Decoding evidence-based entrepreneurship: A systematic review of meta-analytic choices and reporting

Andreas Rauch*
Audencia
Nantes
France
Arauch@audencia.com
and
Johannes Keppler University
Linz
Austria

Saadat Saeed
Durnham University
Durham
UK

Michael Frese
Department of Management & Organisation,
Leuphana University of Lueneburg
Lueneburg
Germany
and
Asia School of Management
Management & Entrepreneurship
Kuala Lumpur, Malaysia

* Corresponding author

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Meta-analysis—the statistical analysis of a large collection of analysis results from individual studies for the purpose of integrating the findings (Glass, 1976, p. 3) substantially contributes to paradigm development in the field of entrepreneurship. Notably, a number of choices are made when conducting a meta-analysis. Many of these choices have implications for the interpretation of the results, affecting one of the core aims of meta-analysis, that is, to generate generalizable best evidence. To better understand meta-analysis evidence in the field of entrepreneurship it is essential to understand how these meta-analyses are conducted, what type of methodological choices have been made and communicated, and how these choices affect the interpretation of findings. To address these issues, we performed a content analysis of 90 meta-analyses up to 2021 and investigate 74 methodological choices made by the authors. We identify and offer suggestions for future practice in seven areas: the study location strategy, the use of a second coding, the assessment of heterogeneity, multivariate analysis, quality checks, the violation of assumptions, and the interpretation of meta-analytical findings. In so doing, we hope to contribute to best practices and to the legitimacy of validity generalization in the domain of entrepreneurship research. Moreover, we provide a comprehensive and evidence-based understanding of the interpretation and implications of meta-analysis practices for theory building and testing and scholarly impact.

Keywords: Meta-analysis, entrepreneurship, quantitative review, research synthesis

Introduction

Meta-analysis has revolutionized the field of entrepreneurship in four ways. First, it has helped to solve vivid debates in the field (Rauch & Gielnik, 2020), e.g. whether personality matters in entrepreneurship (it does) or whether planning is harmful or beneficial (it's beneficial!). Second, because meta-analyses have proven helpful for reaching consensus on dominant relationships and theories, it provides a quantitative way to reach paradigm development and theoretical convergence (O'Boyle, Rutherford & Banks, 2014; Kuhn, 1996) in the domain of entrepreneurship. Third, creating valid inferences from the scientific research conducted in the field enhances the legitimacy of both the method and the discipline as a whole (Steel, Beugelsdijk & Aguinis, 2021). Fourth, entrepreneurship is an applied discipline seeking relevance (Wiklund et al., 2019), and meta-analyses conducted with rigor can play a critical role in facilitating best practice and relevance to practitioners (Frese et al., 2012).

Consequently, meta-analyses have become a popular tool for summarizing the empirical evidence in the field of entrepreneurship. We identified as many as 13 meta-analyses conducted in 2023 alone, and meta-analyses are published in the top entrepreneurship journals such as *Entrepreneurship Theory and Practice* (10 meta-analyses), *Journal of Business Venturing* (13 meta-analyses) and *Journal of Small Business Management* (3 meta-analyses). Moreover, meta-analyses reach much higher citation rates than primary studies (Aguinis et al., 2011).

Given the increasing prominence of meta-analyses in the field of entrepreneurship, it is important for those who conduct, read, and cite meta-analyses that these meta-analyses are performed correctly and interpreted with regard to the many specific choices made during the meta-analytic process. There are widely accepted norms on how to conduct a meta-analysis and, besides some standard works on the topic (for example, Hunter & Schmidt, 2004), there are numerous papers addressing specific considerations of methodological challenges in meta-analysis (Cheung, 2019; DeSimone et al., 2020; Geyskens et al., 2009; Gusenbauer &

Haddaway, 2020; Harari et al., 2020; Huffcutt & Arthur, 1995; O'Boyle et al., 2014; Peterson & Brown, 2005; Schmidt, 2017). Hence, one would expect that the standard meta-analysis applied in the domain of entrepreneurship is of high quality.

However, the rigor of entrepreneurship meta-analysis varies widely. To a large extent, this is due to the fact that the method requires researchers to make many choices during the meta-analysis process, which may affect findings and conclusions. For example, a meta-analysis may be designed to cover only a restricted part of the literature (location choice) or to identify methodologically inadequate studies (study inclusion choice), the strategies applied for coding of studies may lead to meaningless categories, the meta-analytic effects might be nonlinear and multivariate, and sometimes the underlying decisions may not reflect best choices. Intense discussion about the impact of such decisions in the field of management is ongoing (Aguinis, Pierce, Bosco, Dalton, & Dalton, 2011; Eysenck, 1994). For example, Ferguson and Brannick (2012) report publication bias in 40 percent of published meta-analyses in management, and O'Boyle et al. (2014) report similar problems in entrepreneurship meta-analyses. As various tools for addressing publication biases are available (Page et al., 2021), decisions concerning whether and how to address these potential biases are among the many choices that a researcher must make. Even though there is evidence that publication bias does not inflate research findings (Dalton et al., 2012) and, more generally, that meta-analytical choices do not affect the magnitude of effect sizes reported in the management literature (Aguinis et al., 2011; Schalken & Rietbergen, 2017), these choices would still have a number of important consequences. For example, reporting issues are important: Researchers conducting meta-analyses should be explicit about method choices to allow meta-analytical findings to be replicated (for example, the American Psychological Association (APA) reporting standards for meta-analyses, Appelbaum et al., 2018). Moreover, methodological choices in meta-analyses affect how they are conducted, which in turn may artificially inflate (or reduce) results (Arthur et al., 2001). In addition, these choices may affect the interpretation of meta-analytical findings. For example, not addressing unexplained and remaining effect size heterogeneity reduces the generalizability of findings. Some meta-analytical choices might not even be right or wrong but still would affect the interpretation of findings (e.g. whether r or d values are used as effect size estimates). Therefore, a meta-analysis must be interpreted in light of the decisions made during the meta-analysis process. Thus, well conducted meta-analyses can create legitimacy for both the method and the field of entrepreneurship as a whole.

The primary purpose of our systematic review of the use of meta-analysis in the domain of entrepreneurship is to improve future meta-analytic studies. Our contribution lies primarily in methodological critique and recommendations for using meta-analyses in entrepreneurship research. Thus, our goal is not to contribute to theory, but to the methodological choices researchers make when conducting meta-analyses. While emphasizing the methodological issues of meta-analysis, we do not think that this is unimportant from a theoretical perspective. Quite in contrast, we believe that our contributions are of high theoretical importance for evidence-based entrepreneurship. Evidence-based entrepreneurship pursues science-informed practices of entrepreneurship; a prerequisite of evidence-based entrepreneurship is the unbiased accumulation and interpretation of science-based practices in entrepreneurship (Frese et al., 2014). In turn, meta-analysis can produce important contributions to theory (Chan & Arvey, 2012) if results are based on good evidence—and a good way to produce such evidence is the use of meta-analysis.

In this article, we examine how these analyses are conducted to evaluate the methodological choices underlying them, how these choices are communicated, and how the interpretation of findings is affected by these choices. Our review is the first comprehensive review of meta-analysis practices in entrepreneurship research, although such reviews exist in other disciplines. Table 1 lists previous reviews on meta-analyses in the broader context of management and organizational behavior. These reviews differ in scope. Some looked at one specific element (for example, publication bias, heterogeneity, literature search) or at one specific domain (for example, organizational behavior). Other reviews investigating a broad set of meta-analytic practices focus on analyses published in one journal such as the *Journal of Vocational Behavior*. It is also interesting to observe that the two reviews of meta-analyses that have a relatively broad scope (Aguinis et al., 2011; Geyskens et al., 2009) are also relatively dated. Our contemporary review covers more recent trends and developments in meta-analysis, such as meta-analytical regession analysis and meta-analytical structural equation analysis. Moreover, our approach is also unique because we do not restrict our scope to specific aspects of meta-analysis but rather aim to analyze practices of the entire meta-analytic process in the domain of entrepreneurship and thus develop a more holistic analysis.

Our review is guided by three overarching aims: First, we want to provide a comprehensive reference source describing how meta-analyses are conducted in entrepreneurship research. Through a systematic review of existing research on meta-analysis methods applied to entrepreneurship phenomena, we quantify the current state of these methods and identify the gaps and best practices for consideration in future studies. We do not seek to provide another "how to do" or "how to report" guide, as such guides are available (DeSimone et al., 2020; Geyskens et al., 2009; Steel et al., 2021). Instead, we want to examine the meta-analytical choices made by entrepreneurship researchers and understand the consequences of these choices. Thus, our contribution is first and foremost not designed to instruct authors on how to conduct a meta-analysis, but to enable reviewers, editors, and people reading meta-analyses to understand meta-analytical evidence, and to articulate evidence-based best practices. Second, researchers are faced with numerous decision decisions when conducting meta-analyses in the field of entrepreneurship. We articulate seven critical decisions that our analysis identified as challenging in entrepreneurship research: the process used to locate studies, the use of a second coder, the assessment of heterogeneity, the multivariate endeavor, the use of quality checks, the violation of test assumptions, and the interpretation of meta-analytic findings. We further introduce exemplary studies to help academic researchers identify best practices for accumulating scientific knowledge. As such, it is critical that choices are reported and results are interpreted in light of such choices. Thus, while discussing the seven critical decisions offers a resource for rigorously conducting a meta-analysis in the field of entrepreneurship, our central aim is not to suggest best practices but rather focus on the consequences of meta-analysis choices. Thereby, this systematic review, provides a resource for academic entrepreneurship researchers interested in the use and understanding of meta-analysis for research. Third, some researchers argue that meta-analysis can contribute to paradigm development in management (Chan & Arvey, 2012) and entrepreneurship—if the meta-analysis is carefully and comprehensively conducted (O'Boyle et al., 2014). Specifically, meta-analysis can add to what Kuhn (1996) called "normal science" by clarifying constructs and their relationships with other variables, by providing validity information, and by facilitating consensus about phenomena. As a consequence, meta-analysis can help the development of the field by specifying which paradigms are supported or not. We hope that our approach will help meta-analysts conduct meta-studies in such a way that allows the facilitation of this important role of meta-analysis.

The remainder of the article begins with a discussion on the specific challenges associated with meta-analyses in the field of entrepreneurship. Next, we outline our methodology for identifying and coding the meta-analyses. We then describe the results of our content analysis of these studies.

Insert Table 1 about here

The role of meta-analysis in the theory of entrepreneurship

Entrepreneurship is a broad field encompassing numerous subject areas. Many researchers argue that the entrepreneurship literature ought to be a "big tent" and should be multidimensional (Chrisman et al., 2022; Sandberg & Hofer, 1987; Shepherd et al., 2019; Wiklund et al., 2009). One consequence may be that the literature is fragmented, based on different theoretical perspectives and different uses of methods to operationalize constructs (Davidsson et al., 2001; Shepherd et al., 2019). As a result of this fragmentation, the entrepreneurship literature is debating whether dominant paradigms exist in the field and, if so, whether their development leads to theoretical convergence (Audretsch et al., 2015; Davidsson, 2023; Low, 2001; Shepherd et al., 2019). For example, one critical characteristic of entrepreneurship research is that it might be evolving from focusing on a single paradigm toward a perspective that conceptualizes multiple paradigms (Kuhn, 1996). While the papers cited above provided a qualitative answer to the question of paradigm development, meta-analyses can contribute to paradigm development in a quantitative way, for example, by increasing precision and scope in entrepreneurship theory and research (Chan & Arvey, 2012). However, using meta-analysis in this way is associated with some challenges that researchers face and, to anticipate it, require that meta-analyses are conducted in a careful way, that decisions are communicated, and that results are interpreted correctly.

