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REVIEW ARTICLE

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Meta-analysis and traditional systematic literature reviews—What, why, when, where, and how?

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Abstract

Meta-analysis is a research method for systematically combining and synthesizing findings from multiple quantitative studies in a research domain. Despite its importance, most literature evaluating meta-analyses are based on data analysis and statistical discussions. This paper takes a holistic view, comparing meta-analyses to traditional systematic literature reviews. We described steps of the meta-analytic process including question definition, data collection, data analysis, and reporting results. For each step, we explain the primary purpose, the tasks required of the meta-analyst, and recommendations for best practice. Finally, we discuss recent developments in meta-analytic techniques, which increase its effectiveness in business research.

KEYWORDS

meta-analysis, quantitative review, research synthesis, systematic literature review

1 | INTRODUCTION

Scientific knowledge is based on the accumulated findings from prior research in a research domain, where individual studies constitute building blocks (Rowley & Paul, 2021). It is expected that a new study will build on previous findings to contribute to knowledge formation and development in a research domain (Grewal et al., 2018). To accomplish this, authors must define their research objectives based on gaps in the relevant literature, and design a study to addresses this gap (Paul et al., 2021). This requires deep knowledge and understanding of a research domain, which can be facilitated by systematic literature reviews (SLRs).

SLRs can provide authors with an overview of a research domain in a single paper (Rosado-Serrano et al., 2018; Keupp & Gassmann, 2009; Paul et al., 2017). This method is considered to be a scientific and highly informative method for systematically collecting, reviewing, and synthesizing research findings on a particular topic (Paul et al., 2021) to determine what is known –and what is not known—at domain (Card, 2015). SLRs allow readers to glean a deep understanding of literature and also help them to identify research gaps in the area (Paul & Criado, 2020). In this way, an SLR may be viewed as a platform for knowledge advancement (Palmatier et al., 2018).

In contrast to traditional SLR, a meta-analysis takes an objective approach to quantitively synthesizing studies in a research domain, while a traditional SLR is qualitative and subjective in nature (Card, 2015). Meta-analysis statistical assesses the robustness of findings in an area and identifies and resolves conflicting findings in past research to provide more clarity on the topic for scholars and practitioners (Grewal et al., 2018). The advantage of meta-analysis, compared to a single study with small sample size, is its higher power (i.e., combined sample size of individual studies) (Cooper, 2015), which enables the meta-analyst more conclusively characterize the relationships between variables in a domain, and variables which moderate these relationships (Littell et al., 2008). While meta-analysis was introduced in the 1970s as a method to synthesize prior research, its acceptance as tool for advancing knowledge

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development among researchers in the business and management fields has been relatively recent (Aguinis, Dalton, et al., 2011).

Meta-analysis follows very technical and sophisticated procedures to collect, combine, and analyze empirical research (Siddaway et al., 2019). This rigorous approach guarantees the validity and reliability of the method, while at the same time obfuscating the technique for the researchers and practitioners who could benefit from conducting meta-analyses. Given this, the primary objective of this manuscript is to detail current practices and advancements in meta-analysis research and to contrast the technique with traditional SLRs. We eschew technical jargon to enhance the accessibility of our research among readers who do not possess advanced statistical knowledge. Moreover, instead of focusing exclusively on data collection and analysis, we cover the entire meta-analytic process including question definition, data collection, data analysis, and presentation of results. Finally, we will introduce recent advancements in meta-analytic technique to demonstrate the ongoing developments.

2 | TRADITIONAL SLRs AND META-ANALYSIS

There are several fundamental differences between traditional SLRs and meta-analysis, distinguishing these popular methods for accumulating knowledge in a research domain. Table 1 provides an overview of these differences based on five key questions (i.e., What, Why, When, Where, and How). We believe these key questions provide a better picture of both traditional SLRs and meta-analysis and their difference and help researchers choose an appropriate literature review method in their work. Therefore, the rest of this study aims to extend these differences in more detail.

2.1 | Traditional SLRs—What and why?

A traditional SLR is a "process for assembling, arranging, and assessing existing literature in a research domain" (Paul et al., 2021). In this process, assembling involves identification (i.e., defining the literature review domain, main question, and source type/quality) and acquisition (i.e., obtaining papers to be included). The scientific steps for an SLR include organization (i.e., specifying the codes and framework) and purification (i.e., specifying the inclusion and exclusion criteria). The final step is setting the future research agenda, based on a gap analysis (Littell et al., 2008). Following this process helps researchers to meet two main goals: (1) providing a comprehensive picture of what is known in a research domain (i.e., defining its scope overview, identifying inconsistencies, and their probable explanation, and developing a framework to summarize previous research); and, (2) providing directions for future research based on what is not known in that research domain (Paul & Criado, 2020).

Traditional SLRs include: domain-based reviews; theory-based reviews, and method-based reviews. Domain-based reviews synthesize studies in the same research domain to extend the body of literature in this domain. Synthesizing diverse perspectives allows authors to describe state-of-the-art knowledge in the research domain and identify useful paths for research. There are several types of domain-based reviews:

Structured reviews focus on the development of a research domain such as associated theories, models, constructs, contexts, and methods in which authors use tables and figures to provide structured insight into a research domain (Paul & Criado, 2020). Examples include a structured review of entry mode by Canabal and White III (2008) and export barriers by Kahiya (2018).

TABLE 1 Differences between traditional SLRs and meta-analysis

Differences	Traditional SLRs	Meta-analysis
What	A qualitative process for assembling, arranging, and assessing existing literature in a research domain.	A quantitative method that integrates the results of empirical studies to provide an aggregate summary of findings in a research domain.
Why	Providing a comprehensive picture of what is known and proposing directions for future research based on what is not known in that research domain.	To achieve statistically precise and accurate conclusions about the strength and direction of a relationship between variables and moderator role in a research domain.
When	The research topic is evolving to allow a researcher to provide a current view of what is known and define the future direction of the research domain.	The research topic is mature enough to allow a researcher to provide an overall picture of relationships and the role of moderators in a research domain.
Where	Include all types of relevant studies from high-quality journals through subjective selection and interpretation of data to synthesize the findings of prior studies in a systematic manner.	Include published and unpublished studies that empirically examine the relationships of interest through objective and rigorous statistical procedures to synthesize the findings of prior studies and test hypotheses that have not been studied in prior research.
How	Through SLRs process include defining a research question, data collection, data preparation, data analysis, and reporting and using the SLRs approach, that is, domain-based reviews, theory-based reviews, and method-based reviews.	Through meta-analysis process include defining the research question, data collection, data preparation, data analysis, and reporting and meta-analysis approach, that is, main model and moderator analysis.

Abbreviation: SLR, systematic literature review.

Framework-based reviews are papers developed using a classic organizing framework to scientifically synthesize information, as illustrated by Paul and Benito's (2018) ADO (Antecedents, Decisions, and Outcome) framework. The ADO framework has been used by Lim et al. (2021) and Södergren (2021). Another approach to conducting a framework-based review, which is utilized by Xie et al. (2017). Still, another method is Paul and Rosado-Serrano's (2019) TCCM framework for writing reviews and others (e.g., Chen et al., 2021). Although these frameworks suggest a different approach to writing an SLR, they have a common goal: to facilitate the combining and synthesizing research in a domain.

