research* (pp. 57–78). Routledge. https://doi.org/10.4324/9781315248813-3.

Burkert, M., Ivens, B. S., Henneberg, S., & Schradi, P. (2017). Organizing for value appropriation: configurations and performance outcomes of price management. *Industrial Marketing Management, 61*, 194–209.

Button, K. S., Ioannidis, J. P. A., Mokrysz, C., Nosek, B. A., Flint, J., Robinson, E. S. J., & Munafò, M. R. (2013). Power failure: Why small sample size undermines the reliability of neuroscience. *Nature Reviews. Neuroscience, 14*(5), 365–376.

Cabanelas, P., Mora Cortez, R., & Charterina, J. (2023). The buying center concept as a milestone in industrial marketing: Review and research agenda. *Industrial Marketing Management, 108*, 65–78.

Cao, G., & Weerawardena, J. (2023). Strategic use of social media in marketing and financial performance: The B2B SME context. *Industrial Marketing Management, 11*, 41–54.

Chang, C. W., & Huang, H. C. (2022). How global mindset drives innovation and exporting performance: The roles of relational and bricolage capabilities. *Journal of Business & Industrial Marketing, 37*(12), 2587–2602.

Claro, P. D., Plouffe, R. C., & Vieira, A. V. (2023). Sales compensation plan type and sales opportunity coverage: "Double-edged" sword effects on sales performance. *Industrial Marketing Management, 113*, 153–167.

Çolak, H., & Kağnıcıoğlu, C. H. (2023). Predicting the Blockchain technology acceptance in supply chains with inter-firm perspective: An integrated DEMATEL and PLS-SEM approach. *Journal of Business-to-Business Marketing, 30*(2), 125–148.

Cortes, C., Mohri, M., Riley, M., & Rostamizadeh, A. (2008). Sample selection bias correction theory. In *, 5254 LNAI. Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics)* (pp. 38–53).

Crick, J. M. (2021). Qualitative research in marketing: What can academics do better? *Journal of Strategic Marketing, 29*(5), 390–429.

Dowell, D., Morrison, M. A., & Heffernan, T. (2015). The changing importance of affective trust and cognitive trust across the relationship lifecycle: A study of business-to-business relationships. *Industrial Marketing Management, 44*, 119–130.

Eby, L. T., Hurst, C. S., & Butts, M. M. (2009). Qualitative research: The redheaded stepchild in organizational and social science research? In C. E. Lance, & R. J. Vandenberg (Eds.), *Statistical and methodological myths and urban legends: Doctrine, verity and fable in the organizational and social sciences* (pp. 219–246). Routledge/Taylor & Francis Group.

Enders, C. K., & Bandalos, D. L. (2001). The relative performance of full information maximum likelihood estimation for missing data in structural equation models. *Structural Equation Modeling, 8*(3), 430–457.

Engelen, A., & Brettel, M. (2011). Assessing cross-cultural marketing theory and research. *Journal of Business Research, 64*(5), 516–523.

Faber, J., & Fonseca, L. M. (2014). How sample size influences research outcomes. *Dental Press Journal of Orthodontics, 19*(4), 27–29.

Fahey, L. (2019). Getting to insight: The value and use of small data. *Strategy & Leadership, 47*(3), 27–33.

Forman, H., & Hunt, J. M. (2005). Managing the influence of internal and external determinants on international industrial pricing strategies. *Industrial Marketing Management, 34*(2), 133–146.

Gelo, O., Braakmann, D., & Benetka, G. (2008). Quantitative and qualitative research: Beyond the debate. *Integrative Psychological and Behavioral Science, 42*, 266–290.

Getele, G. K., Arrive, T. J., & Ruoliu, X. (2022). Understanding the influence of business strategy in corporate social responsibility: Evidence from Chinese firms in Africa. *Journal of Business & Industrial Marketing, 37*(12), 2573–2586.

Glaser, B. G., & Strauss, A. (1967). *The discovery of grounded theory: Strategies for qualitative research.* Chicago, IL: Aldine Pub. Co.

Gnizy, I., & Shoham, A. (2018). The power of international marketing functions: Antecedents and consequences. *Journal of Business-to-Business Marketing, 25*(2), 67–89.

Gölgeci, I., & Kuivalainen, O. (2020). Does social capital matter for supply chain resilience? The role of absorptive capacity and marketing-supply chain management alignment. *Industrial Marketing Management, 84*, 63–74.

Goodhue, D., Lewis, W., & Thompson, R. (2006). PLS, small sample size, and statistical power in MIS research. In *Proceedings of the 39th Annual Hawaii International Conference on System Sciences (HICSS'06), USA*.