First, most meta-analyses in entrepreneurship research did not analyze multiple paradigms and did not try to integrate multiple constructs (an exception is, for example, Song et al., 2008) but rather focused on one construct or on the relationship between two constructs. Subsequently, these meta-analyses investigated boundary conditions (moderators) affecting this relationship, thus aiming to increase the precision and scope of relationships. The challenge with such an approach is that it ignores the multidimensional nature of entrepreneurship. For example, any single predictor of growth and entrepreneurial orientation might have small effects, a multivariate analysis accounting for direct and indirect effects could explain much larger effects sizes (30 to 40 percent of the variance, Wiklund et al., 2009). Thus, bivariate effect sizes may show only weak relationships with the dependent variables.

Second, small effects may also be expected when there are multivariate effects on the dependent variable (Prentice & Miller, 1992) that are beyond the control of entrepreneurial actions. For example, firm growth is affected by the general economic situation or by dramatic environmental changes, such as the COVID-19 pandemic. These multivariate influences contaminate any single study's findings; this is particularly the case in such a dynamic field as entrepreneurship.

Third, small effects may also result from reduced variance in independent variables. For example, many people in developed countries are well-educated, reducing the variance of human capital producing small effects on performance in developed countries (Unger et al., 2011). One of the most difficult problems is the selection effect leading to reduced variance in all variables: Empirically, entrepreneurship research usually bases its results on existing firms—these firms are by necessity already a subset of firms in general as only the best firms survive. As a consequence, and as the results of the weakest firms are not included in primary studies, meta-analytical effect sizes are smaller due to range restrictions than they would be in unselected populations of firms. Thus, surviving firms inevitably reduce variance in all important variables.

Finally, the field focuses on practice and relevance, and it studies phenomena in the real world (Wiklund et al., 2019). As a consequence, true controlled lab experiments are seldom done in entrepreneurship research. This produces ample noise in the data, which makes it difficult to detect consistent relationships in entrepreneurship research.

As a result of these challenges, small effect sizes are commonly reported in entrepreneurship research. Small effect sizes are difficult to detect even though they can have important practical and theoretical implications. Aguinis and Harden (2009) discussed a number of examples of how small effects (for example, 1 percent gender differences in performance appraisals) can have important consequences (for example, only 35 percent of top positions held by women). Moreover, small effect sizes can be important when the effects accumulate to meaningful outcomes (Abelson, 1985). However, small effects can only indicate strong evidence if effects are carefully established and if they can be interpreted in face of methodological choices communicated by the researcher conducting the meta-analysis (for example, whether or not heterogeneity could be addressed or whether there is a risk to validity or threats of biases).

This situation—a discipline relying on multiple interrelated paradigms, a lot of noise in the data, and the need to provide relevant practice suggestions—makes it particularly important that meta-analyses within the context of entrepreneurship are conducted rigorously, that the choices made in the meta-analysis and their implications are communicated clearly, and that the results are interpreted correctly. In the following, we present how we located, coded, and analyzed the meta-analyses focusing on entrepreneurship research.

Methodology

Study location

The aim of our study was to identify all meta-analyses conducted in entrepreneurship research up to 2022. Thus, we did not set a starting date for the studies we located. We searched the databases Web of Science, Abi/Inform, and EconLit. Web of Science is interdisciplinary. It captures open access publications, journal articles, and conference proceedings. Both EconLit and ABI/Inform focus on business and economics, which are primary areas of entrepreneurship research. In addition, they permit the identification of unpublished studies such as dissertations. In addition, we searched for meta-analyses in the most important entrepreneurship journals included in the FT50 list: *Entrepreneurship Theory and Practice*, *Journal of Business Venturing*, and *Strategic Entrepreneurship Journal.* In addition, we selected three broader non-entrepreneurship journals that previously published entrepreneurship meta-analyses: *Academy* *of Management Journal*, *Journal of Business Research*, and *Journal of Family Business.* As we cannot search "all" journals, such a strategy is necessarily selective. Nevertheless, it is common to supplement the search in databases by checking additional core journals (Schwens et al., 2018; Steinmetz et al., 2021). We used the key words meta-analys* combined with entrepreneur* and small business for both databases and journal search. Moreover, we included all meta-analyses that were included in previous meta-reviews in the domain of entrepreneurship (Brandstaetter, 2011; Frese et al., 2012; O'Boyle et al., 2014; Rauch & Gielnik, 2020).

Criteria for inclusion

To be included in our analysis, the meta-analyses had to meet several criteria. First, the meta-analysis had to report the data on which it is based: the number of studies, the number of participants in these studies, and the effect size statistic. Second, we wanted to analyze independent meta-analyses, thus, each meta-analysis should be included only once in the analysis. Next, all meta-analyses investigated entrepreneurship broadly defined, including those focusing on young ventures (for example, Song et al., 2008), small ventures (Schwenk & Shrader, 1993), owner-managed firms (Zhao & Seibert, 2006), family firms (O'Boyle et al., 2012), as well as meta-analyses that defined their sample into the domain without further specifying the type of ventures included in the analysis (Collins et al., 2004). We appreciate such a broad approach because it avoids biasing our results to a subclass of entrepreneurship research (Prince et al., 2021). Moreover, each of the subfields of entrepreneurship contribute and improve the understanding of entrepreneurship as a whole (Baker & Welter, 2017). Needless to say, our quantitative approach allows us to control for potential differences between different subclasses of entrepreneurship research.

We took several steps to determine which studies should be included in our review (compare Figure 1). First of all, our broad study location procedure resulted in 2,019 records.

After identifying and deleting duplicates, 625 records remained. Of these, we identified 504 studies that were not meta-analyses as defined by Glass (1967). The next step entailed reading the meta-analyses in detail; this led to the exclusion of another 31 studies for the reasons indicated in Figure 1. Notably, we also did not locate and include two meta-studies that re-analyzed previous meta-analyses in entrepreneurship research (O'Boyle et al., 2014; Rutherford et al., 2017) as the meta-analyses included in these reviews are already included in our database, thereby, we aimed at having independent assessments of meta-analysis choices. Thus, applying our inclusion criteria resulted in 90 meta-analyses. Appendix 1 provides a complete listing of the meta-analyses included in this review.

Insert Figure 1 here

Coding procedure

Our coding protocol was inspired by the APA's reporting standards for meta-analyses (Appelbaum et al., 2018). The APA's reporting standards integrate similar efforts of many fields, focus on social science research, were developed in an international context, and serve as a communication tool that allows us to assess the choices that are made during the meta-analytical process. Appelbaum et al (2018) described 56 methodological choices that need to be reported, referring to inclusion and exclusion criteria, information sources (study location), study selection, validity assessment, methods of synthesis, and bias analysis. Inspecting these guidelines, it became clear that some important information required to assess meta-analyses in the domain of entrepreneurship must also be added such as, for example, whether an outlier analysis has been performed and how multivariate meta-analysis has been performed. Therefore, we inspected additional coding schemes that have been used in reviews of meta-analyses (Aguinis, Dalton, et al., 2011; DeSimone et al., 2020; Geyskens et al., 2009) to ensure that we included all relevant meta-analytical decisions in our coding. Ultimately, our coding protocol describes 78 decisions made in the meta-analyses, thus, our analysis is more detailed than other analyses of methodological meta-analysis choices. Table 2 summarizes the most important choices we coded (Appendix 2 contains the complete coding protocol). There may have been additional decisions and checks that we did not report in our final analysis, but due to our primary interest in the communication of the choices and the respective interpretation of study results, the information reported in the articles is the appropriate level of analysis. In addition to the methodological choices, we searched and added the impact factor of each respective publication outlet. Moreover, we calculated the overall effect size of each meta-analysis using the data provided in the respective meta-analysis.

We content-analyzed each of the meta-analyses and coded the choices made by the authors. Whereas one member of the author team performed the full coding, two others each coded 10 percent of the meta-analyses. The coding was highly reliable, with an agreement of 96.67 percent. The coding is generally based on facultative information, asking the coder to determine whether a decision was reported or not. The exception was one item asking coders to count the number of databases used. We also coded the quality of reported selection criteria on a 5-point scale. Because there is no standard in reported selection criteria, these could be comparatively vague or specific. We used anchors for coding this item, assigning 1 if the description was vague and 5 if the description was specific and would allow readers to replicate the study selection process. In addition, we coded the detailedness of the information about primary studies included in each meta-analysis, assigning 5 if the information was very detailed, including the coding of moderators and the effect size, and assigning 1 if only the study reference was provided.

Insert Table 2 about here.

Results

Table 2 shows the frequencies and the percentages of meta-analytical decisions made in the 90 meta-analyses. We organized the results displayed in Table 2 into four broad sections: decisions made before the meta-analysis was conducted (for example, study location, inclusion criteria, coding process), decisions made regarding the analysis (effect size metric used, corrections made, choice to use multivariate analyses and how they are conducted), decisions involving quality checks and post-hoc analyses (for example, analysis of outliers, publication bias), and decisions made related to interpretation of meta-analysis findings.

The table is informative about normative practices in the field (for example, it is common to have multiple strategies to search literature, to use the effect size statistic r, and to report the observed variance). While many decisions are in line with golden standards of meta-analysis (Hunter & Schmidt, 2004), we also identified some critical issues that need more attention in entrepreneurship meta-analyses. The following sections focus on these issues because they directly affect the potential of providing a theoretical contribution to the field of entrepreneurship. Therefore, we highlight the critical issues that we identified in the meta-analyses of entrepreneurship research and then provide recommendations for better practice.

Critical practice 1: Study location process

Reporting of the literature search strategies is adequate (for example, 64.45 percent of all meta-analyses reported at least three different strategies used to locate studies). Also, the meta-analyses made use of an average of 5.34 databases to locate studies; this is a reasonable number of databases and more than reported in other domains (Harari et al., 2020). Overall, the meta-analyses used as many as 44 different databases to locate studies (Table 3), a likely underestimate: For example, ProQuest and Web of Science include multiple databases, which might differ depending on the specific licenses used. As Table 3 indicates, ABI Inform (used

57 times), Google Scholar (used 50 times), EBSCO (used 30 times), JSTOR (used 30 times), EconLit (used 27 times), and Web of Science (used 26 times) are the most frequently searched databases. Critically, only 5.56 percent of the meta-analyses conducted in entrepreneurship justified the choice of the databases they used. However, databases differ considerably in terms of the number and type of studies they identify, which could affect the results of a meta-analysis (Harari et al., 2020). For example, ABI Inform identifies only about 55 percent of the relevant studies for inclusion to a meta-analysis (Harari et al., 2020). Other databases, such as PsycINFO (used in 20 meta-analyses), identify more than 60 percent of relevant studies for inclusion but are not often taken into consideration in entrepreneurship meta-analyses. Google Scholar, which was used quite often, identifies about 98 percent of relevant studies for inclusion; however, the percentage of articles that are relevant for a specific question is low. Moreover, Google Scholar is not transparent about the algorithm it uses and results are not always reproducible (Gusenbauer & Haddaway, 2020), a core requirement in meta-analyses. Therefore, one should be aware that Google Scholar is useful for exploratory search, but it may not provide the same precision that other search engines provide. Other databases are restricted to research published by a specific publisher, such as Sage, Wiley, Springer, Emerald, or Elsevier. No less than 20 of the meta-analyses in our sample used publisher databases; however, due to their biased nature, they should only be used to supplement the study location process. It makes sense to use databases that are specific to a discipline and focus on papers that match the topic under investigation. In short, while meta-analyses in the entrepreneurship domain should continue to use multiple databases, authors should clearly justify their choices. For example, some authors selected a specific database because it enabled them to identify unpublished studies in entrepreneurship research (Chen et al., 2021; Rosenbusch et al., 2013). In addition, authors should utilize multiple strategies to locate research, such as unpublished studies, searching, for example, conference proceedings, placing announcements on listservers, and directly asking research groups that are known for their work on a specific topic. For

example, Wagner et al. (2015) decided to utilize multiple strategies to locate all relevant studies by looking at four databases, all of which were broad in scope. They also analyzed previous reviews, manually searched journals, contacted experts, and made announcements on listservers.