Bibliometric reviews entail analyzing bibliographic data of published literature by using statistical tools to highlight trends and, therefore, provide an overview of the body of knowledge in a research domain. Writing bibliometric reviews is facilitated by available software such as Visualization of Similarities (VOS Viewer). However, critics assert that bibliometric reviews do not adequately describe theories, methods, and constructs in a particular domain (Paul & Criado, 2020). Randhawa et al. (2016) open innovation, Goyal and Kumar (2021) financial literacy, and Pattnaik et al. (2020) trade credit are examples of the bibliometric reviews.

Hybrid reviews combine elements of different review types (Paul & Criado, 2020). For example, some reviewers supplement a bibliometric review with a structured review (Bahoo et al., 2020) and develop a robust hybrid review. For example, Kumar et al. (2020) masstige marketing, Dabić et al. (2020) immigrant entrepreneurship and Rebouças and Soares (2021) voluntary simplicity utilized hybrid reviews for their domain-based literature reviews.

Finally, *conceptual reviews* aim for theory, model, and/or propositions development in a research domain (Paul et al., 2021). For example, Pansari and Kumar (2017) proposed customer engagement framework and Paul's (2019) marketing in emerging markets model to enhance the knowledge in the research domain.

Theory-based and method-based SLRs follow a similar process, from defining research questions to reporting findings (Cooper, 2015); meta-analyses feature key differences. While traditional qualitative literature reviews include all type of relevant studies, meta-analyses only include studies that empirically examine the relationships of interest (Geyskens et al., 2009). Moreover, in qualitative literature reviews, researchers typically focus on publications from higher-quality journals to increase the quality of output. However, meta-analyses feature different kind of manuscripts—both published and unpublished—from variety of sources and account for variations in journal tier/quality analytically (Barari et al., 2021). Also, in qualitative SLRs, the subjective selection and interpretation of authors play an important role in developing an analytical framework to integrate prior studies in a research domain. In contrast, a meta-analysis follows an objective and rigorous statistical procedure which limits the scope of authors' own interpretations (Siddaway et al., 2019). Finally, meta-analyses not only synthesize the findings of prior studies, but also enable researchers to test hypotheses that have not been studied in prior research (Lipsey & Wilson, 2001).

2.2 | Meta-analysis: What and why?

Meta-analysis is a collection of statistical methods that integrates the results of a large number of studies to provide an aggregate summary of knowledge in a research domain (Littell et al., 2008). The advantage of meta-analysis over an individual study is in its higher power (i.e., sample size; Geyskens et al., 2009). A meta-analysis combines the findings of single studies for specific relationships, it allows authors to achieve statistically precise and accurate conclusions about the strength and direction of a relationship between variables (Littell et al., 2008), and to resolve contradictory results in prior studies by examining the impact of moderator variables (Geyskens et al., 2009). Meta-analysts calculate an "effect size," which indicates the direction and strength of association between two variables (Card, 2015), and is a standardized metric that is comparable across studies (Lipsey & Wilson, 2001). The researcher extracts information from each study comprising the meta-analytic database to calculate an effect size from every single study (Geyskens et al., 2009). After calculating an effect size, for each study, the meta-analyst combines all of the effect sizes to determine the strength and direction of associations between pairwise relationships at the aggregate level (Geyskens et al., 2009). Popular effect sizes in business and management are the correlation coefficient (r) and, standardized mean difference coefficient (e.g., Hedges's g and Cohen's d; Littell et al., 2008).

Usually, there are conflicting findings in a literature stream. Therefore, the meta-analyst identifies appropriate moderators in an attempt to explain variations across studies (Card, 2015). Some control variables may also be defined to account for other sources of variation in effect sizes. In their meta-analysis, Rubera and Kirca (2012) studied the impact of firm innovativeness on firm performance. In addition to measuring how firm innovativeness influences firm performance, these researchers assess the impact of control variables such as product diversification, firm age, intangible factors, and competitive intensity on their relationships. They also explore the moderating impact of firm size, advertising intensity, industry, and country.

3 | CONDUCTING A META-ANALYSIS—WHEN?

Deciding on the right time to conduct meta-analysis is quite challenging (Paul et al., 2021). The research topic covered in the meta-analysis must be mature enough to allow a researcher to include enough homogeneous empirical research in terms of subjects, interventions, and outcomes (Haidich, 2010). This allows researchers to statistically sensitize findings in a domain to provide a state-of-the-art view and encourage further development in that domain (Grewal et al., 2018). When there is not enough empirical research, it might be better not to perform a meta-analytic review. Instead, researchers could employ qualitative SLRs to synthesize research in that domain (Borenstein et al., 2021).

The number of effect sizes for the relationship of interest in a meta-analysis conceptual model provides practical guidance about the right time for conducting meta-analysis. There is no agreement among meta-analysts about the minimum number of effect sizes required for a relationship to include in a meta-analysis. For instance, Pigott (2012) proposed two as the minimum effect size for conducting a meta-analysis on a pair. However, it seems two effect sizes as a threshold could not fully reflect the complexity of relationships (Palmatier et al., 2006). Thus, other researchers offer a higher required effect size as a threshold. For instance, in the study of the role of customer relational benefits on customer response, Gremler et al. (2020) only considered relationships with at least five effect sizes in their study.

Suppose an existing meta-analysis has been published in a high-quality journal in recent years. In that case, it is not beneficial to conduct further meta-analysis unless the new meta-analysis could provide substantially new insight into the research domain. For instance, Palmatier et al.'s (2006) meta-analysis studies the effectiveness of factors influencing relationships marketing, providing an excellent overview of the relationship marketing research area. Later, Samaha et al. (2014) used meta-analysis to study the role of culture in relationship marketing in the international context, which has not been studied in previous meta-analyses. Furthermore, Verma et al. (2016) used meta-analysis to study relationship marketing in an online context.

4 | META-ANALYSIS STRUCTURE—WHERE AND HOW?

Meta-analysts make critical decisions at each step of the meta-analytic process (Geyskens et al., 2009). As shown in Table 2, steps in a meta-analysis include defining the research question, data collection, data preparation, data analysis, and reporting results.

Table 3 details the main goal of each step and its substeps to provide an overview of the meta-analysis process. Importantly, although the steps are invariable, how the researcher performs each step and make judgment category throughout, is subjective (Grewal et al., 2018). However, we offer suggestions to make guide researchers' decision-making. In the sections that follow, we describe the tasks of the meta-analyst in each step of the process.

4.1 | Defining the research question

The first step in a meta-analysis is defining the main research question (Paul et al., 2021). It is important for authors to have a clear vision of the main research question before conducting the meta-analysis (Paul & Criado, 2020), because this will impact the entire process—especially data collection and data analysis. The research questions in a meta-analysis typically address a focal concept (e.g., commitment across cultures; Fischer & Mansell, 2009), examining relationships between two or more focal concepts (e.g., corporate social performance and financial performance; Orlitzky et al., 2003; or investigate antecedents and consequences of a focal concept or construct (e.g., antecedents and consequences of leader-member exchange; Dulebohn et al., 2012). The research question for a meta-analysis could be formulated around specific theory (e.g., regulatory fit theory; Motyka et al., 2014) or model (e.g., technology acceptance model; King & He, 2006)). Defining a research question in meta-analysis requires a deep understanding of the topic and literature, and entails specifying a valuable, feasible question that prefaces the meta-analytic framework that will guide authors through data collection and analysis.

4.1.1 | In-depth understanding of research topic/literature stream

Meta-analysis provides an overview of relationships in a research area, resolves conflicts, and identifies directions for further research in a mature research domain (Borenstein et al., 2021). The meta-analyst must possess an overarching knowledge of the current research domain (Paul & Criado, 2020) to define an appropriate research question and develop a conceptual framework (Paul et al., 2021). With this in mind, authors might begin by reading highly cited papers, to gain an understanding of the topic and extant research. Researchers might also review qualitative SLRs to enrich their understanding.