Goodhue, D. L., Lewis, W., & Thompson, R. (2012). Does PLS have advantages for small sample size or non-normal data? *MIS Quarterly*, 981–1001.

Guenther, P., Guenther, M., Ringle, C. M., Zaefarian, G., & Cartwright, S. (2023). Improving PLS-SEM use for business marketing research. *Industrial Marketing Management, 111*, 127–142.

Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer Nature.

Haq, M. Z. U., & Huo, B. (2021). Enhancing supply chain learning and innovation performance through human resource management. *Journal of Business & Industrial Marketing, 36*(3), 552–568.

Hekler, E. B., Klasnja, P., Chevance, G., Golaszewski, N. M., Lewis, D., & Sim, I. (2019). Why we need a small data paradigm. *BMC Medicine, 17*, 1–9.

Highhouse, S., & Gillespie, J. Z. (2009). Do samples really matter that much? In C. E. Lance, & R. J. Vandenberg (Eds.), *Statistical and methodological myths and urban legends: Doctrine, verity and fable in the organizational and social sciences* (pp. 247–265). New York: Routledge.

Hirshberg, R. S., & Shoham, A. (2017). A behavioral model of international channel relationships. *Journal of Business-to-Business Marketing, 24*(4), 257–282.

Hirunyawipada, T., Paswan, A. K., & Blankson, C. (2015). Toward the development of new product ideas: asymmetric effects of team cohesion on new product ideation. *Journal Of Business And Industrial Marketing, 30*(7), 855–866.

Holton, F. E., & Burnett, F. M. (2006). The basics of quantitative research. In *Research in Organizations: Foundations and Methods in Inquiry* (pp. 29–49).

Hossain, M. T., & Gilbert, J. R. (2021). Satisfactory listening: The differential role of salesperson communication in (co)creating value for B2B buyers. *Industrial Marketing Management, 98*, 222–240.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1–55.

Hulland, J., & Houston, M. B. (2020). Why systematic review papers and meta-analyses matter: An introduction to the special issue on generalizations in marketing. *Journal of the Academy of Marketing Science, 48*, 351–359.

Irmer, J. P., Klein, A. G., & Schermelleh-Engel, K. (2024). Estimating power in complex nonlinear structural equation modeling including moderation effects: The powerNLSEM R-package. *Behavior Research Methods*, 1–35.

Jia, F., Moore, E. W. G., Kinai, R., Crowe, K. S., Schoemann, A. M., & Little, T. D. (2014). Planned missing data designs with small sample sizes: How small is too small? *International Journal of Behavioral Development, 38*(5), 435–452.

Jin, J. L., Shu, C., & Zhou, K. Z. (2018). Product newness and product performance in new ventures: Contingent roles of market knowledge breadth and tacitness. *Industrial Marketing Management, 76*, 231–241.

Jobber, D., & Shipley, D. (2012). Marketing-orientated pricing: understanding and applying factors that discriminate between successful high and low price strategies. *European Journal of Marketing, 46*(11/12), 1647–1670.

Karayanni, D. A. (2015). A model of Interorganizational networking antecedents, consequences and business performance. *Journal of Business-to-Business Marketing, 22*(4), 293–312.

Kelley, W. T. (1965). Marketing intelligence for top management. *Journal of Marketing*, 19–24.

Kim, K. H. (2005). The relation among fit indexes, power, and sample size in structural equation modeling. *Structural Equation Modeling, 12*(3), 368–390.

Kitchin, R., & Lauriault, T. P. (2015). Small data in the era of big data. *GeoJournal, 80*, 463–475.

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal, 28*(1), 227–261.