Insert Table 3 about here.

Critical practice 2: Use of a second coder

One of the proposed standards in meta-analysis is to report measures that assess the accuracy of the selection, extraction, and coding processes (Appelbaum et al., 2018). Coding involves examining the study selection, the extraction of relevant information from it, the aggregation of the data, and making it suitable for calculating meta-analytic estimations (Villiger et al., 2022). Thus, the coding of meta-analyses involves not only constructs but also the various stages of the meta-analysis process, perhaps including the initial screening of title and abstracts, a more detailed secondary screening, and the data extraction process (Belur et al., 2018).

Coding might be inaccurate especially if it involves constructs and decisions. Moreover, a number of biases can affect the coding process. Only 50 percent of the meta-analyses in our sample used more than one coder and only few (39 percent) reported the coder agreement This may not be unique to entrepreneurship, as reporting of coding agreement is also low in other disciplines (Yeaton & Wortman, 1993). However, a recent analysis of meta-analyses conducted in organizational behavior reported that 73 percent of studies relied on more than one coder and 71 percent of studies reported intercoder reliability (Villiger et al., 2022). These numbers are considerably higher than those in the entrepreneurship literature.

Inaccurate coding introduces measurement error that might result in severely underestimating the effect size. Obviously, replicability of the coding system is low if coder agreement is not reported. In addition, coding is not just a technical task, as it connects the research question with the outcome of the analysis. Therefore, inaccurate coding can lead to false results and an inability to answer the research question.

While the practice of using a second coding in meta-analyses is well accepted (Cooper, Hedges & Valentine, 2019), we suggest that coding should involve more than one coder and decisions in various phases in the project, at least in the study selection and the coding of constructs. Ideally, codes for each article should be reported in the table that summarizes all studies included in the meta-analysis.

Moreover, all of the meta-analyses in entrepreneurship included in our analysis used an across-the-board reporting of an overall reliability estimate; this strategy, however, overestimates reliabilities because some codes on facts (such as the average age of sample participants) produce very high reliabilities. When reporting on meta-analyses, we suggest that authors provide readers with more coder agreement information on the coding of each construct. Specifically, entrepreneurship meta-analyses often involve complex constructs that are challenging to code, such as effectuation, ambidexterity, and opportunity identification. For example, Bierwerth et al (2015) coded the constructs strategic renewal, innovation, and corporate venturing. To ensure that these constructs were reliably identified, they carefully defined and operationalized these constructs and reported Cohen's kappa for each of their codings. A detailed discussion on the coding of meta-analyses can be found in Villiger et al. (2022).

Critical practice 3: Assessment of heterogeneity

Meta-analyses aim to explain heterogeneity, that is, variability in the data, by differentiating between heterogeneity that can be explained by methodological artifacts and heterogeneity that cannot (the latter is often referred to as "residual heterogeneity"). The heterogeneity statistic in meta-analyses is most important when interpreting findings because heterogeneity directly affects the generalizability of the findings.

Overall, our analysis indicates that researchers in the entrepreneurship domain usually report information about the distribution of effect sizes (as 96.63 percent of the studies in our sample report the standard deviation of effect sizes), and only 11 studies did not report any heterogeneity statistic. As a matter of fact, 87.78 percent of meta-analyses in entrepreneurship research reported at least one heterogeneity statistic; this number is lower than in the broader management literature, where 97 percent of studies do so (Kepes et al., 2022). We noticed several other issues. First, most authors concluded that heterogeneity suggested the presence of moderators, so they conducted a moderator analysis, but they did not report and interpret the moderator analysis in light of any remaining heterogeneity (20 percent of studies did report whether the moderator analysis reduced residual variance). Thus, they focused on differences in the magnitude of relationships, although one aim of a moderator analysis is to explain and reduce heterogeneity (Hunter & Schmidt, 1990). Any moderator analysis, be it bivariate or multivariate, should communicate whether unexplained variance could be reduced and to what extent. Second, few articles justified the choice of heterogeneity statistic (7 studies did so), possibly because each statistic has advantages and disadvantages. In general, heterogeneity statistics can be differentiated into measures that look at absolute heterogeneity quantifying the amount of heterogeneity (such as the Q-test used in 39 studies and the credibility interval used in 31 studies) and measures that look at relative heterogeneity quantifying the percentage of variation that is due to real differences, rather than chance (the 75 percent rule and the related I^2 statistic used in 49 studies). The Q-test is easy to conduct and interpret, but it has all the flaws of significance testing. While the 75 percent rule avoids significance testing, it relies on a rule of thumb and does not provide information about the range of variation. To address the advantages and disadvantages of individual heterogeneity tests, we recommend conducting two tests of heterogeneity, one that assesses absolute heterogeneity and one that addresses relative heterogeneity. A good practice of heterogeneity testing is demonstrated in the meta-analysis by Allen et al. (2021) that not only reports three tests for detecting the heterogeneity in results (Q-test, the I^2 statistic, and the 80 percent credibility interval) but also an explanation of the specific information that is provided by each of these tests. Importantly, meta-analyses conducting moderator analyses need to show that moderator analyses reduce heterogeneity in a substantial way (Hunter & Schmidt, 1990). Thus, varying effect sizes of moderator variables alone provide only a weak indication of moderator effects.

Critical practice 4: The multivariate endeavor

Multivariate meta-analysis provides opportunities for higher-level assessments, such as comparing and evaluation theories that involve multiple predictors, mediators, moderators, and outcome variables (Shaw & Ertug, 2017). More than half of the meta-analyses conducted in entrepreneurship research performed some kind of multivariate analysis (45 studies reported a meta-regression and 19 studies reported a meta-analytic structural equation model [MASEM]). Such analyses are useful to contribute theoretically to the field of entrepreneurship as such models specify the mechanism by which an independent variable affects a dependent variable (Rauch, 2019). We observed a number of red flags when we content-analyzed the studies using multivariate meta-analysis. The use of meta-regressions is a methodology that builds on a number of sometimes restrictive assumptions, just as in other applications of regression analyses. For example, depending on the number of moderators, meta-regressions must include a certain number of studies to produce stable solutions (compare Schmidt, 2017, for a detailed discussion of these issues). However, only 22 percent of the studies that used meta-regressions reported the number of studies they included in the analysis. Moreover, 24 meta-regressions, thus more than half of those conducted, are based on less than 15 studies per predictor included in the equation. In all these cases, a subgroup approach to moderator testing would have led to better and more robust results (Schmidt, 2017). In addition, only 12 studies that used meta-regressions reported statistics that address remaining heterogeneity. Such information is essential as it points to additional moderators that are not covered by the meta-regressions. A study taking these considerations into account is Stephan et al. (2022), who used meta-regressions to identify moderators affecting the relationship between entrepreneurship and positive well-being. The equation is based on 199 studies and included seven predictor variables. The heterogeneity statistic indicated that 86 percent of the variance in effects remained unexplained, motivating the authors to conduct additional robustness checks.

One of the bigger problems of meta-regressions is that meta-analyses are constrained by the types of studies they find. However, the interpretation of regression coefficients usually assumes that all of the relevant variables for one theory are included. Of course, that is difficult to achieve even in normal regression analyses of variables. Furthermore, it is practically never the case in meta-analyses. Therefore, every meta-analysis should also include the robust type of single random correlations coefficients or d coefficients as advised by Hunter and Schmidt (2004).

Moreover, while few of the 19 MASEMs performed in entrepreneurship meta-analyses specified the specific type of MASEM conducted, it is reasonable to assume that the majority used the two-step approach suggested by Viswesvaran and Ones (1995). The two-step approach requires a meta-analytical correlations table that is then used as an input file to conduct a MASEM analysis. The number of studies is usually created by using the harmonic mean, so the number of studies included is usually sufficient for conducting such an analysis. Notably, it is very seldom to have a full correlation matrix from meta-analysis, so some relationships are simply estimated or are based on a small number of studies. Moreover, the Viswesvaran and Ones (1995) approach treats the correlations as homogeneous, suggesting a fixed effect analysis. This practice is inconsequential, as we found that heterogeneous effects are prevalent in entrepreneurship meta-analyses, indicating that relationships are based on diverse samples from different countries, industries, and contexts. Accordingly, it is difficult to generalize the findings of a MASEM. For example, Carney et al. (2015) report significant heterogeneity in predicting the relationship between private family firms and performance in bivariate and meta-regression analyses but treat the correlations as homogenous when performing MASEM. This practice is common in MASEMs that are conducted in the domain of entrepreneurship (Crook et al., 2011; Miao et al., 2017; Rosenbusch et al., 2013), but it would be better to take heterogeneity into account, as some MASEM procedures discussed in the literature do (Cheung et al., 2018; Yu et al., 2018). In entrepreneurship, the meta-analysis by Haus et al. (2013) is based on a stepwise procedure where the homogeneity assumption was explicitly tested in a first step of the MASEM procedure.

Critical practice 5: Quality checks

The value of any meta-analysis is dependent on the lack of bias in the primary studies included in the meta-analysis (Thompson & Pocock, 1991). Some of the biases even increase the likelihood of committing a type one error, thus, increase the likelihood of reporting false positive results (Greco et al., 2013). Many of the numerous concerns and critiques of meta-analyses could be addressed by conducting robustness tests, sensitivity tests, and other quality checks. Unfortunately, there is not an agreed-upon standard on which quality checks should or should not be performed. We suggest that meta-analyses should at least control for publication bias, extreme values and outliers, and perform additional robustness tests that concern the specific decisions made in the respective meta-analyses.

Publication bias

Publication bias occurs when certain kinds of research findings are less (or more) likely to be published than others. For example, authors may bias publications if they decide not to submit findings they find uninteresting, negative, or unexpected, and both editors and reviewers may be concerned when findings contradict dominant theories. Publication bias might also result when papers with positive findings are accepted earlier than other papers. The fact that only 58.89 percent of the studies included in our review performed a publication bias analysis gives us pause, particularly because a large part of the entrepreneurship research shows publication bias (O'Boyle et al., 2014). Eleven of the 53 studies that reported the results of publication bias analysis found significant bias in their results. These numbers may still underestimate the problem, as 10 of the 53 studies that tested for publication bias did not report the results of the bias analysis and some used poor detection methods. For example, 28 studies used the failsafe N (Rosenthal, 1979), which assesses the number of null findings that would have to be included to lead to an insignificant effect size. This method provides a first attempt to quantify the robustness of findings, but it cannot detect publication bias because it builds on the unrealistic assumption that unpublished studies provide null findings. Furthermore, it does not specify what constitutes an acceptable failsafe N. (Aguinis et al., 2011). Similarly, a funnel plot (used in 15 meta-analyses) can provide first evidence of publication bias. A funnel plot maps out a study's effect size against its standard error. In the absence of publication bias, the funnel plot would be symmetric given that the standard errors vary randomly around the mean effect size estimate. A disadvantage of funnel plots is that visual inspection and interpretation require experience and subjective judgment. A number of other tests have been used to detect publication bias (compare Rothstein et al., 2005). For example, Egger's test focuses on detecting bias by testing the symmetry of the funnel plot. However, the test provides a point estimate and has low power to detect bias. Other tests focus on assessing the size of the bias, such as the trim-and-fill test. While this test works in many circumstances, it is important to note that asymmetry can be caused by many other factors such as moderators and is, thus, not always due to publication bias.

Additionally, publication bias does not always result in published studies having higher effect sizes. For example, studies that investigate personality traits face a negative publication bias, as published studies show lower effect sizes than unpublished studies (Rauch & Frese, 2007). Similarly, studies investigating gender differences in entrepreneurial intentions revealed a negative publication bias (Steinmetz et al., 2021). Because publication bias can be either positive or negative, it does not affect the average magnitude of effect sizes, as reported in the literature (Dalton et al., 2012). Nevertheless, it is present and should be tested (O'Boyle et al., 2014). Given the tools to detect publication bias and the likelihood that such bias exists, we suggest that meta-analyses in the entrepreneurship domain conduct several tests of publication bias, including an assessment of both the presence and the size of publication bias. Such a triangulation of different methods to detect publication bias increases confidence in findings, particularly if different tests come to the same conclusion (Harrison et al., 2014).