4.1.2 | Specify a valuable and feasible question

The quality of Meta-analytic output depends on the quality of the research question (Paul & Criado, 2020). Valuable research questions

TABLE 2 Meta-analysis process

Step	Purpose
Defining research question	Formulating the main research question to be considered in the meta-analysis framework development
Data collection	Collecting all related and qualified quantitative studies from the literature that are matched with the research question
Data preparation	Extracting and checking effect size and required data from individual studies for main and moderator/control analysis
Data analysis	Use corrected and combined effect size to test the relationship in the meta-analysis framework and do moderator and control variable analysis
Reporting	Report all required details in a logical formation to reflect completeness and transparency of meta-analysis review

TABLE 3 Meta-analysis process

Step	Suggestions
Defining research question	
Depth of knowledge of an area	• Read related publications in high impact factor journals • Review current qualitative literature review in a research domain
Specify a valuable and feasible question	• Define a question that helps to resolve contradictory results and add new insight through the main model and moderator analysis • Needs to be broad enough to include enough quantitative studies and limited enough to define a unique position in the research domain
Develop meta-analysis framework	• Define focal concepts, their conceptual and operational definitions • Define the relationships between concepts and variables which moderate them • Use a logical model or theory to underpin relationships in a meta-analysis framework
Data collection	
Searching literature	• Define keyword search in related or unrelated research field • Define popular databases for search • Manually review the top journals' issues • Check the references of high cited papers • Communicate with top researchers and Post requests on academic list services
Define inclusion/exclusion	• Include quantitative research which tested desired relationships • Include research in a specific time frame • Specify other criteria based on the meta-analysis framework
Data coding and final sample description	• Develop a coding manual to code pairwise relationships, moderator, and control variables • Employ at least two coders in studies coding • Calculate inter-coder agreement, report discrepancies, and strategies to deal with them
Data preparation	
Effect size selection and extraction	• Correlation and standard mean differences are common effect sizes in meta-analysis • The research design of most original studies determines the effect size metric • When the effect size value is not reported, use available information in the original study to calculate the effect size
Effect size extraction issues	• In the original study, effect sizes from the same sample need to be combined • In the original study, effect sizes from the independent samples are independent
Effect size correction	• The correct effect size for measurement error, range restriction, and dichotomization
Deal with outliers	• Use sample-adjusted meta-analytic deviancy statistic (SAMD) for outlier identification • Conduct sensitivity analysis to see the role of outliers on the result and decide about how to deal with outliers
Publication bias	• Use techniques such as file drawer N, win fail-safe N, or trim and fill to assess publication bias
Effect size combination	• Use weighted average to combine effect sizes from individual studies
Moderator and control extraction	• Assign a quantity (categorical or continuous) to these variables based on available data in the original studies
Data analysis	
Model selection	• Choose fixed-effects model or random-effects model, however, the latter is preferable
Homogeneity test	• Use the Q and I^2 tests to analyze the heterogeneity in the effect sizes • Use the results of heterogeneity analysis to confirm your model selection, not vice versa
Overall analysis	• Use univariate and/or meta-analytic structural equation modeling analysis to analyze the direction and indirect relationships and their strength of the relationship • Include additional tests to compare relationships in the univariate analysis model.
Moderator analysis	• Use subgroup analysis, meta-regression, or multilevel analysis to test the effect of moderators in the meta-analytic conceptual model
Software to conduct a meta-analysis	• Comprehensive Meta-Analysis (CMA), Review Manager (RevMan), and Stata are commercial software but R packages for meta-analysis are free and open-source • Commercial software is easy to use and does not require programming skill • R packages are flexible but require a basic knowledge of R software and programming

(Continues)

TABLE 3 (Continued)

Step	Suggestions
Reporting	
Title	• Include main concept/construct and meta-analysis or meta-analysis review in the title
Abstract	• Overview of the main question in the meta-analysis • A brief overview of the method, especially the number of studies and effect size • The main focus is on the major findings of the analysis and its implications
Introduction	• Start with a real example to highlight the topic of interest • Overview of your main question and its importance • Describe research streams in your research topic • Highlight the variability in prior studies in your research topic • Illustrate the role of meta-analysis in the synthesis of prior studies and resolve the variabilities
Background and theoretical framework	• Review of history, evaluation, definitions, and main research streams in a research topic • Develop a framework underpinned by theory, model, or research streams • Justify the hypothesized relationship in the framework, moderator, and control variables.
Method	• Include all items related to data collection, then describe data preparation and data analysis procedures in the meta-analysis
Data analysis	• Descriptive analysis to explain outlier, publication bias, heterogeneity test results • The overall analysis results • Moderator analysis and control variables findings
Conclusion	• Research theoretical and empirical contributions in a summary table • Explain research limitations and define further research avenues to extend the research topic
Appendix	• The studies included in the research, formulas and their calculations, and extra analysis

allow a researcher to resolve contradictory results about the relationship between concepts, the direction of these relationships, and variables that moderate these relationships (Paul et al., 2021). Moreover, valuable research questions allow a researcher to test relationships that have not been previously studied through both the overall analysis and moderator analyses (Geyskens et al., 2009).

The meta-analytic research question needs to be sufficiently broad so that researcher may find enough quantitative studies (Paul et al., 2021), but bound enough to occupy a unique position in a research domain (Paul & Criado, 2020). Consider, for example, Crook et al. (2011). These researchers study how human capital affects firm performance—relationships for which there are enough quantitative studies to permit examination through meta-analysis, for which there are controversial findings.

4.1.3 | Developing a meta-analytic conceptual framework

In a meta-analysis, it is necessary to define the focal concept and relationships, as well contextually moderators to these relationships a priori (Grewal et al., 2018). In defining the main concept in a meta-analysis, the existing literature may use the same or different terms for the same concept (Card, 2015). Having clear conceptual and operational definitions of focal concepts are critical in a meta-analysis especially during data gathering and data preparation (Kirca & Yaprak, 2010). The researcher also needs to define the relationships between variables and moderators to these relationships (Cooper, 2015). Often, there are numerous-sometimes contradictory—definitions and relationships proposed by different researchers. Thus, authors must have clear conceptualizations and strong justification for relationships in their meta-analytic framework (Kirca & Yaprak, 2010).

Authors might tap into extant theories or models to specify the relationships between focal concepts and how moderator variables moderate key relationships (Grewal et al., 2018). Consider, for example, corporate social responsibility (CSR) initiatives study in previous research. Vishwanathan et al. (2020) developed the strategic CSR concept to include different types of CSR in their meta-analysis and tested its impact on firm corporate financial performance. Moreover, variables such as context, industry type, the potential impact of product type, and culture are explored as moderators.

4.2 | Data collection

Data collection in a meta-analysis begins with searching the literature, then applying inclusion/exclusion criteria to finalize the mate-analytic database. Data collection in a meta-analysis should employ a funnel model, in which various sources are examined so as

to identify as many publications as possible in the search process. Then, through screening, the researcher can eliminate publications that do not meet inclusion criteria (Grewal et al., 2018). It is very important to keep detailed records of the screening process to report in the meta-analysis to demonstrate transparency and accuracy (Paul et al., 2021). Some meta-analysts use PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses; Moher et al., 2009) or SPAR-4-SLR (Paul et al., 2021) to document this process.