Lakshman, M., Sinha, L., Biswas, M., Charles, M., & Arora, M. K. (2000). Quantitative vs qualitative research methods. *Indian Journal of Pediatrics, 67*, 369–377.
Larson, P. D., & Chow, G. (2003). Total cost/response rate trade-offs in mail survey research: Impact of follow-up mailings and monetary incentives. *Industrial Marketing Management, 32*(7), 533–537.
Lenth, R. V. (2001). Some practical guidelines for effective sample size determination. *The American Statistician, 55*(3), 187–193.
Levy, J. P., & Varela, J. (2003). *Multivariate analysis for the social sciences* (pp. 249–257). Madrid: Pearson Prentice Hall.
Liu, X., Chau, Y. K., Liu, X., & Huang, F. (2023). The determinants of customer intentions to use Fintech Services in a Commercial Chinese Bank. *Journal of Business-to-Business Marketing, 30*(3), 257–276.
Loehlin, J. C. (1992). *Latent Variable Models: An introduction to factor, path and structural analysis* (2nd ed). New Jersey: Hillsdale.
MacInnis, D. J. (2011). A framework for conceptual contributions in marketing. *Journal of Marketing, 75*(4), 136–154.
Marquardt, A. J. (2013). Relationship quality as a resource to build industrial brand equity when products are uncertain and future-based. *Industrial Marketing Management, 42*(8), 1386–1397.
Maxwell, S. E. (2000). Sample size and multiple regression analysis. *Psychological Methods, 5*(4), 434–458.
McIntosh, A. R. (1975). Improving efficiency of sample surveys in industrial markets. *Journal of the Market Research Society, 17*(4), 219–231.
McShane, B. B., & Bockenholt, U. (2016). Planning sample sizes when effect sizes are uncertain: The power-calibrated effect size approach. *Psychological Methods, 21*(1), 47–60.
McShane, B. B., Bradlow, E. T., Lynch, J. G., & Meyer, R. J. (2024). Statistical significance and statistical reporting: Moving beyond binary. *Journal of Marketing*. https://doi.org/10.1177/00222429231216910
Mehdikhani, R., & Valmohammadi, C. (2022). The effects of green brand equity on green word of mouth: The mediating roles of three green factors. *Journal of Business & Industrial Marketing, 37*(2), 294–308.
Minerbo, C., Samartini, A. L. S., & Brito, L. A. L. (2023). Sharing the benefits: How different dimensions contribute to value creation and capture. *Industrial Marketing Management, 108*, 251–262.
Mitchell, R. K., Mitchell, J. R., & Smith, J. B. (2008). Inside opportunity formation: Enterprise failure, cognition, and the creation of opportunitiesStrategic. *Entrepreneurship Journal, 2*(3), 225–242.
Mora Cortez, R., Clarke, A. H., & Freytag, P. V. (2021). B2B market segmentation: A systematic review and research agenda. *Journal of Business Research, 126*, 415–427.
Mora Cortez, R., & Johnston, W. J. (2017). The future of B2B marketing theory: A historical and prospective analysis. *Industrial Marketing Management, 66*, 90–102.
Mora Cortez, R., & Lecaros, R. (2024). Developing a global B2B strategy for products and services management: Practical guidance from the field. *The Journal of Business and Industrial Marketing, 39*(9), 1922–1927.
Morgan, N. A., Whitler, K. A., Feng, H., & Chari, S. (2019). Research in marketing strategy. *Journal of the Academy of Marketing Science, 47*, 4–29.
Moschko, L., & Blažević, V. (2023). Managing digitization of industrial incumbents through innovation-oriented leadership. *Industrial Marketing Management, 113*, 232–242.
Mwesiumo, D., Harun, M., & Hogset, H. (2023). Unravelling the black box between coopetition and firms' sustainability performance. *Industrial Marketing Management, 114*, 110–124.
Najafi-Tavani, Z., Zaefarian, G., Naudé, P., & Giroud, A. (2015). Reverse knowledge transfer and subsidiary power. *Industrial Marketing Management, 48*, 103–110.
Navarro-García, A., Peris-Oritz, M., & Barrera-Barrera, R. (2016). Market intelligence effect on perceived psychic distance, strategic behaviours and export performance in industrial SMEs. *Journal of Business & Industrial Marketing, 31*(3), 365–380.
Nunnally, J. C. (1978). *Psychometric theory* (2nd ed.). New York: McGraw-Hill.
Nyadzayo, M. W., Casidy, R., & Thaichon, P. (2020). B2B purchase engagement: Examining the key drivers and outcomes in professional services. *Industrial Marketing Management, 85*, 197–208.
Palmatier, R. W., Houston, M. B., & Hulland, J. (2018). Review articles: Purpose, process, and structure. *Journal of the Academy of Marketing Science, 46*, 1–5.
Paul, J., & Criado, A. R. (2020). The art of writing literature review: What do we know and what do we need to know? *International Business Review, 29*(4), Article 101717.