Outlier analysis

Outlier studies show effect sizes that differ from other studies to such an extent that they may be caused by mechanisms related to data entry, measurement errors, or sampling problems, but they may also occur as a normal variation (Hawkins, 1980). Outliers can have a considerable influence on the magnitude of relationships between variables and, as a consequence, on the interpretation of meta-analytic results. In addition, outliers are particularly important in meta-analysis because they increase the residual variance and therefore tend to affect whether one concludes that moderators affect the relationships. Therefore, meta-analyses should include a check to determine whether outliers affect reported results. We found that only 17.78 percent of the meta-analyses did so. Unfortunately, there are no clear guidelines on how to detect and deal with outliers although the literature does provide a general discussion of outliers (Aguinis et al., 2013) and suggestions on how to detect them in meta-analyses (Huffcutt & Arthur, 1995). Accordingly, meta-analyses in the domain of entrepreneurship use different methods to identify outliers, such as the sample adjusted meta-analytical deviance score (Gupta & Chauhan, 2021; Williams & Crook, 2021), Cook’s distance metric (Duran et al., 2019), and deviations by more than two standard deviations (Chliova et al., 2015; Schweiger et al., 2019). Notably, sample adjusted deviance score procedures tend to overidentify outliers, while using cut-off scores likely leads to eliminating good, albeit extreme studies (Beal et al., 2002). Therefore, it might be useful to combine both procedures and to eliminate only studies that are identified by the sample adjusted deviance score and that have values exceeding a defined cut-off score.

Quality checks

Numerous other quality issues can affect the results of a meta-analysis and, therefore, it is commonly suggested to control for the quality of primary studies included in a meta-analysis (Hunter & Schmidt, 2004). In general, any quality concern can be addressed by coding or by performing robustness tests. About 43 percent of meta-analyses conducted in the domain of entrepreneurship performed analyses of the quality and robustness of results, but two types of checks are particularly important. First, even when using the most stringent selection criteria and controlling for all eight of the artifacts suggested by Hunter and Schmidt (2004), study quality will vary because of the trade-off between the quality criteria and the number of studies that can be included in the meta-analysis. Some meta-analyses coded study quality (for example, Rauch & Hatak, 2016) and checked whether study quality affects results. Others conducted robustness checks assessing whether study characteristics affect results (Zhao & Liu, 2022). Second, the various judgments of the meta-analysts may affect the results, so they may be well advised to address the influence of such judgments in additional robustness checks. For example, Mathias et al. (2021) conducted robustness tests to check their analytical choices, the effects of their coding of the independent variable, and the effects of omitted variables. When quality checks provide equivalent results, they increase confidence in meta-analytical findings, and even when they do not result in equivalent findings, they identify issues and open new avenues for future research.

Critical practice 6: Violation of test assumptions

Violating test theoretical assumptions is possibly more common that one would assume, however, such practices bias results (Yuan et al., 2020). Therefore, it is concerning that a number of meta-analyses in our sample violated some basic assumptions of meta-analyses that are based on the axioms of classical test theory. For example, 22.47 percent of the meta-analyses in our sample analyzed regression coefficients (beta weights), and 16.67 percent conducted the analyses on the effect size level rather than on the study or sample level.

Using partial correlations or beta weights

While it is standard in meta-analysis to synthesize bivariate effects across primary studies, using partial correlations implies converting statistics taken from regression analyses. As a simulation has shown that results are similar to those of bivariate correlations (for example, Peterson & Brown, 2005), this practice is increasingly used in entrepreneurship meta-analyses. Using partial correlations allows more effect sizes to be included and thus more power in the analysis. In addition, some authors suggest that partial correlations are more appropriate than bivariate correlations because the influence of control variables is handled in a better way (Carney et al., 2015). This argument ignores the intense discussion in the literature about whether including control variables leads to more accurate results (for example, Spector & Brannick, 2010). Moreover, the use of partial correlations leads to substantial bias in findings by underestimating the true correlation up to 70 percent and inflating the observed variance up to 300 percent (Roth et al., 2018). Therefore, meta-analyses in entrepreneurship should rely on bivariate effect size estimates rather than using partial correlations and, at the very least, do a robustness check with only bivariate correlations.

Using the effect size level for the analysis

Another basic assumption in meta-analysis is that estimates are based on independent effect sizes. This assumption necessitates synthesizing effect sizes within a study if it reports multiple effect sizes, such as by averaging them. Fifteen meta-analyses examined data at the effect size level rather than at the sample level, thus violating the assumption of independent effect sizes. This means that some meta-analyses that report many effect sizes receive much more weight in the analysis than meta-analyses reporting only one effect size. Such a bias might even be systematic if studies of lower quality use this practice more often. The decision to analyze data at the effect size level may be attractive because it increases the power of the analysis, but because the same studies are included multiple times in one effect size, the sampling errors will be correlated and the heterogeneity of results will be underestimated, affecting the generalizability of the results. Thus, results will be substantially biased (Abbas-Aghababazadeh et al., 2020). It is reasonable to include a study multiple times if it includes independent replications. However, the 15 meta-analyses alluded to here used multiple effect sizes from a single sample. The independence assumption can be violated in several ways, such as when the same datasets are used in different studies included in a meta-analysis or the same study is published multiple times. In both cases, the data is nested. Hunter and Schmidt (2004) recommend ways to deal with independent effect sizes, all of which require including each sample only once in a meta-analytical estimate. More recently, Cheung (2019) suggests techniques for dealing with such nested designs in meta-analysis. In entrepreneurship, one meta-analysis (Block et al., 2023) accounted for the nested design when reanalyzing Duran et al.'s (2016) meta-analysis and showed that the original nested results cannot be replicated with a more sophisticated analysis that accounts for the nonindependence of effect sizes. This example shows the value of ensuring that assumptions of meta-analysis are met.

Critical practice 7: Interpreting meta-analytic findings

Finally, meta-analyses in the entrepreneurship domain should be more careful with regard to the interpretation of findings. Although many meta-analyses published in the entrepreneurship domain check for heterogeneity and publication bias, almost all lack diligence and rigor in interpreting the results. Only 26.97 percent of the meta-analyses discussed findings in face of heterogeneity, which is comparable to practices in organization behavior (Kepes et al., 2022). Most meta-analyses focus instead on the magnitude and significance of direct and moderated relationships. However, magnitude and significance are meaningful only when the analyses explain heterogeneity. Since all but one of the meta-analyses in our sample reported heterogeneity, the majority of findings cannot be generalized, because the nature and the boundary conditions of these findings are not identified and understood. Notably, even small effect sizes can have substantial consequences if they are consistent and accumulate over time (Aguinis & Harden, 2009). Therefore, the size of a relationship can only be discussed in light of the distribution of effect sizes around the mean relationship (Schmidt et al., 2017). The interpretation of meta-analytic findings in entrepreneurship research should focus less on the magnitude of identified relationships and more on the distribution of results around the mean effect, just as the early literature that addresses this methodology suggests; otherwise, these meta-analyses run into the same problems that are associated with statistical significance testing (Schmidt, 1996). For example, Jiao et al. (2021) concluded in the first paragraph in their discussion section that: "The … mixed findings about moderators suggest that the boundary conditions of the experience–performance relationship may be more complicated than could be uncovered through extant quantitative studies. More research is essential to account for the inconsistent results from different studies and to further the application of human capital theory and knowledge-based view in the entrepreneurship field" (p. 25). Such an interpretation of findings is not only more accurate than most interpretations we found in our analysis, but it also points to areas of future research.

Additional analyses

Appendix 3 includes zero-order correlations of overall study effect size, journal characteristic (impact factor and entrepreneurship versus not entrepreneurship journal) and decision choices. In general, the decision choices are not correlated with each other. Many meta-analyses were based on some very good choices, but some meta-analyses are systematically better (or worse) in reporting and conducting them. It seems that the meta-analyses in which a MASEM was conducted are less concerned about heterogeneity (r = -.23,

$p < .05$ and $r = -.28$, $p < .01$, for credibility interval and for other heterogeneity tests, respectively) and are more likely to conduct the analysis on the effect size level ($r = .32$, $p < .01$) and/or by relying on partial correlations ($r = .29$, $p < .01$). In general, meta-analyses using partial correlations reported smaller effect sizes ($r = -.26$, $p <. 05$). This is more or less in line with the concerns about partial biases discussed above. Finally, it seems that journals with a higher impact factor are more likely to publish meta-analyses that report multivariate results, specifically meta-regressions, and that report more quality checks, such as outlier analysis ($r = .24$, $p <.05$) and robustness tests ($r = .40$, $p < .01$).

These results motivated us to perform some additional sensitivity analyses to determine whether the journal in which a meta-analysis was published affects the reporting practices and whether these practices have changed over time (Appendix 4). The results indicate that the top entrepreneurship journals (Entrepreneurship Theory and Practice, Journal of Business Venturing and Strategic Entrepreneurship Journal) tend to have higher standards than other entrepreneurship journals. In addition, the reporting of decisions has improved over time. However, the table in Appendix 4 points to the recent increase of some questionable practices such as analyzing partial correlations (the number of meta-analyses using partial correlations increased from 2 to 14) and conducting analyses at the level of effect sizes (the number of meta-analyses using partial correlations increased from 4 to 10).

Table 4 summarizes the critical issues that we identified in this section and provides some recommendations on how to deal with them.

Insert Table 4 about here

The future of meta-analysis in entrepreneurship research

Our goal to quantify the state of entrepreneurship meta-analysis research with the aim of improving the quality, the interpretation, and the communication of future meta-analysis findings in the entrepreneurship domain necessarily includes an outlook of trends that (hopefully) will have an impact how future meta-analyses are conducted. We found that some practices reported in meta-analyses in the domain of entrepreneurship lag behind practices reported in other fields (for example, infrequent use of second coder and heterogeneity testing). At the same time, we identified a number of meta-analyses conducted with high rigor. We argue that high rigor is essential in entrepreneurship as this is a complex and applied field. Moreover, and related to rigor, entrepreneurship meta-analyses need to focus more on the variance in research findings in entrepreneurship. Explaining variance in research findings might imply contextualizing research. Meta-analyses can play an important role in contextualizing entrepreneurship research by specifying boundary conditions for findings. In addition to the practices and illustrative examples discussed here, we also identified omissions that can enhance future entrepreneurship meta-analyses but which—to our knowledge—have not yet been implemented.

First, it is now time to employ second-order meta-analyses - a meta-analysis of statistically independent first order meta-analyses (Schmidt & Oh, 2013). A considerable amount of heterogeneity cannot be explained in meta-analyses in the domain of entrepreneurship (and this is possibly more widespread in entrepreneurship research than in other research areas). Second-order meta-analyses combine the mean effect sizes from meta-analyses and do not (necessarily) rely on the statistics of the primary studies that are included in the second-order meta-analyses (Schmidt & Oh, 2013). A major goal of a second-order meta-analysis is to determine the second-order sampling error that could not be explained in the primary meta-analyses, thus arriving at more robust estimates (Schmidt & Oh, 2013). A second-order meta-analysis may also provide aggregated effect sizes that allow the assessment of accumulated knowledge as it relates to new questions, for example, by comparing subfields, predictors, or outcomes.

Another opportunity for future meta-analysis is the use of more advanced methods to identify relevant research. Future systematic reviews like meta-analyses will have access to a significant amount of information for synthesis, which will eventually require technology to manage (Gusenbauer & Haddaway, 2020). For example, increasingly accurate automatic translation software will overcome the outdated practice of including only English-language studies in meta-analyses. In addition, we assume that big data and artificial intelligence (AI) will be helpful in accessing more research evidence, such as by identifying unpublished studies. Big data will compete with meta-analysis as "best evidence" because the big data can analyze a much higher number of firms, far beyond the numbers included in many meta-analyses. Using big data could reduce the variance in sampling error and thereby result in better estimates. However, the validity of such data is often uncertain and involves ethical and other concerns, and because human inspection of the data is impossible, meta-analysis will still be an important element of evidence-based studies in entrepreneurship. Future developments may combine meta-analysis with big data and AI and thus produce higher statistical power.