4.2.1 | Literature search

"Data" in a meta-analysis include prior studies on the topic of interest which they must seek out in the search process (Littell et al., 2008). Authors should define the search terms based on focal concepts in their conceptual model to search them in different databases later. For instance, to assess the effectiveness of customer involvement in the new product development, Chang and Taylor (2016) consider search terms such as "customer participation," "customer involvement," "cocreation," "coproduction," and "crowdsourcing" in combination with search terms like "new product" and "new service" to search all publications related to their meta-analysis framework.

The authors could use a keyword search to search the data from related and unrelated research fields based on the research question. This method would allow the authors to synthesize their findings across disciplines and enhance the quality of their work. However, research requires close attention to the meaning of the keywords in different research fields. For example, Barari et al. (2021) meta-analysis of antecedent and consequences of customer engagement, only includes studies in which engagement is toward for-profit firms to limit their search to the field of marketing research. Engagement is a popular research area in different fields such as education, human resource, and computer science, while its meaning differs across different research fields. However, Blut and Wang's (2020) meta-analysis of technology readiness includes "innovativeness" as one of the technology readiness motivators. Researchers from different research fields use different terms for this concept. Therefore, they searched for "consumer innovativeness" in the marketing literature but "personal innovativeness" in the information system literature.

When collecting data, authors should consider both published works (e.g., journal articles, book chapters, and published conference papers) and unpublished works (e.g., theses, working papers, unreleased papers, and conference papers). Doing so would decrease the publication bias (Cooper, 2015), which is a serious issue with meta-analysis, as including unpublished work may change the results (Geyskens et al., 2009). One way to cast a wide net in one's search is to use comprehensive electronic databases in business and management to search out both published and unpublished work (e.g., ABI/Inform Global, ProQuest, PsycINFO, SSRN, and EBSCO; Geyskens et al., 2009). A manual review of premier journals publishing papers in a research domain can also be helpful in identifying individual papers (Grewal et al., 2018). This strategy helps ensure the researcher did not miss any related studies. Meta-analysts should also check the reference lists of top papers on the research topic (Steel et al., 2021). To do this, authors might use Web of Science or Google Scholar to identify relevant papers and seminal articles with high citations and review their reference lists, as usual as more recent research citing the top papers. Some meta-analysts also contact leading researchers in the research domain and request their unpublished, forthcoming, and recent work on the topic of interest. For example, Fischer and Mansell (2009) contacted 25 researchers who conducted studies on employee commitment among different cultures to obtain their unpublished work. Finally, a meta-analyst might post a request on academic list-server websites or email lists to request papers, especially unpublished work (Jeyaraj & Dwivedi, 2020). To illustrate, Zhao et al. (2022) complete their meta-analysis database by sending emails to the Academy of Management e-mail lists, asking researchers to send their working and unpublished publications.

4.2.2 | Define inclusion/exclusion criteria

After collecting all related publications in the search process, authors must specify inclusion/exclusion criteria to ensure all studies ultimately included in meta-analysis have similar, desired features (Grewal et al., 2018). Here, we explain some of inclusion/exclusion criteria that are common in most meta-analyses. First, meta-analyses involve only quantitative studies (Jeyaraj & Dwivedi, 2020); hence, researchers should exclude all review papers, qualitative research, and papers with descriptive analyses from the meta-analytic database. Moreover, the original studies must contain the required statistical information (e.g., correlation coefficients, standardized beta coefficients, and *t*-values) to calculate a common effect size (Grewal et al., 2018). Most studies in high-quality journals provide enough information to calculate an effect size (Jeyaraj & Dwivedi, 2020); however, when this information is not reported in a paper, the meta-analyst may contact the authors to retrieve this information or remove the study from the meta-analytic database (Card, 2015). Second, all studies included in a meta-analysis must quantitively test the association between the variables of interest (Jeyaraj & Dwivedi, 2020). To ensure the "right" relationships are measured, authors must develop a coding manual with clear conceptual and operational definitions of all variables in the meta-analytic framework and include only research that tests at least one pairwise relationship in that meta-analytic framework. Third common criteria for papers in a meta-analytic would be the time frame (i.e., the period from which studies are drawn), which may be a consideration. For example, in their meta-analysis examining the impact of strategic resources on performance, Crook et al. (2008) chose 1991 as the starting point of data collection. Because this is the year resource-based theory was introduced. Finally, the meta-analyst might impose various research design criteria, so long as there is strong justification for it. To illustrate, Knoll and Matthes (2017) included only quantitative studies with experimental research designs in their meta-analysis of celebrity endorsements effectiveness, because it allows causality inference.

4.2.3 | Data coding and final sample description

In this step, researchers code the different characteristics of individual studies for use in data analysis. Specifically, the meta-analyst must code: (1) pairwise relationship (s) which have been studied in each individual study; (2) characteristics from prior studies which may moderate relationships in the meta-analytic framework; and, (3) characteristics to control for the conceptual framework. Initially, researchers must determine which pairwise relationships in the meta-analytic framework have been tested each original study, and extract the effect sizes corresponding to these relationships. For example, Jiang et al. (2012) were examined the interrelationships between HR practice, human capital, employee motivation, voluntary turnover, operational, and financial outcomes in their meta-analysis of the role of human resource management on organizational outcomes. Thus, they examined each original study to determine which of these pairwise relations were tested and captured the corresponding correlation coefficients.

Researchers also code different moderators that could explain the fluctuation in pairwise relationships (Higgins et al., 2019), including study design characteristics (Jeyaraj & Dwivedi, 2020). A review of previous empirical studies and extant meta-analyses on a research topic often helps authors complete their list of potential moderators. Study design characteristics might include subjects' age, gender, and nationality, as well as year of publication and type of research design. For example, Fischer and Mansell's (2009) meta-analysis of employee commitment, the country in which studies were conducted, sample sizes, percentage male/female, mean age, whether the sample was blue or white collar, response rate, industry, organization, and job type.

Finally, meta-analysts typically code probable control variables to role them out as a source of heterogeneity in the relationships between the main variables. Including control variables in the meta-analytic framework enhance the rigor of work (Grewal et al., 2018). As with moderator selection, authors might follow prior studies or previous meta-analyses on the topic to refine their list of control variables. In their meta-analysis of customer relational benefits, Gremler et al. (2020) include several control variables (e.g., single vs. multiple industries, student vs. nonstudent samples, and published vs. unpublished studies) to ensure that fluctuations in effect sizes are not because of these variables.

Data coding involves developing manual to minimize subjectivity and increase the reliability of the coding process (Jeyaraj & Dwivedi, 2020). A clear coding manual is useful when different terms are used for the concept of interest. A coding manual typically includes each concept's conceptual and operational definitions and common aliases (Higgins et al., 2019).

It is important to involve at least two coders who keep track of discrepancies and calculate inter-coder agreement to demonstrate reliability in the coding process. The agreement rate is a percentage from 0% to 100% where higher percentage represents higher agreement between coders and higher quality in the coding process. In addition to reporting the inter-coder agreement, the meta-analyst should report how coders addressed disagreements in coding. For instance, in Jiang et al.'s (2012) meta-analysis, the first and third authors independently coded all studies, and reported their inter-coder agreement (96%). They also specified that disagreements were resolved through discussion.

Finally, the meta-analyst should describe the final sample characteristics of the studies included in the meta-analysis (Jeyaraj & Dwivedi, 2020). To illustrate, Dulebohn et al. (2012) describe their meta-analysis sample based on the type of organization (63% private and for-profit, 16% public sector, 15% education, and 6% health sector), sample location (83% the United States and 17% rest of the word), and research design (97% study reported cross-sectional results and only 3% reported longitudinal data).