Queirós, A., Faria, D., & Almeida, F. (2017). Strengths and limitations of qualitative and quantitative research methods. *European Journal of Education Studies, 3*(9), 369–387.
Rahman, M., & Lambkin, M. (2015). Creating or destroying value through mergers and acquisitions: A marketing perspective. *Industrial Marketing Management, 46*, 24–35.
Rangarajan, D., Peasley, M., Paesbrugghe, B., Srivastava, R. V., & Stewart, G. T. (2021). The impact of adverse life events on salesperson relationships with customers. *Journal of Business & Industrial Marketing, 36*(12), 2126–2138.
Ranjan, P., & Nayak, J. K. (2023). Market-based organizational learning, pricing capability and business performance: The moderating effects of coordination mechanism and environmental dynamism. *The Journal of Business and Industrial Marketing, 38*(11), 2360–2378.
Reid, D. A., & Plank, R. E. (2004). *Fundamentals of business marketing research*. Binghamton, NY: Haworth Press, Inc.
Reinartz, W., Haenlein, M., & Henseler, J. (2009). An empirical comparison of the efficacy of covariance-based and variance-based SEM. *International Journal of Research in Marketing, 26*(4), 332–344.
Rigdon, E. E. (2013). Partial least squats path modelling. In G. R. Hancock, & R. O. Mueller (Eds.), *Structural equation modeling: A second course*. Charlotte, NC: Information Age Publishing.
Rigdon, E. E. (2023). How improper dichotomization and the misrepresentation of uncertainty undermine social science research. *Journal of Business Research, 165*, Article 114086.
Rigdon, E. E., & Sarstedt, M. (2022). Accounting for uncertainty in the measurement of unobservable marketing phenomena. *Review of Marketing Research, 19*, 53–73.
Rigdon, E. E., Sarstedt, M., & Ringle, C. M. (2017). On comparing results from CB-SEM and PLS-SEM: Five perspectives and five recommendations. *Marketing: ZFP–Journal of Research and Management, 39*(3), 4–16.
Rindfleisch, A., & Antia, K. D. (2012). Chapter 37: Survey research in B2B marketing: Current challenges and emerging opportunities. In *Handbook of business-to-business marketing*. Cheltenham, UK: Edward Elgar Publishing.
Rindfleisch, A., Malter, A. J., Ganesan, S., & Moorman, C. (2008). Cross-sectional versus longitudinal survey research: Concepts, findings, and guidelines. *Journal of Marketing Research, 45*(3), 261–279.
Rust, R. T., & Cooil, B. (1994). Reliability measures for qualitative data: Theory and implications. *Journal of Marketing Research, 31*(1), 1–14.
Rutherford, B. N., Troncoza, M., Ambrose, S. C., Anaza, N., & Matthews, R. (2023). One does not fit all: What is in a salesperson sample? *Journal of Personal Selling & Sales Management, 43*(4), 354–367.
Shamsollahi, A., Chmielewski-Raimondo, D. A., Bell, S. J., & Kachouie, R. (2021). Buyer–supplier relationship dynamics: A systematic review. *Journal of the Academy of Marketing Science, 49*(2), 418–436.
Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research, 104*, 333–339.
Sullivan, G. M., & Feinn, R. (2012). Using effect size—Or why the P value is not enough. *Journal of Graduate Medical Education, 4*(3), 279–282.
Thomson, S. B. (2010). Sample size and grounded theory. Grounded theory-sample size. *Journal of Administration and Governance, 5*(1), 45–52.
Tripathy, S., Aich, S., Chakraborty, A., & Lee, G. M. (2016). Information technology is an enabling factor affecting supply chain performance in Indian SMEs: a structural equation modelling approach. *Journal of Modelling in Management, 11*(1), 269–287.
Valtakoski, A. (2020). The evolution and impact of qualitative research. In journal of services marketing. *Journal of Services Marketing, 34*(1), 8–23.
Vashishth, A., Chakraborty, A., Gouda, S. K., & Gajanand, M. S. (2021). Integrated management systems maturity: drivers and benefits in Indian SMEs. *Journal of Cleaner Production, 293*, 126243.
Viglia, G., Zaefarin, G., & Ulqinaku, A. (2021). How to design good experiments in marketing: Types, examples, and methods. *Industrial Marketing Management, 98*, 193–206.
Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. *Journal of Marketing, 80*, 97–121.
Wilson, E. J. (1999). Research Practice in Business Marketing. *Industrial Marketing Management, 28*(3), 257–260.
Wongsansukcharoen, J., Trimetsoontorn, J., & Fongsuwan, W. (2015). Social CRM, RMO and business strategies affecting banking performance effectiveness in B2B context. *Journal of Business & Industrial Marketing, 30*(6), 742–760.
Yee, J. L., & Niemeier, D. (1996). *Advantages and disadvantages: Longitudinal vs. repeated cross-section surveys*.
Zhang, C. B., & Li, Y. N. (2019). How social media usage influences B2B customer loyalty: Roles of trust and purchase risk. *Journal of Business & Industrial Marketing, 34*(7), 1420–1433.