It is also important to recognize that meta-analysis creates an ideal scenario, making it possible to correct for methodological artifacts and allowing researchers to analyze large sample sizes. Notably, meta-analyses suffer from all the weaknesses of the primary studies included in the meta-analysis; some of these issues might actually inflate relationships. For example, few if any primary studies included in meta-analyses in entrepreneurship rely on true experiments, creating threats to internal validity. P-hacking (reporting only significant findings) and HARKing (hypothesizing after results are known) might further inflate the findings of meta-analysis. Accordingly, meta-analyses should address concerns of overestimating relationships by analyzing and addressing potential biases in a way that allows the adjustment of reporting and thus avoiding likely exacerbation of the problems of publication biases and selective reporting. Moreover, meta-analyses should be fully transparent with regard to all decisions and judgments so they are open to replication. Fully transparent meta-analyses also increase understanding of the context of the findings.

There are different methods for accumulating knowledge in the field of entrepreneurship research (Chrisman et al., 2022), and scientific evidence is ideally achieved by triangulating meta-analysis findings with those of other methods used to achieve evidence, such as replication studies. Replication studies are all but absent in entrepreneurship research—exceptions include Block et al. (2023), Crawford et al. (2022), and Honig and Samuelsson (2014)—while meta-analyses have become increasingly important in the field. Although meta-analyses and replication studies are related and both are important to accumulate scientific knowledge, they serve different aims. The purpose of a replication study is typically to assess whether results are stable and can be reproduced (Crawford et al., 2022). In general, they report smaller effect sizes than original studies because original studies can suffer from publication bias and selective reporting, issues that the reproducibility crisis literature discusses (Abdallah et al., 2019). Preregistered true replication studies in particular minimize biases because there is no p-hacking present. In addition publication practices such as reporting make it often difficult to replicate findings (Crawford et al., 2022). The primary aim of meta-analysis is generalization. Meta-analyses build on replication studies, although they typically build on constructive replication (studies that deviate to some extent from each other) rather than true replication studies. As a consequence, replication studies report effect sizes that are up to three times smaller than those of meta-analyses (Kvarven et al., 2020). If both meta-analyses and replication studies report a significant effect, this would considerably increase confidence in the findings.

Another call for future meta-analysis is to develop and test more meta-frameworks that better account for the interdisciplinary nature of the field when taking into account interdependencies that occur between constructs and domains. Thus, the entrepreneurship domain needs meta-analyses that test or even develop theory; multivariate analyses are required to achieve these aims (Combs et al., 2021), so the focus of meta-analyses would shift from looking at the magnitude of the effect size from simple bivariate meta-analyses to models that specify the mechanism through which such effects occur. The phenomenon of entrepreneurship is also multilevel. For example, most meta-analyses in the entrepreneurship domain look at individual-level or firm-level constructs moderated, for example, by institutional contexts. Thus, individual-level effects are nested in firms, which are nested in institutional contexts. Multilevel meta-analyses would help to specify the level at which effects occur.

Limitations

The conclusions of this review must be interpreted in light of its limitations. All meta-analyses select the studies to include in their reviews based on certain criteria, as we did in our review. We de-selected seven meta-analyses after encountering difficulty in extracting information about their underlying decisions. If some of these papers were of low quality in other ways, our analysis might be biased toward higher-quality meta-studies.

Any empirical study has to balance the relationship between breadth and depth (Shepherd, key note ACERE conference 2023). As we sought to make a general assessment of the meta-analysis literature in the entrepreneurship domain, we arrived at a moderate level of both. In some instances, this decision came at some expense. For example, even though we reported whether the studies in our sample featured a publication bias analysis, we did not discuss the advantages and disadvantages of each type of bias in detail. Similarly, we wanted to determine whether the studies looked at intercoder agreement, but we did not discuss situations in which a percentage measure of interrater agreement is superior to kappa coefficients. We provided references to readings that are more specific to some of the many topics discussed in this review, allowing interested readers the possibility to examine this in more detail, if needed.

Finally, we coded 75 choices used in the studies in our sample to assess these studies' reporting and interpretation of decisions made during the meta-analysis process. Additional choices can be made during a meta-analysis, and we could have coded these decisions into more specific subcategories. However, we used and extended an accepted coding scheme suggested by the APA (Appelbaum et al., 2018) and checked the coding schemes of previous reviews as well (Aguinis, Dalton, et al., 2011). Given the goal of our review, we doubt that additional or more specific codes would have changed the overall conclusions of our study.

Conclusions

We examined how meta-analyses are conducted in the entrepreneurship domain, how the meta-analysis process is communicated, and how results are interpreted. While the quality of meta-analyses in the entrepreneurship domain is generally high, we identified seven areas in which practices can improve communication of decisions and interpretation of their consequences: the strategy used for locating studies, the use of a second coding, assessment of heterogeneity, the use of multivariate analysis, the use of quality checks, violation of assumptions, and interpretation of meta-analysis findings. We also provided recommendations to improve how these issues are addressed.

Meta-analyses, which are increasingly used in entrepreneurship research, will be important in the future. They summarize the status of certain subfields in entrepreneurship research, resolve debates in the field, test theories, point to areas where more research is needed, and support paradigm development. However, the validity of such contributions depends to a large extent on the soundness of the meta-analyses. While this is true for quantitative reviews in any discipline, some circumstances may make high-quality reviews in the domain of entrepreneurship particularly important. The domain is interdisciplinary, and many constructs affect the dependent variables in entrepreneurship research, so simple bivariate relationships are often contaminated by other variables, making effects smaller and more heterogeneous than they are in disciplines that are more homogeneous and that might allow for more rigorous study designs. Because it might be more difficult to detect relationships in entrepreneurship, it is all the more important that estimates are precise and that the decisions made to arrive at these estimates are valid and are communicated and interpreted in the face of these results and decisions. Finally, creating valid inferences from meta-analyses that are conducted in the field enhances the legitimacy of both the method and the discipline as a whole.

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Table 1 Overview of studies in management analyzing reporting standards in meta-analysis

Authors	Purpose	Data	General findings
Aguinis, Dalton, et al. (2011)	How methodological choices affected the obtained effect sizes in important ways and thus improved the predictive potential and usefulness of our theories	196 meta-analyses published in 5 top management journals	Choices and judgment do not affect the magnitude if effect sizes are reported in the literature
Dalton et al. (2012)	Checked whether published studies are biased	6,935 correlations used as input in 51 meta-analyses published in *Academy of Management Journal*, *Journal of Applied Psychology*, *Personnel Psychology*	The file drawer problem does not produce an inflation bias and does not pose a serious threat to the validity of meta-analytically derived conclusions
Appelbaum et al. (2018)	APA guidelines on reporting	No data	Provides tables for reporting, addressing different research designs including meta-analysis
DeSimone et al. (2020)	Review focusing on organizational research	No data	Provides a detailed checklist for reviewers
Geyskens et al. (2009)	Analyzed the analytical practices of meta-analyses in management	69 meta-analytic studies published between 1980 and 2007 in 14 management journals	Focus is on the analysis itself. Identified a number of problems such as infrequent use of corrections, publication bias analysis, outlier analysis. Provides a list of issues that could be done in a better way
Kepes et al. (2022)	Analyzed heterogeneity and interpretation of heterogeneity in management and applied psychology	70 meta-analyses published in *Strategic management Journal, Journal of Business Venturing, Journal of Applied Psychology, Personnel Psychology*	Poor quality of heterogeneity reporting
Steel et al. (2021)	Summarized best practices for conducting a meta-analysis	No data	Best practice recommendations: offer recommendations and specific implementation guidelines
Rudolph et al. (2020)	Analysis of meta-analyses reported in *Journal of Vocational Behavior* (JVB)	68 meta-analyses published in JVB	19 associated best practices to improve the quality of meta-analyses
Harari et al. (2020)	Analyzed the literature search strategy in systematic reviews	152 systematic reviews in applied psychology	Database selection can have a huge effect on conclusions of reviews
O'Boyle et al. (2014)	Analyzed meta-analyses in entrepreneurship to assess publication bias	15 meta-analyses on firm performance in the domain of entrepreneurship	73 percent of studies showed at least some publication bias

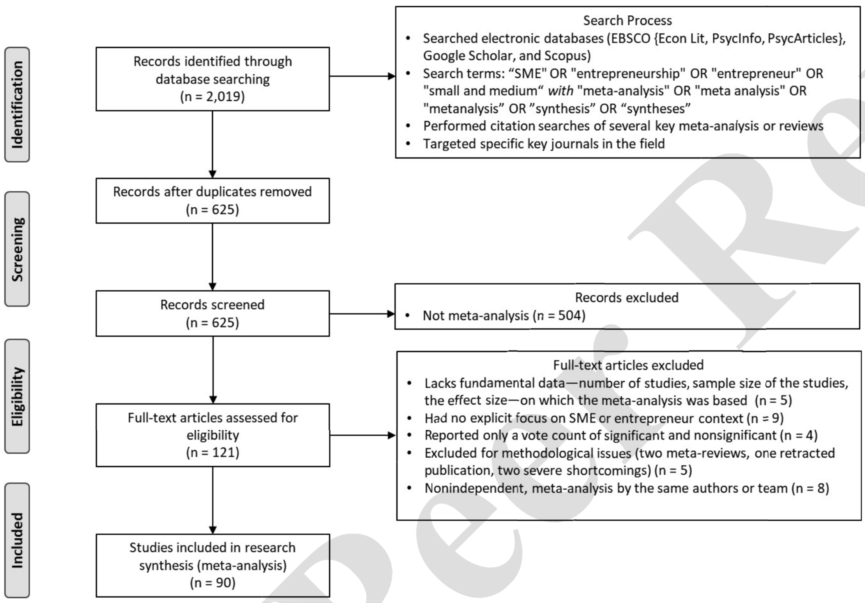

Figure 1. Study location process flowchart

Table 2. Systematic review findings

Meta-analytic decision stages	*N*	Percentage
1. Decisions made before the analysis is conducted		
1.1 *Literature searching strategies*		
1.1.1 The study location procedure using at least three search strategies?	58	64.45
a. Search two or more databases	78	86.67
b. Reported databases' names	86	95.56
c. Average number of databases	*M* = 5.34	*SD* = 2.7
d. Manual search (journal articles)	63	70.0
e. Conference proceedings	30	33.34
f. Backward search	61	67.78
g. Lexicon of search terms	58	64.45
h. Announcements (for example, listservers)	8	8.89
i. Researchers contacted	39	43.34
j. Search restrictions (for example, published only)	9	10
1.1.2 Provided a justification of database selection	5	5.56
1.2 *Selection/screening process*		
1.2.1 Documented elements used to select studies	59	66.56
1.2.2 Selection criteria reported	78	86.67
1.2.3 Quality of reported selection criteria (1=low, 5=high)	*M* = 2.92	*SD* = 1.33
1.2.4 Excluded studies reported	16	17.78
1.2.5 Selection decision performed by a single person	74	82.22
1.2.6 Handling of same study/same sample reported	61	67.78