4.3 | Data preparation

In this step, researchers extract the required information from each individual study. For the pairwise relationship, the meta-analyst extracts or calculates an effect size from each individual study, which indicates the direction and strength of the association between two variables (Card, 2015). While there are different statistics to consider, in business and management correlation coefficients and standard mean difference coefficients are the meta-analysis effect size metrics. For moderator and control variable, the meta-analyst uses available information from each individual study to assign value to these variables (e.g., based on type of market, studies conducted in the business-to-business context = 1, and studies conducted in the business to customer context = 0).

4.3.1 | Choose an effect size metric

Choosing the right effect size depends on the research design of the studies included in the meta-analytic database (Steel et al., 2021). If most studies employ an experimental design with control and experimental groups, the authors are limited to the mean difference metric as the effect size (Card, 2015). If most studies administered as a survey, then authors would likely use correlation coefficients as the effect size (Kirca & Yaprak, 2010). In contrast to correlation or mean difference coefficient, metrics such as regression beta coefficient, *t*-test, X^2 test, *F*-test values are not an effect size because they cannot combine and compare them between individual studies. However, these data can be used to calculate the desired effect size.

Correlation as an effect size

Correlation as an effect size metric is very popular in business and management. Some meta-analyses use Fisher's *z*-transformed correlation for data analysis (Card, 2015). In contrast to the correlation coefficient, a *z*-transformed correlation has an approximately normal distribution (Geyskens et al., 2009). However, the *z*-transformed correlation is not comparable across studies. Thus, there is an ongoing debate about using the correlation coefficient or

z-transformed correlation for meta-analysis (Kirca & Yaprak, 2010). Importantly, if some studies did not report the correlations between research variables, it is possible to calculate the correlation coefficient from different statistics such as regression beta coefficient, *t*-value, *f*-value, X^2 statistic, *z*-value, and mean differences.

Standard mean differences as an effect size

A mean difference as an effect size metric indicates the magnitude of the difference between the mean of two groups as a function of the group standard deviation (Jeyaraj & Dwivedi, 2020). The two main mean difference metrics are Hedges's *g* and Cohen's *d* (Card, 2015). They differ in their standard deviation calculation in the denominator of the formula. With large sample sizes they are identical, so some regard them as similar (Higgins et al., 2019). These two effect size metrics are convertible to each other. In business and management, mostly Cohen's *d* as standard mean difference is used in meta-analysis. Similar to the correlation coefficient, it is possible to calculate this metric based on available information in an individual study (Kirca & Yaprak, 2010).

4.3.2 | Issues in effect size extraction

There are some issues in the effect size extraction worth noting (Steel et al., 2021). It is common in business and management studies to conduct multiple studies to test the same relationships in a framework through different research designs in an effort to enhance the robustness of findings (Jeyaraj & Dwivedi, 2020). In such cases, there are more than one effect size for the same pairwise relationships in an individual study. In this situation, if these effect sizes are from the same sample, the preferred procedure is to combine them to calculate a single effect size for a relationship in a study. The meta-analyst might use the Hunter and Schmidt (2004) method to calculate a composite correlation. If there is not enough information to calculate the composite correlation, the best alternative would be the average of the equivalent correlations (Geyskens et al., 2009). However, if authors conduct several independent substudies in a single study with an independent sample to test the same pairwise relationships, extracting an effect size from each substudy is appropriate (Steel et al., 2021). Regarding, it is important to role that in a meta-analysis, the number of effect sizes may be higher than the number of individual studies.

4.3.3 | Effect sizes corrections

After extracting/calculating the effect size, the meta-analyst corrects it before using it in the data analysis. This correction is due to some artifacts that lead to biases (Geyskens et al., 2009), such as measurement error, imperfect validity in variable measurement, or an imperfect sample that does not represent the whole population (Jeyaraj & Dwivedi, 2020). Although there are several artifact corrections in the meta-analysis literature (Borenstein et al., 2021), we only focus on the most common artifact correction procedures in business and management, beginning with the measurement error correction.

The measurement error correction is necessary because individual studies fail to measure the variables correctly and perfectly (Geyskens et al., 2009). To correct effect size for this artifact, the authors could use Hunter and Schmidt's (2004) formula, where the effect size (r_{xy}) needs to be divided by the square root of two variable measurement reliability products $\sqrt{(r_{xx})}*\sqrt{(r_{yy})}$. This correction may result in an effect size greater than one, in this case, the meta-analyst must consider one as the effect size. Second, the meta-analyst corrects for range restriction (Jeyaraj & Dwivedi, 2020), in which the standard deviation of effect size from the original study is smaller than the population's standard deviation. Both variables in an effect size will be corrected. Authors must divide the sample standard deviation of a study by the reference population standard deviation. A third, effect size correction is related to artificial dichotomization (Geyskens et al., 2009). If one or both of the variables believed to be associated are artificially dichotomized, a correction is required. The meta-analysts need first to know the dichotomization method. They could then employ the Hunter and Schmidt (2004) procedure to restore its original value.

4.3.4 | Dealing with outliers

Authors must deal with outliers, which are extremely small or large effect sizes that may influence the accuracy of data analysis (Geyskens et al., 2009). Schematic plot analyses or analyzing the number of standard deviations from the mean are common methods for outlier identification (Jeyaraj & Dwivedi, 2020); however, these techniques do not take the sample size of individual studies into account, so they are not optimal for use in meta-analyses (Card, 2015). One popular and sophisticated method for outlier identification in meta-analysis is the Huffcutt and Arthur (1995) sample-adjusted meta-analytic deviancy statistic (SAMD). Here, the authors calculate the difference between each original study's effect size and the mean sample-weighted coefficient without including the original study's effect size in the coefficient calculation to identify the outliers. When outliers are identified, the meta-analyst must decide whether to eliminate them or conduct sensitivity analysis. With a sensitivity analysis, the meta-analyst examines data with and without outliers to see the impact of outliers on results (Geyskens et al., 2009). If the outlier has an impact on result, the author might report the result with and without the outlier (Geyskens et al., 2009). As the outlier could not make a study automatically incorrect, the author needs to be careful about removing outliers from database (Grewal et al., 2018).

4.3.5 | Publication bias

Meta-analysts have easier access to published studies; however, there may be some unpublished studies on topics that authors do not

include in the meta-analysis (Jeyaraj & Dwivedi, 2020). It is possible that the inclusion of such publications in the data analysis would change the magnitude, direction, or significance of relationships between pairwise relationships in the meta-analysis (Card, 2015). As mentioned previously, comprehensive database development can remedy this issue. There are also several methods to provide additional evidence of the robustness of the results, and to demonstrated that publication bias is not a problem (Steel et al., 2021). A traditional metric is the file drawer *N* procedure in which researchers show how many null effects studies would need to exist to change a significant relationship in a meta-analysis to a nonsignificant one (Grewal et al., 2018). A second technique is the Orwin fail-safe *N* procedure, which indicates how many missing effect sizes are required to bring an effect size to a nonzero value. Finally, the meta-analyst may use Duval and Tweedie's (2000) Trim and Fill method to identify and correct for publication bias. This method includes removing (i.e., trim) the extreme effect sizes to reduce the variance. Then add (i.e., fill) removed studies to correct the variance of the adjusted effect size (Grewal et al., 2018).

4.3.6 | Effect sizes combination

In the final step of data preparation, the meta-analyst would combine effect size from different studies (Steel et al., 2021). Because each study in the meta-analytic database has a different sample size, the point estimation of the true effect size varies (Jeyaraj & Dwivedi, 2020). A study with a larger sample size would have a more precise estimation. Thus, simply averaging effect sizes is inappropriate because it does not take into account these differences across studies. The first approach is the reciprocals of the estimated variances of the observed effect sizes (Steel et al., 2021), which determine the weight of each study. This approach gives more weight to studies with smaller standard errors than other studies. The meta-analyst may also calculate the weighted average of effect sizes for each pairwise relationship based on the sample size of each study. In business and management authors usually use a weighted average to combine effect sizes from individual studies (Geyskens et al., 2009).

4.3.7 | Moderator and control variables

To examine the impact of moderator and control variables, the meta-analyst must assign a value to include these variables in analyses (Geyskens et al., 2009). How such values are assigned depends on the nature of these variables and the information reported in the original studies (Jeyaraj & Dwivedi, 2020). These variable values might be categorical or continuous values, like for demographic moderators such as age, gender, education, or income (Steel et al., 2021). For other moderators such as culture, authors could use the Hofstede et al. (2005) cultural dimension index (ranging from 1 to 100)—a continuous variable. Similar to moderator variables, information in the original studies are used to assign a value to the control variables.

In their meta-analysis, Gremler et al. (2020) designated type of service and type of market as two main moderators. They defined two levels of type of service (i.e., encounter service = 0 and relationships service = 1). Similarly, for the type of market, they defined two levels (i.e., business-to-customer = 0 and business-to-business = 1). They also included control variables such as sample type (student sample = 1 and nonstudent sample = 0) and publication state (published paper = 0 and unpublished paper = 1).

4.4 | Data analysis

Before data analysis, the meta-analyst must choose between a fixed-effects model or random-effects model, and assess variation in the effect sizes through a heterogeneity test (Steel et al., 2021). Choosing between a fixed-effects model or random-effects model is a critical step and will affect the whole data analysis process (Aguinis, Dalton, et al., 2011). This selection is based on the researcher's assumptions about the population from which studies come. After this, the main model is analyzed to determine the significance and strength of relationships in the meta-analytic. Corrected and combined effect sizes and univariate analysis are then used to further assess pairwise relationships in the model. Moreover, to explain the heterogeneity in the relationships between variables of interest, the authors conduct a moderator analysis. Subgroup analysis or meta-regression are used to test the role of moderators in the framework. Finally, the probable role of control variables in the meta-analytic framework is tested.

4.4.1 | Fixed-effects model

In the fixed-effects model, the researcher assumes all studies are based on the same population and thus share the same underlying true effect size. Because of this, the model is used as a singular term in the fixed-effects model (Steel et al., 2021). As all studies try to estimate the same parameter (i.e., population effect size), the only source of variation among the different studies is sampling errors in each study (i.e., within-study error). Therefore, in the fixed-effects model, the meta-analytic findings are generalizable only to studies included in the meta-analysis (Grewal et al., 2018).

4.4.2 | Random-effects model

In contrast to the fixed-effects model, with random-effect models, studies are not assumed to come from the same population, and each study estimates a unique parameter. Thus, the researcher uses models as a plural term in the random-effects models (Steel et al., 2021). Sources of variation or heterogeneity in the effect sizes are the sampling error of each study population (i.e., within-study variance) and sampling error of the universe of all relevant populations (i.e., between-studies variance; Grewal et al., 2018). More importantly, the generalization of meta-analysis results in the

random-effect model is not limited to studies included in a meta-analysis. Therefore, most of the meta-analyses in business and management prefer to choose a random-effects model.

4.4.3 | Homogeneity analysis

Homogeneity analyses help authors to test variation among effect sizes in prior studies necessary and to define appropriate moderators to capture and justify this variation. Q and I^2 tests are used to test the homogeneity between effect sizes (Steel et al., 2021). Q statistics test the null hypothesis of homogeneity versus heterogeneity. If the result exceeds the X^2 critical value, indicates the heterogeneity of effect sizes (Card, 2015). When there is no heterogeneity among the effect sizes, the result would be one with a higher number denoting higher heterogeneity between effect sizes. In business and management, this statistic is usually higher than one, indicating heterogeneity in effect sizes from individual studies. Q-tests, however, cannot indicate the magnitude of the heterogeneity in effect sizes; therefore, authors use the I^2 statistic which indicates the percentage of variability between effect sizes attributable to the total variability among effect sizes. Since I^2 is in the form of a percentage, it shows the magnitude of heterogeneity among effect sizes. Usually, an effect size of 25% is considered as small, 50% is medium, and higher than 75% is considered large heterogeneity (Card, 2015).

4.4.4 | Overall analysis

In the overall analysis, the meta-analyst tests the relationships in the proposed framework. Two main methods for the overall analysis are univariate analyses and meta-analytic structural equations modeling.

Univariate analyses

In the overall analysis, we test the pairwise relationships in our framework through univariate analyses. Univariate analysis involve testing the significance of combined and corrected effect sizes for each pairwise relationship (Steel et al., 2021). Moreover, univariate analysis allows the researcher to determine the direction and strength of the relationship between two variables, and thus provide insight into the relationships between concepts in the meta-analytic framework. Palmatier et al. (2006) use univariate analysis to study relationships between customer, seller, and dyadic antecedents and customer-focused relational mediators (e.g., commitment, trust, and relationship satisfaction) to study both influences of different antecedents on mediators and interrelationships among these antecedents.

Meta-analytic structural equation modeling

Univariate analyses only involve effect sizes of pairwise relationships; however, with meta-analytic structural equations modeling (SEM), the researcher correlates all variables in the meta-analytic framework with the correlation matrix. The correlation matrix is used as input for SEM to test different relationships between variables of interest (Jak, 2015). Because the sample size for different correlations is not equal, authors must calculate the harmonic mean for analysis. Compared to the arithmetic mean, the harmonic mean gives less weight to large sample sizes and thus parameter estimation is better. As with SEM, the researcher uses statistics to assess the model fit with the data. Based on these statistics, the optimal model which has the best fit with data is determined. Jiang et al. (2012) employ meta-analytic SEM in their study, defining several mediation variables to provide in-depth analysis of how three dimensions of human resource (HR) practices affect organizational performance. Their optimal model highlights that HR practices through mediation variables (i.e., human capital, employee motivation voluntary turnover, and operational outcome) impact firm financial outcomes.

4.4.5 | Analysis of moderators and control variables

A moderator analysis allows researchers to capture variations in the relationship(s) of interest and resolve contradictory findings (Steel et al., 2021). With a meta-analysis, authors can include new moderators which have not been tested in the original studies to provide more insight on the topic. The meta-analyst examines control variables to determine if the variability in the effect size for the pairwise relationship is because of these variables. Three main approaches for conducting a moderator analysis are subgroup analysis, meta-regression, and multilevel analysis.

Subgroup analysis

Subgroup analysis is used to test moderator effects in a meta-analysis (Steel et al., 2021). In a subgroup analysis, the meta-analyst computes the mean effect for different subgroup studies (Borenstein & Higgins, 2013). Then, the means of two or more sets of studies are compared and analysis of variance or t-tests are used to analyze the significance of differences (Borenstein et al., 2021). Subgroup analysis is limited to moderators that are categorical; continuous variables require dichotomization, which degrades information and reduces statistical power.