1.3 *Coding process*		
1.3.1 More than one coder	45	50.00
1.3.2 Coder agreement, percentage	18	20.00
1.3.3 Coder agreement reliability	17	18.89
1.3.4 Across-the-board approach	90	100
2. Decisions made during the analysis		
2.1 Bivariate analysis		
2.1.1 Reported model to calculate combined effect	43	47.78
2.1.2 Effect size metric used		
a. Correlations (*r*)	81	90.00
b. Standardized mean difference (*d* or *g*)	7	7.78
c. Other	3	3.33
2.2 *Weighting and attenuation*		
2.2.1 Sample size	70	79.55
2.2.2 Inverse variance	16	18.18
2.2.3 Reliability independent variable	45	50.00
2.2.4 Reliability dependent variable	48	55.17
2.2.5 Range restriction	7	7.78
2.2.6 Other corrections	1	1.12
2.3 *Heterogeneity tests*		
2.3.1 Variance statistics reported (for example, *SD* of *r* or *d*)	86	96.63
2.3.2 Confidence interval	81	90.00
2.3.3 Credibility interval	31	34.44
2.3.4 Q-test	39	43.33
2.3.5 Residual variance statistic (75 percent rule or I^2)	49	54.44
2.3.6 Other heterogeneity statistic	3	3.33
2.3.7 Heterogeneity not reported	11	12.36
2.3.8 Heterogeneity significant?	75	94.94
2.3.9 Moderator analysis reduced residual variance	16	20.00
2.3.10 Justification of heterogeneity statistic	7	8.75
2.4 *Multivariate analysis*		
2.4.1 Meta-regression	45	50.00

2.4.1.1 Meta-regression *k* reported	20	22.27
2.4.1.2 Meta-regression heterogeneity reported	12	13.33
2.4.1.3 Meta-regression: Number of predictors < 15	24	26.97
2.4.2 Meta-analytic structural equation model	19	21.11
2.4.2.1 Meta-analytic structural equation model not addressing heterogeneity	14	16.28
2.5 Whether and which computer program used for the analysis	25	26.97
3. Quality checks		
3.1 *Publication bias (any test)*	53	58.89
3.1.1 Published vs. unpublished studies	18	20.00
3.1.2 Funnel plot	15	16.67
3.1.3 Trim and fill	15	16.67
3.1.4 File drawer	28	31.11
3.1.5 Other	15	16.85
3.1.6 Significant (yes)	11	12.36
3.1.7 Tested but not reported	10	11.23
3.2 *Outlier analyses*	16	17.78
3.3 *Other quality checks*		
3.3.1 Additional analysis conducted?	53	58.89
3.3.2 Controlling for quality	38	42.70
3.3.3 List of primary studies included in the manuscript	78	86.67
3.3.4 Detailedness of the information about primary studies included in each meta-analysis	$M = 3.64$	$SD = 1.44$
3.3.5 Meta-analyzing partial correlations	20	22.47
3.3.6 Meta-analyzing on the effect size level	15	16.67
4. Decisions regarding the interpretation of findings		
4.1 Abstract reporting effects in face of heterogeneity	9	10.11
4.2 Abstract reporting effects in face of other issues (for example, publication bias)	0	0
4.3 Discussion reporting effects in face of heterogeneity	24	26.97
4.4 Discussion section discussing effects in the face of other issues (for example, publication bias)	3	3.41

Note. M = mean; SD = standard deviation; I^2 = the percentage of the variance that is not due to statistical artifacts

Table 3. Databases used in meta-analyses in entrepreneurship

Database	Frequency	Percentage
ABI Inform	57	63.33
Google Scholar	50	55.56
EBSCO	30	33.33
JSTOR	30	33.33
EconLit	27	30.00
Web of Science	26	28.90
ScienceDirect	21	23.33
Social Science Citation Index	21	23.33
ProQuest Dissertations & Theses	20	22.22
PsycINFO	20	22.22
Social Science Research Network	19	21.11
Business Source Premier	14	15.56
Scopus	12	13.33
Business Source Complete	11	12.22
Dissertation Abstracts	8	8.89
Emerald	7	7.78
Academic Search Complete	6	6.67
Business Source Elite	6	6.67
Google	6	6.67
Wiley Online Library	5	5.56
ERIC	4	4.44
SpringerLink	4	4.44
China National Knowledge Infrastructure	3	3.33
National Bureau of Economic Research	3	3.33
RePEc	3	3.33
ResearchGate	3	3.33

Academic Search Elite	2	2.22
Academic Search Premier	2	2.22
APA PsycArticles	2	2.22
Business Search Premier	2	2.22
Elsevier	2	2.22
IEEE Explore	2	2.22
Sage	2	2.22
Other	11	12.22

Table 4. Critical issues and recommendations for valid reporting in entrepreneurship meta-analysis

Critical issues	Problems/ issues	Recommendations
1. Literature searching strategies	Electronic databases are a cornerstone for meta-analytic studies. Reliance on a single database or single strategy can constrain the comprehensiveness of the literature search. The outcome of the study location might well depend on the database used.	1. Search multiple databases, justify choices, and report them 2. Develop multiple strategies (for example, forward and backward searches, manual search, and nonindexed sources by manually searching conference programs or by contacting experts directly or via listservers)
2. Coding of information: Assessing the accuracy of the selection, extraction, and coding	Many potential biases, difficult to code complex constructs. May introduce measurement error. Affects replicability as well as the ability to answer the research question.	3. Use more than one coder (except coding facts) 4. Coding decisions are required at different phases of the project 5. Avoid presenting across-the-board coding results 6. Report coder agreement
3. Assessment of heterogeneity	Affects the generalizability of findings. Remaining heterogeneity after looking for mediators is still important. Same applies for multivariate analyses. No best choice of heterogeneity statistics as all have advantages and disadvantages.	7. Use combination of procedures, possibly looking at absolute (for example, Cochran's Q) and relative heterogeneity (for example, I^2) 8. Justify the test used to test heterogeneity 9. Report heterogeneity also in multivariate results
4. Multivariate meta-analysis	The violation of assumptions. Difficult to have enough studies to conduct a multivariate analysis. Bivariate heterogeneity might not be addressed or explained in multivariate analysis.	10. Prefer random effects (RE) or varying coefficient (VC) methods 11. Assess the minimum number of studies needed to run a meta-regression 12. Report remaining heterogeneity 13. MASEM must address heterogeneity and report full correlation matrix used
5. Quality checks	There are multiple bias and quality issues possible at different stages of the meta-analysis.	14. Conduct a publication bias analysis. Assess both the presence and the amount of publication bias 15. Do not use file drawer analysis 16. Code and test quality of primary studies

		17. Report list of primary studies included in the manuscript (with any additional moderator coding) 18. Conduct robustness and sensitivity tests
6. Violating assumptions of meta-analysis and classical test theory	Partial correlations bias results downwards and inflates observed variance. Effect size level analysis reduces observed variance.	19. Be extremely cautious, particularly if violations cannot be controlled for 20. In case of multiple correlations of the same relationship, consider using nested design with multilevel meta-analytic approach or group variance approach 21. Avoid duplicate studies using same sample
7. Interpretation of findings	Focus on magnitude and significance of findings is misleading and might lead to wrong interpretations.	22. Interpret heterogeneity related information to justify presence of moderators 23. Always interpret and discuss findings relying on the distribution of effect sizes and recognize the boundary conditions or limits. We suggest that this should be achieved both in the abstract and in the discussion section

Appendix 1 Meta-analyses included in the review

Year	Author	Title	Journal
1991	Boyd	Strategic planning and financial performance: A meta-analytic review	Journal of Management Studies
1993	Schwenk and Shrader	Effects of formal strategic planning on financial performance in small firms: A meta-analysis	Entrepreneurship Theory and Practice
1994	Miller and Cardinal	Strategic planning and firm performance: A synthesis of more than two decades of research	Academy of Management Journal
2001	Stewart and Roth	Risk propensity differences between entrepreneurs and managers: A meta-analytic review	Journal of Applied Psychology
2003	Combs and Ketchen	Why do firms use franchising as an entrepreneurial strategy? A meta-analysis	Journal of Management
2004	Collins et al.	The relationship of achievement motivation to entrepreneurial behavior: A meta-analysis	Human Performance
2006	Zhao and Seibert	The Big Five personality dimensions and entrepreneurial status: A meta-analytical review	Journal of Applied Psychology
2007	Bausch and Krist	The effect of context-related moderators on the internationalization-performance relationship: Evidence from meta-analysis	Management International Review
2007	Rauch and Frese	Let's put the person back into entrepreneurship research: A meta-analysis on the relationship between business owners' personality traits, business creation, and success	European Journal of Work and Organizational Psychology
2007	Stewart and Roth	A meta-analysis of achievement motivation differences between entrepreneurs and managers	Journal of Small Business Management
2008	Song et al.	Success factors in new ventures: A meta-analysis	Journal of Product Innovation Management
2009	Rauch et al.	Entrepreneurial orientation and business performance: An assessment of past research and suggestions for the future	Entrepreneurship Theory and Practice
2009	Read et al.	A meta-analytic review of effectuation and venture performance	Journal of Business Venturing
2010	Brinckmann et al.	Should entrepreneurs plan or just storm the castle? A meta-analysis on contextual factors impacting the business planning-performance relationship in small firms	Journal of Business Venturing
2010	Zhao et al.	The relationship of personality to entrepreneurial intentions and performance: A meta-analytic review	Journal of Management
2010	Wang	The correlation between personality traits and entrepreneurial intention: A meta-analysis	ProQuest Dissertations
2011	Rosenbusch et al.	Is innovation always beneficial? A meta-analysis of the relationship between innovation and performance in SMEs	Journal of Business Venturing
2011	Unger et al.	Human capital and entrepreneurial success: A meta-analytic review	Journal of Business Venturing

2011	Crook et al.	Does human capital matter? A meta-analysis of the relationship between human capital and firm performance	Journal of Applied Psychology
2012	O'Boyle et al.	Exploring the relation between family involvement and firms' financial performance: A meta-analysis of main and moderator effects	Journal of Business Venturing
2013	Martin et al.	Examining the formation of human capital in entrepreneurship: A meta-analysis of entrepreneurship education outcomes	Journal of Business Venturing
2013	Rosenbusch et al.	Does acquiring venture capital pay off for the funded firms? A meta-analysis on the relationship between venture capital investment and funded firm financial performance	Journal of Business Venturing
2013	Rosenbusch et al.	The mediating role of entrepreneurial orientation in the task environment–performance relationship: A meta-analysis	Journal of Management
2013	Mayer-Haug et al.	Entrepreneurial talent and venture performance: A meta-analytic investigation of SMEs	Research Policy
2013	Haus et al.	Gender effects on entrepreneurial intention: A meta-analytical structural equation model	International Journal of Gender and Entrepreneurship
2013	Schweiger et al.	The complementarity of strategic orientations: A meta-analytic synthesis and theory extension	Strategic Management Journal
2013	Zolfaghari et al.	International entrepreneurship from emerging economies: A meta-analysis	Current Issues in International Entrepreneurship
2013	Enke and Bausch	A meta-analytic review of the ambidexterity–performance relationship	European Journal Of Management
2013	Mueller et al.	Success patterns of exploratory and exploitative innovation: A meta-analysis of the influence of institutional factors	Journal of Management
2014	Stam et al.	Social capital of entrepreneurs and small firm performance: A meta-analysis of contextual and methodological moderators	Journal of Business Venturing
2014	Bae et al.	The relationship between entrepreneurship education and entrepreneurial intentions: A meta-analytic review	Entrepreneurship Theory and Practice
2014	Cho and Honorati	Entrepreneurship programs in developing countries: A meta-regression analysis	Labour Economics
2014	Saeed et al.	On cultural and macroeconomic contingencies of the entrepreneurial orientation–performance relationship	Entrepreneurship Theory and Practice
2015	Bierwerth et al.	Corporate entrepreneurship and performance: A meta-analysis	Small Business Economics
2015	Chliova et al.	Microcredit a blessing for the poor? A meta-analysis examining development outcomes and contextual considerations	Journal of Business Venturing
2015	Sarooghi et al.	Examining the relationship between creativity and innovation: A meta-analysis of organizational, cultural, and environmental factors	Journal of Business Venturing
2015	Schlaegel et al.	"Why not now?" Triggers and barriers of new venture creation: A meta-analysis and multinational comparison of entrepreneurs' perspectives	International Journal Of Entrepreneurial Venturing
2015	Carney et al.	What do we know about private family firms? A meta-analytic review	Entrepreneurship Theory and Practice