Meta-regression

With meta-regression, the meta-analyst uses regression analysis to study whether fluctuations in effect sizes for pairwise relationship(s) are explained by a moderator variable (Steel et al., 2021). In this analysis, moderator variables are predictors and effect sizes are dependent variables. Meta-regression can accommodate both continuous and categorical variables in the analysis (Aguinis, Pierce, et al., 2011); however, a high correlation between independent variables (i.e., multicollinearity) can cause problems with fit for model and interpreting results. The authors could use WLS regression instead of ordinary least squares to reduce the multicollinearity in the meta-regression (Steel & Kammeyer-Mueller, 2002). To illustrate, Blume et al. (2010) studied the impact of independent variables (i.e., trainee

characteristics, work environment, and training interventions) on the transfer of training using meta-regression analysis. Tasks and context-based moderators (e.g., employee experience and pretraining self-efficacy) were also assessed. Their results confirm the ability of these moderators to explain the inconsistencies in the impact of predictor variables on the transfer of training.

Multilevel analysis

In business and management, we extract multiple effect sizes from an original study. As these effect sizes are not independent, ignoring these tendencies led to the underestimation of standard error (Grewal et al., 2018). In the multilevel meta-regression, we define multiple levels to account for this issue, providing a more accurate estimation (Gremler et al., 2019). Multilevel models in a meta-analysis usually include two levels: (1) level one indicates information that varies within studies (i.e., effect size level); and, (2) level two includes characteristics that vary between studies (i.e., study level). Similar to meta-regression, effect sizes are the dependent variable while mediators and outcome variables are predictors in level one. Moderators and control variables are in the second level. To test the model, an iterative generalized least squares procedure is used which provides maximum likelihood estimates and variables that are centered in the model (Gremler et al., 2019). For example, Roschk and Hosseinpour (2020) used multilevel analysis to assess moderators to the relationship between ambient scents and customer responses. They defined a different group of moderators such as scent characteristics, scent perceptual properties, environmental factors, research operational factors, and individual factors to provide a clear and detailed overview of the role of in-store ambient scents on customer wide ranges of responses such as mood, evaluations and, behaviors.

4.4.6 | Meta-analytic software

Comprehensive Meta-Analysis

Comprehensive Meta-Analysis (CMA) software is employed wide in meta-analyses in business and management (Rana & Paul, 2020). This software enables the meta-analyst to import effect sizes in different formats or directly input effect sizes into the program. It also allows authors to conduct different statistics into the desired effect size metric (e.g., a correlation coefficient or standard mean difference). Furthermore, CMA helps researchers assess outlier, publication bias, and heterogeneity in the database and examine both fixed- and random-effects models.

Review Manager

Review Manager (RevMan) is a web-based software that manages the entire literature review process and meta-analysis. The meta-analyst uploads all studies to RevMan library, where they can be managed and exanimated for inclusion. Like CMA, RevMan enables authors to conduct overall analysis and moderator analysis.

Stata

Stata allows authors to conduct a wide range of statistical analyses, including meta-analyses. Stata enables the meta-analyst to develop forest plots to analyze outliers and to conduct a heterogeneity analysis. Further, researchers can conduct univariate analysis for the overall analysis, and subgroup, meta-regression, and multilevel regression for the moderator analysis. Stata also estimates both fixed-effects and random-effects models.

R packages

R has several packages developed for meta-analyses, such as the *psychmeta* (Dahlke & Wiernik, 2019) and *metafor* (Viechtbauer, 2010). These packages cover almost all aspects of data analysis in a meta-analytic study such as effect size corrections/combination, outlier analysis, publication bias estimation, and both the overall analysis and moderator analysis. Compared to commercial software/programs, such as CMA, RevMaN, and Stata, R is open-source and free; however, some familiarity with R coding is necessary to install packages, import data, and conduct the meta-analysis.

4.5 | Reporting

One of the challenging parts of meta-analysis is writing the report. The meta-analyst must comprehensively describe the details of each step of the meta-analysis in a logical, and easy-to-follow sequence (Siddaway et al., 2019). Based on prior meta-analyses in business and management, we propose a structure for writing up a meta-analysis. Like manuscript paper, a meta-analysis includes a title, abstract, introduction, theoretical background, conceptual framework and hypotheses, methodology, data analysis, and general discussion. However, with a meta-analysis, the content of each section is somewhat different.

4.5.1 | Title

A meta-analysis title should reflect the primary relationships, concept (s), or construct (Cooper, 2015). Moreover, it is better to include the term “meta-analysis” or “meta-analytic review” in the title, to gain the audience's attention and ensure it can easily be located in database searches (Kepes et al., 2013). An example of an appropriate title for a meta-analysis is “A Meta-analysis of Customer Engagement Behaviour” (Barari et al., 2021), which describes the focal relationships and includes “meta-analysis” in the title.

4.5.2 | Abstract

Summarizing a meta-analytic study in a short paragraph can be a challenging task. The meta-analyst should mention the main relationships explored in the meta-analysis, and explain its importance (Cooper, 2015). The number of studies and observations should be

highlighted to demonstrate the power of meta-analysis (Kepes et al., 2013). The abstract of meta-analysis should also summarize key findings and takeaways. Specifically, the meta-analyst should provide an overall view of results from the overall analysis and moderator analysis, and highlight significant contributions of meta-analysis to the research domain (Cooper, 2015).

4.5.3 | Introduction

The introduction of a meta-analysis could begin with a real example to highlight the topic of interest and its importance for the meta-analytic study (Siddaway et al., 2019). Then, authors should provide a brief history of the main research topic, explain key concepts, construct, and theories in the research domain (Cooper, 2015). The meta-analyst should also describe the relevant literature, highlighting conflicting findings in prior studies and unresolved research questions (Kepes et al., 2013). Doing so helps to justify the necessity of a meta-analysis and engage readers. The author should explain how the meta-analysis will help resolve discrepancies in the literature and provide an overview view of the research domain (Cooper, 2015). For example, in Iyer et al.'s (2020) meta-analysis of impulse buying behavior, the introduction explains the importance of this topic from a practical and academic perspective, and describes various research streams that examine the triggers of impulse buying from different perspectives. They also explain why a meta-analysis on impulse buying is necessary (i.e., to combine and synthesize these diverse studies). Finally, the authors briefly explain their meta-analytic framework, and how their work contributes to this study domain.

4.5.4 | Background and theoretical framework

A meta-analysis aims to provide a comprehensive inventory view of a specific research domain (Grewal et al., 2018). Thus, it is necessary to discover the history, relevant definitions, and research stream in the background section of the manuscript (Siddaway et al., 2019). Tables may be used to depict different aspects of research domain. The authors should also develop a Meta-analytic framework based on prior research streams in the topic, drawing on relevant theory to explain relationships between key variables and formulate hypotheses (Cooper, 2015). To illustrate, the background section of Rana and Paul's (2020) meta-analysis of organic food purchase, first illustrates organic food, then discovers organic food consumers and factors that affect consumers' organic food purchases. They then develop a meta-analytic framework that depicts the relationships between health motives and consumers' organic food purchases.

4.5.5 | Methodology

A meta-analysis should feature a method section that is transparent and accurate, rationalize methodological choices made by researchers (Siddaway et al., 2019). In this section, the meta-analyst should detail the data collection, procedure used, and explain the data preparation and analysis process (Cooper, 2015). In the data collection section, meta-analyst should provide details of the search strategy and process employed (i.e., keywords, databases, manual searches, and others effort(s)) to identify all related publications and decrease publication bias (Cooper, 2015). Authors must also describe inclusion/exclusion criteria and data coding processes (i.e., the coding manual, who coded the papers, and coder agreement rate) and explain these decisions (Kepes et al., 2013). After this, the meta-analyst must describe the final sample characteristics to provide an overview of studies included in the meta-analysis (Siddaway et al., 2019). In data preparation, authors need to explain effect size extraction/calculation, corrections employed, and any issues involved in this process (Cooper, 2015). Moreover, authors need to describe analyses to assess outliers, publication bias, and heterogeneity and their meta-analytic model (i.e., a fixed-effects model or a random-effects model). Finally, the authors must describe the overall analysis and moderator analysis, regarding software that was used (Cooper, 2015).

4.5.6 | Data analysis

In the data analysis section, the meta-analyst describes the descriptive analysis, overall analysis, and moderator and control variables analysis (Cooper, 2015). The descriptive analysis section details result of the outlier analysis, and how the researcher dealt with them, as well as the publication bias check and heterogeneity test. In the overall analysis, researchers statistically characterize the relationships between variables in the meta-analytic framework and their significance. The authors can use different statistical techniques to maximize their analysis in the overall analysis (Kepes et al., 2013). For example, in their meta-analysis investigating the relationship between HR practices and organizational outcomes, Jiang et al. (2012) *Z*-test statistic to study relative impact of HR practice on employee motivation and human capital. Moreover, meta-analytic SEM is employed to test how Human Resources practice through a mediation process influences the organizational outcome. The moderator analysis entails defining numerous variables that may impact variations in the original studies. Ancillary analyses may also be conducted to extend findings or explore specific relationships (Cooper, 2015). For example, in their meta-analysis of customer responses to in-store ambient scents (Roschk & Hosseinpour, 2020) explored numerous moderators and examined specific interaction effects to enrich their moderator analysis.

4.5.7 | Discussion

This section address how researchers might describe theoretical and managerial implications of conducting meta-analysis, limitations assigned with this technique, and future research directions (Kepes et al., 2013). In discussing implications, the authors should consider using a table to summarize their key research findings, organized by

research hypothesis or the meta-analytic framework. They could then discuss the theoretical and managerial implications of these key findings. For example, Palmatier et al.'s (2006) meta-analysis on factors affecting the effectiveness of relationship marketing presents a table with key findings for antecedents, outcomes, and moderators, which illustrates theoretical and managerial implications of their research. As with often methods, a meta-analysis has specific limitations that must be acknowledged (Siddaway et al., 2019). This also helps authors to identify avenues for future research. For example, a meta-analysis is based on and restricted by prior studies, and there might not be enough effect sizes for all relationships of interest to analyze. Similarly, many potentially interesting moderators may not be examined because of insufficient information because insufficient information in the original studies prohibit systematic coding. Moreover, meta-analysis involves a combination of statistical techniques and each of which has limitations. The meta-analyst must explain such limitations and explain their method selection (Siddaway et al., 2019). Involvement in the meta-analytic process enables researchers to identify the areas where more scholarly attention is needed, and topics for extended research.

4.5.8 | Appendix

An appendix in a meta-analysis typically provides supporting data and analyses, such as studies included in the meta-analysis and its coding (Siddaway et al., 2019). The authors could include complete descriptions of all pairwise relationships in the appendix, along with ancillary data analyses and results. For example, Gremler et al.'s (2020) appendix included a list of journals manually searched by researchers, studies included in the meta-analysis, sample characteristics, moderator and control variable coding, study characteristics, and results of all pairwise analyses and extra analyses.

5 | META-ANALYSIS ADVANCEMENTS

In this section, we describe meta-analytic advancements in recent years, which have enhanced the accelerating of scientific knowledge development and its accuracy.

5.1 | Bayesian analysis

Bayesian meta-analysis is based on Bayes' theorem, which asserts that the probability of an event is based on prior knowledge of that event (Joyce, 2003). The main advantage of the Bayesian approach is incorporating prior knowledge or information about a phenomenon into inferences, which improves analysis (Rossi et al., 2012). Bayesian analysis has recently been introduced to meta-analysis (Higgins et al., 2009). A distinctive feature of Bayesian meta-analysis is in the effect size combination step, when researchers take a different approach to pool effect sizes from individual studies and create a combined effect size. The Bayesian analysis allows authors to include a prior expected sampling distribution of a quantity of interest (Higgins et al., 2019). Bayesian analysis aids in estimates of an alternative distribution of variability among effect sizes from prior research, which is more accurate. Some researchers believe that, compared to traditional meta-analysis, the Bayesian method is more accurate and less unbiased for effect size variance estimation (Steel et al., 2015).

5.2 | Network analysis

Researchers are often interested in determining the relative effectiveness of different interventions and treatments in a population (Higgins et al., 2019). This is difficult to do using the traditional meta-analytic technique; however, network meta-analysis allows researchers to review the comparative effectiveness of competing interventions. For studies with more than two interventions, when the direct compression between a network of interventions is available, network analysis allows indirect comparisons of multiple interventions. The meta-analyst uses mathematical combinations of direct interventions effect available to estimate the indirect comparisons between interventions. In a network meta-analysis, authors combine these direct and indirect estimates across a network of interventions in a single study and make more meaningful comparisons (White, 2015).

5.3 | Machine learning in meta-analysis

Machine learning is a computer algorithm that learns from experience to perform a specific task through the statistical modeling of data (Mitchell, 1997). One of the important implications of machine learning is handling large-scale data and unstructured data. A sample of data is entered into the algorithm as a training data set to teach the algorithm; then, the task is completed based on this training. This process can facilitate data analysis, especially when manual work would be very time-consuming. In a meta-analysis, researchers follow various strategies to include all related publications in their databased development, and devote considerable time to extracting the required information from each individual study. Through training and test data, the authors set out to develop an algorithm that could help meta-analysts complete these tasks and increase the quality of their work (Marshall et al., 2018). Marshall and Wallace (2019) discuss the role of machine learning in facilitating their meta-analysis, and provide practical suggestions for using machine learning algorithms to extract aspects of the meta-analysis process, including data collection, screening, and data extraction.

6 | CONCLUSION

Meta-analysis is an effective way to advance current knowledge in business and management, and is more scientific than a pure bibliometric type of SLRs. Therefore, there is increasing interest

among researchers to publish meta-analysis papers because of their impact on knowledge development. However, the technical nature of meta-analyses may prove daunting for academics and practitioners to understand and conduct. Thus, in the current research, we demonstrate this study method to facilitate researchers' understanding of how to conduct meta-analysis.

A meta-analysis begins with a fruitful and novel research question, such as reconciling the conflicting findings in a research domain. This question definition helps researchers develop a Meta-analytic framework to guide the whole meta-analysis process. The authors then engaged in data collection, employing different strategies to include different types of publication in the process and applying logical inclusion/exclusion criteria to finalize the meta-analytic database. Then, the meta-analyst uses a coding manual to code primary variables, moderators, and control variables in each individual study, extracting or calculating the effect sizes, assessing outliers and publication bias, and combining effect sizes. Once the meta-analyst has selected a fixed-effects model or random-effects model, heterogeneity is assessed and the overall testing pairwise relationships in the framework are conducted. Moderators are then analyzed. Various software packages are available for conducting meta-analyses including commercial programs (e.g., CMA, Review Manager, and Stata) and open-source (R packages) software. Finally, the meta-analyst reports the result. This manuscript proposes an overarching structure to cover all important aspects of a meta-analysis in business and management.

It is worth noting that meta-analysis is an evolving method that has seen several advancements in recent years that expand the effectiveness and accuracy of results. Meta-analytic Bayesian analysis and network analysis are examples of promising advancements in meta-analyses. Finally, employing machine learning in meta-analysis has been shown to facilitate the meta-analytic process and increase its quality. This promising approach is in its initial stages and needs more development before use in practice.

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