2015	van Essen et al.	How does family control influence firm strategy and performance? A meta-analysis of US publicly listed firms	Corporate Governance: An International Review
2015	Wagner et al.	A meta-analysis of the financial performance of family firms: Another attempt	Journal of Family Business Strategy
2016	Rauch and Hatak	A meta-analysis of different HR-enhancing practices and performance of small and medium sized firms	Journal of Business Venturing
2016	Rauch et al.	The effectiveness of cohesive and diversified networks: A meta-analysis	Journal of Business Research
2016	Canvanty et al.	Opportunity recognition and prior knowledge: A meta-analysis	Academy of Management Proceedings
2016	Duran et al.	Doing more with nothing. Innovation input and output in family firms	Academy of Management Journal
2017	Fodor and Pintea	The "emotional side" of entrepreneurship: A meta-analysis of the relation between positive and negative affect and entrepreneurial performance	Frontiers in Psychology
2017	Miao et al.	The mediating role of entrepreneurial orientation: A meta-analysis of resource orchestration and cultural contingencies	Journal of Business Research
2017	Miao et al.	The relationship between entrepreneurial self-efficacy and firm performance: A meta-analysis of main and moderator effects	Journal of Small Business Management
2017	Jin et al.	Entrepreneurial team composition characteristics and new venture performance: A meta-analysis.	Entrepreneurship Theory and Practice
2017	Garrett et al.	Entrepreneurial spawning and knowledge-based perspective: A meta-analysis	Small Business Economics
2017	Wagner	A meta-analysis about the relationship between family firms and firm performance	SSRN
2017	Miao et al.	An exploratory meta-analysis of the nomological network of bootstrapping in SMEs	Journal of Business Venturing Insights
2018	Mathias et al.	Managing the tension between exploration and exploitation: The role of time	Strategic Entrepreneurship Journal
2018	Miao et al.	Emotional intelligence and entrepreneurial intentions: An exploratory meta-analysis	Career Development International
2018	Nason and Wiklund	An assessment of resource-based theorizing on firm growth and suggestions for the future	Journal of Management
2018	Schwens et al.	International entrepreneurship: A meta-analysis on the internationalization and performance relationship	Entrepreneurship Theory and Practice
2018	Yang et al.	Meta-analysis of the influence between entrepreneurial orientation and firm performance	25th Annual International Conference on Management Science and Engineering
2018	Canavati	Corporate social performance in family firms	Journal of Family Business Management
2018	Gloss	A meta-analysis of entrepreneurial self-evaluations, socioeconomic constraints, and entrepreneurial success	ProQuest Dissertations

2019	Kim and Park	A meta-analysis comparing factors affecting the growth of SMEs: The case of Germany and South Korea	Journal Of Scientific and Industrial Research
2019	Brinckmann et al.	Of those who plan: A meta-analysis of the relationship between human capital and business planning	Long Range Planning
2019	Zaremohzzabieh et al.	Predicting social entrepreneurial intention: A meta-analytic path based on the theory of planned behavior	Journal Of Business Research
2019	Soares and Perin	Entrepreneurial orientation and firm performance: An updated meta-analysis	RAUSP Management Journal
2019	Peng et al.	Institutions, resources, and strategic orientations: A meta-analysis	Asia Pacific Journal of Management
2019	Duran	The impact of institutions on the competitive advantage of publicly listed family firms in emerging markets	Global Strategy Journal
2020	Schloemer-Lauf and Rauch	Succession in family businesses: A meta-analysis on the exit routes of incumbents - evidence from Germany	Journal of Family Business Management
2020	Berrone et al.	Impact of informal institutions on the prevalence, strategy, and performance of family firms: A meta-analysis	Journal of International Business Studies
2020	Hansen and Block	Exploring the relation between family involvement and firms' financial performance: A replication and extension meta-analysis	Journal of Business Venturing Insights
2020	Debicki et al.	Internationalization and family firm performance	Cross Cultural and Strategic Management
2020	Allen et al.	What matters more for entrepreneurship success? A meta-analysis comparing general mental ability and emotional intelligence in entrepreneurial settings	Strategic Entrepreneurship Journal
2020	Bitencourt	The extended dynamic capabilities model: A meta-analysis	European Management Journal
2020	de Oliveira Santini et al.	Antecedents, consequents and moderators of business models in SMEs: A meta-analytical research study	Journal of Small Business and Entrepreneurship
2020	Kosmidou	A meta-analytic examination of the relationship between family firm generational involvement and performance	Management Research Review
2021	Mathias et al.	A meta-analysis of agglomeration and venture performance: Firm-level evidence	Strategic Entrepreneurship Journal
2021	Wenke et al.	Too small to do it all? A meta-analysis on the relative relationships of exploration, exploitation, and ambidexterity with SME performance	Journal of Business Research
2021	Canavati et al.	Relationship between human capital, new venture ideas, and opportunity beliefs: A meta-analysis	Strategic Entrepreneurship Journal
2021	Chen et al.	The effectiveness of effectuation: A meta-analysis on contextual factors	International Journal of Entrepreneurial Behavior and Research
2021	Gupta and Chauhan	Firm capabilities and export performance of small firms: A meta-analytical review	European Management Journal

2021	Jiao et al.	Does prior experience matter? A meta-analysis of the relationship between prior experience of entrepreneurs and firm performance	Journal of Small Business Management
2021	Steinmetz et al.	Gender differences in the intention to start a business	Zeitschrift für Psychologie
2021	Marconatto et al.	Characteristics of owners and managers in different countries: A meta-analytical investigation of SMEs' growth	Journal of Small Business Enterprise Development
2021	Lerman et al.	The (not so) dark side of entrepreneurship: A meta-analysis of the well-being and performance consequences of entrepreneurial stress	Strategic Entrepreneurship Journal
2021	Zhao et al.	Age and entrepreneurial career success: A review and a meta-analysis	Journal of Business Venturing
2021	Williams and Crook	Unpacking the age at initial internationalization–performance relationship: A meta-analytic investigation	Journal of Business Venturing Insights
2021	Rostain	The impact of organizational culture on entrepreneurial orientation: A meta-analysis	Journal of Business Venturing Insights
2021	Huang and Madhavan	Dumb money or smart money? Meta-analytically unpacking corporate venture capital	Strategic Entrepreneurship Journal
2022	Miroshnychenko et al.	Family firms and environmental performance: A meta-analytic review	Family Business Review
2022	Block et al.,	Are family firms doing more innovation output with less innovation input? A replication and extension	Entrepreneurship Theory and Practice
2022	Zhao and Liu	Entrepreneurial passion: A meta-analysis of three measures	Entrepreneurship Theory and Practice
2023	Stephan et al.	Happy entrepreneurs? Everywhere? A meta-analysis of entrepreneurship and wellbeing	Entrepreneurship Theory and Practice
2022	Kraft et al.	Overconfidence and entrepreneurship: A meta-analysis of different types of overconfidence in the entrepreneurial process	Journal of Business Venturing

Appendix 2: Coding protocol

1. Selection criteria (1 = reported)
    a. Independent variable defined (1 = yes)
    b. Dependent variable defined (1 = yes)
    c. Selection criteria detailed (1 to 5). 5 = if authors clearly depict how each respective study was selected allowing replication of their study, 1 = if criteria are vague, available information would not allow a replication of the procedure.
    d. Definition of the sample included in the meta-analysis
        i. Owner/manager (1 = yes)
        ii. Firm size (for example, SMEs, large firms, < 500) (1 = yes)
        iii. Labeled (entrepreneurs, SME not further defined, entrepreneurship education) (1 = yes)
    e. Eligible study designs reported (1 = yes)
    f. Handling of duplicated studies/same samples reported (1 = yes)
    g. Handling of excluded studies reported (1 = basically when attempts are made to obtain the data)
2. Study location procedure (1 = reported)
    a. Databases used (1 = yes)
    b. Justification of database used (1 = yes)
    c. Search strategies reported (for example, key words, Boolean connectors, literature reviews, reference lists) (1 = yes)
    d. Names of specific journals that were searched (1 = yes)
    e. Number of researchers contacted (and response rate) 1 = other researchers contacted, for example, listservers
    f. Search strategies in addition to the above (1 = yes)
    g. Search restricted (for example, only published) (1 = yes)
3. Study selection/coding process
    a. Document elements used to make decision about inclusion (for example, searched title, abstract, key words) (1 = yes)
    b. Qualification of those who made these decisions (for example, whether trained or not) (1 = yes)
    c. Whether decision was based on single person) (1 = yes) (Note, code 1 also when not reported, assuming that it was made by one coder only)
    d. Characteristics of coding described (for example, coding criteria and anchors predefined) (1 = yes)
    e. Multiple coders (1 = yes)
        i. Percentage agreement reported (1 = yes)
        ii. Reliability reported (1 = yes)
        iii. Across-the-board approach reporting of reliability (1 = yes)
4. Analysis
    a. Effect size metric used

i. Correlations (1= yes)
ii. Mean differences (1= yes)
iii. Ratios (1= yes)
iv. Other (1= yes)

5. Method of synthesis
    a. Method to combine effect sizes reported (mixed, random, fixed effects (1 = yes)
    b. Rationale for method to combine effect sizes reported provided? (1 = yes)
    c. Justification of heterogeneity statistic used (1 = yes)
    d. Methods for assessing heterogeneity (imprecision) (1 = yes [any measure of variance])
        i. Confidence interval (1 = yes)
        ii. Credibility interval (1 = yes)
        iii. *Q*-test (1 = yes)
        iv. I-test and 75 percent rule (1 = yes)
        v. Other (1 = yes)
        vi. Heterogeneity significant (1 = yes)
        vii. Moderator analysis reduced residual variance (1 = yes)
    e. Corrections for attenuation
        i. Unweighted (1 = yes)
        ii. Weighted by
            1. Sample size (1 = yes)
            2. Inverse variance (1 = yes)
        iii. Reliability independent variable (1 = yes)
        iv. Reliability dependent variable (1 = yes)
        v. Range restriction (1 = yes)
        vi. Other (1 = yes)
    f. Additional analyses
        i. Subgroup (1 = yes)
        ii. Meta-regression (1 = yes)
        iii. MASEM (1 = yes)
        iv. Other (1 = yes)
        v. Additional analyses specified versus post hoc (1 = specified)
    g. Whether and which computer program used (1 = yes)
    h. Publication bias (1 = yes)

i. Published versus unpublished (1 = yes)
ii. Trim and fill (1 = yes)
iii. File drawer (1 = yes)
iv. Other (1 = yes)
v. Publication bias: significant = 3, not significant = 2, tested but not reported = 1, other = 0

i. Provide a table with studies included plus including study characteristics and principal variables (1 = yes)
j. Detailedness of table (1 to 5) 5 = if effect sizes and moderator coding is included along with other study characteristics, such as date, journal, and others. Note: also coded if the table is in the online supplement, which is often the case in more recent studies

6. Results
    a. Bivariate analysis reported (1 = yes)
    b. Multivariate analysis reported (1 = yes)
    c. Extreme values analyzed (1 = yes)
    d. Quality assessment results (1 = yes) (this coding includes any check, for example, operationalization of constructs, robustness checks, sensitivity analysis, and so on)
7. Description of external validity in discussion
    a. Is interpretation conducted in the face of heterogeneity? (1 = yes)
    b. Is interpretation conducted in light of publication bias? (1 = yes)
8. Description of external validity in abstract
    a. Is interpretation conducted in the face of heterogeneity? (1 = yes)
    b. Is interpretation conducted in light of publication bias? (1 = yes)
9. Meta-regression
    a. *k*/predictors in regression analyses >=15 (1 = yes)
    b. Regression reporting heterogeneity (1 = yes)
10. MASEM
    a. With heterogeneous correlations imputed into SEM without addressing this (1 = yes)
11. Hurdles
    a. Partial correlations analyzed (1 = yes)
12. Independent effect sizes violated (analysis performed on the effect size level versus study level) (1 = yes)

Appendix 3: Intercorrelations of effect sizes, journal characteristic (impact factor and entrepreneurship versus not entrepreneurship), and decision choices

Criteria	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1.Overall effect size	1.000																				
2.Impact factor	.027	1.000																			
3.Journal group	.110	-.364**	1.000																		
4.Search strategies total	-.157	.047	-.190	1.000																	
5.No. of databases	.131	-.101	-.120	.328**	1.000																
6.Multiple coders	.148	.156	-.125	-.164	.055	1.000															
7.Coder agreement	.203	.130	-.063	-.227*	.036	.791**	1.000														
8.Credibility interval	.051	.150	-.101	.120	.167	-.083	-.051	1.000													
9.*Q*-test	.170	-.186	.020	.098	.141	.195	.204	-.413**	1.000												
10.Other tests (*I*-test & 75 percent rule)	-.038	-.104	-.041	.066	.091	-.045	-.094	.287**	-.080	1.000											
11. Heterogeneity not tested	-.083	-.130	.011	-.062	-.047	-.040	-.089	-.199	-.265*	-.408**	1.000										
12.Meta-regression	-.090	.256*	.017	.181	.051	.084	-.013	-.056	.229*	.018	-.186	1.000									
13.MASEM	-.142	.121	.111	.044	.107	-.037	-.009	-.234*	.035	-.287**	.195	-.051	1.000								
14.Published versus unpublished	-.010	.184	-.309**	.205	.102	.202	.171	.281**	-.056	.178	-.102	-.078	-.079	1.000							
15.Funnel plot	-.293**	-.154	-.113	.105	-.206	-.095	-.173	-.073	.200	.110	-.076	.070	.035	.000	1.000						
16.Trim-and-fill	.019	-.051	-.045	.146	.065	.019	.071	.178	.020	.050	-.076	.129	-.106	-.149	.280**	1.000					
17.File drawer	.023	.040	-.037	-.051	-.022	.078	.005	-.134	.123	-.012	-.104	.162	.083	.084	.021	.021	1.000				
18.Outlier analysis	.010	.243*	-.049	-.112	.117	.157	.166	.091	-.123	.017	.004	.037	.018	.058	-.208*	-.052	-.061	1.000			
19.Robustness test	.056	.397**	-.205	.065	.084	.261*	.176	.168	-.060	.080	-.052	.208*	-.005	.235*	-.150	.090	.090	.297**	1.000		
20.Partial correlations analyzed	-.262*	-.043	.026	.092	-.138	.046	.075	-.168	.271*	-.055	-.106	.078	.291**	-.003	.405**	-.027	-.063	-.027	-.029	1.000	
21.Non-independence	-.094	-.123	.158	-.098	.099	.133	.194	-.324**	.320**	-.249*	.106	.249*	.317**	-.075	.040	-.120	.150	-.130	-.030	.477**	1.000
22.Interpretation of heterogeneity	-.025	.144	-.187	.062	.055	.139	.043	.034	-.193	.257*	-.228*	-.085	.080	.198	-.003	-.138	.025	-.071	.141	-.089	-.071

Note: *$p < .05$; ** $p < .01$

Appendix 4: Comparison of meta-analytical practices: Journal type and publication year

	Findings by type of journal			Findings by publication year		
	Top three entrepreneurship journals ($N = 29$)	Other entrepreneurship focused journals ($N = 18$)	Other fields ($N = 43$)	1991 to 2009 ($N = 13$)	2010 to 2016 ($N = 31$)	2017 to 2022 ($N = 46$)
1. Decisions made before the analysis is conducted						
1.1 *Literature searching strategies*						
1.1.1 The study location procedure using at least three search strategies?	25 (86%)	15 (83%)	34 (79%)	8 (61%)	27 (87%)	39 (85%)
a. Two or more databases searched	26 (90%)	16 (88%)	37 (86%)	8 (62%)	27 (87%)	39 (85%)
b. Reported database names	29 (100%)	17 (95%)	40 (93%)	8 (62%)	16 (88%)	42 (91%)
c. Manual search (journal articles)	21 (72%)	13 (72%)	15 (83%)	11 (85%)	30 (97%)	45 (98%)
d. Conference proceedings	11 (38%)	7 (37%)	12 (28%)	7 (54%)	23 (74%)	33 (72%)
e. Backward search	21 (72%)	11 (61%)	30 (70%)	5 (38%)	11 (35%)	14 (30%)
f. Search terms	21 (72%)	11 (61%)	27 (63%)	6 (46%)	24 (77%)	32 (70%)
g. Announcements (for example, listservers)	5 (17%)	2 (11%)	1 (2%)	5 (38%)	21 (68%)	33 (72%)
h. Researchers contacted	15 (52%)	9 (50%)	15 (35%)	0	4 (13%)	4 (9%)
i. Search restriction (for example, published only)	1 (3%)	3 (17%)	5 (12%)	6 (46%)	15 (48%)	18 (39%)
1.2 *Selection/screening process*						

1.2.1 Documented elements used to select studies	20 (69%)	13 (72%)	26 (60%)	8 (62%)	19 (61%)	32 (70%)
1.2.2 Selection criteria reported	23 (82%)	15 (83%)	40 (93%)	11 (82%)	27 (87%)	40 (87%)
1.2.3 Quality of reported selection criteria (1 = low, 5 = high)	Mean = 2.9 (*SD* = 1.45)	Mean = 2.9 (*SD* = 1.23)	Mean = 2.9 (*SD* = 1.32)	Mean = 2.7 (*SD* = 1.18)	Mean = 2.54 (*SD*=1.30)	Mean = 3.02 (*SD* = 1.32)
1.2.4 Excluded studies reported	7 (25%)	3 (17%)	6 (14%)	1 (8%)	4 (13%)	11 (24%)
1.2.3 Selection decision performed by single person	24 (83%)	16 (89%)	34 (79%)	9 (69%)	23 (74%)	42 (91%)
1.2.5 Handling of same study/ same sample reported	21 (75%)	12 (67%)	28 (65%)	8 (62%)	20 (65%)	33 (72%)
1.3 *Coding:*						
1.3.1 More than one coder	17 (59%)	10 (56%)	19 (44%)	4 (31%)	18 (58%)	24 (52%)
1.3.2 Coder agreement, percentage	5 (17%)	5 (28%)	9 (21%)	2 (15%)	4 (13%)	12 (26%)
1.3.3 Coder agreement reliability	9 (31%)	1 (6%)	8 (19%)	2 (15%)	7 (23%)	9 (20%)
2. Decisions made during the analysis						
2.1 Bivariate analysis						
2.1.1 Reported model to calculate combined effect	14 (50%)	7 (39%)	21 (49%)	3 (23%)	12 (39%)	28 (61%)
2.1.2 Effect size metric used						
a. Correlations	26 (90%)	16 (89%)	39 (91%)	9 (69%)	28 (90%)	44 (96%)
b. Standardized mean difference	3 (10%)	1 (6%)	3 (7%)	4 (31%)	2 (6%)	1 (2%)
2.2 *Weighting and attenuation*						
2.2.1 Sample size	24 (89%)	13 (76%)	32 (74%)	12 (92%)	24 (77%)	34 (77%)
2.2.2 Inverse variance	2 (7%)	3 (18%)	11 (26%)	1 (8%)	6 (19%)	9 (20%)
2.2.3 Reliability independent variable	13 (45%)	9 (50%)	23 (53%)	9 (69%)	15 (48%)	21 (46%)
2.2.4 Reliability dependent variable	17 (59%)	8 (47%)	23 (56)	6 (60%)	17 (55%)	25 (54%)
2.2.5 Range restriction	2 (7%)	6 (40%)	5 (12%)	1 (8%)	2 (6%)	4 (9%)

2.3 *Heterogeneity tests*						
2.3.1 Any variance statics reported						
2.3.2 Confidence interval	28 (97%)	15 (83%)	38 (88%)	9 (23%)	30 (97%)	42 (91%)
2.3.3 Credibility interval	12 (41%)	6 (33%)	13 (30%)	3 (23%)	16 (52%)	12 (26%)
2.3.4 *Q*-test	11 (38%)	9 (50%)	19 (44%)	1 (8%)	12 (39%)	26 (57%)
2.3.5 Residual variance statistic (75 percent rule and I^2)	15 (29%)	13 (72%)	21 (49%)	7 (54%)	19 (61%)	23 (50%)
2.3.6 Heterogeneity significance reported						
2.4 *Multivariate analysis*						
2.4.1 Meta-regression	16 (55%)	7 (38%)	23 (53%)	3 (23%)	21 (68%)	21 (46%)
2.4.1.1 Meta-regression *k* reported	6 (21%)	2 (11%)	12 (29%)	1 (8%)	8 (26%)	11 (24%)
2.4.1.2 Meta-regression heterogeneity reported	3 (10%)	1 (6%)	8 (19%)	0	4 (13%)	8 (17%)
2.4.1.3 Meta-predictors < 15	8 (29%)	4 (18%)	12 (29%)	3 (23%)	14 (45%)	7 (16%)
2.4.2 MASEM	6 (21%)	2 (11%)	12 (28%)	1 (8%)	7 (23%)	11 (24%)
2.4.2.1 MASEM not addressing heterogeneity	3 (10%)	0 (0%)	9 (22%)	0	5 (17%)	9 (21%)
2.5 Whether and which computer program used for the analysis	7 (24%)	5 (28%)	13 (30%)	2 (15%)	6 (19%)	17 (37%)
3. Quality checks						
3.1 *Publication bias (any test)*	20 (69%)	12 (67%)	23 (53%)	3 (23%)	17 (55%)	33 (72%)
3.1.1 Published versus unpublished studies	11 (38%)	3 (17%)	4 (9%)	0	12 (39%)	6 (13%)
3.1.2 Funnel plot	5 (17%)	6 (33%)	4 (9%)	0	2 (6%)	13 (28%)
3.1.3 Trim and fill	5 (17%)	2 (11%)	7 (16%)	0	0	15 (33%)
3.1.4 File drawer	10 (34%)	5 (28%)	13 (30%)	3 (23%)	10 (32%)	15 (33%)
3.2 *Other quality checks*						
3.2.1 Additional analysis conducted?	16 (55%)	7 (39%)	15 (35%)	4 (31%)	23 (74%)	26 (57%)
3.2.3 List of primary studies included	28 (97%)	17 (94%)	33 (77%)	12 (92%)	28 (90%)	38 (83%)

3.2.4 Quality of the list of primary studies included (1 to 5)	Mean = 3.89 (*SD* = 1.40)	Mean = 3.70 (*SD* = 1.45)	Mean = 3.40 (*SD* = 1.48)	Mean = 3.16 (*SD* = 1.47)	Mean = 3.65 (*SD* = 1.57)	Mean = 3.65 (*SD* = 1.42)
3.2.5 Meta-analyzing partial correlations	6 (21%)	4 (24%)	10 (23%)	1 (8%)	2 (16%)	14 (31%)
3.2.6 Meta-analyzing on the effect size level (independent effect sizes violation)	3 (10%))	2 (11%)	10 (23%)	1 (8%)	4 (13%)	10 (22%)
4. Decisions regarding the interpretation of findings						
4.1 Abstract reporting effects in the face of heterogeneity	4 (14%)	1 (6%)	4 (10%)	5 (42%)	2 (6%)	2 (4%)
4.2 Abstract reporting effects in the face of other issues (for example, publication bias)	0	0	0	0	0	0
4.3 Discussion reporting effects in the face of heterogeneity	11 (39%)	5 (28%)	8 (19%)	5 (42%)	10 (32%)	9 (20%)
4.4 Discussion reporting effects in the face of other issues (for example, publication bias)	1 (4%)	0	2 (5%)	0	1 (3%)	2 (5%)