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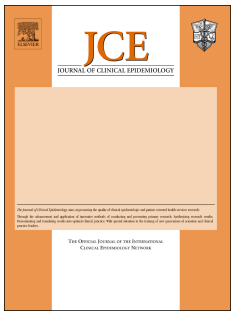

Approaches for reporting and interpreting statistically nonsignificant findings in evidence syntheses: A systematic review

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Approaches for reporting and interpreting statistically nonsignificant findings in evidence syntheses: A systematic review

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Abstract

Objective

To systematically review approaches for reporting and interpreting statistically nonsignificant findings with clinical relevance in evidence synthesis, and to assess their methodological quality and the extent of their empirical validation.

Study Design and Setting

We searched Ovid MEDLINE ALL, Scopus, PsycInfo, Library of Guidance for Health Scientists, and MathSciNet for published studies in English from January 1, 2000, to January 30, 2025 for (1) best practices in guidance documents for evidence synthesis when interpreting clinically relevant nonsignificant findings, (2) statistical methods to support the interpretation, and (3) reporting practices. To identify relevant reporting guidelines, we also searched the Enhancing the QUAlity and Transparency Of health Research Network. The quality assessment applied the Mixed Methods Appraisal Tool, Appraisal tool for Cross-Sectional Studies, and checklists for expert opinion and systematic reviews from the Joanna Briggs Institute. At least two reviewers independently conducted all procedures, and a large language model facilitated data extraction and quality appraisal.

Results

Of the 5332 records, 37 were eligible for inclusion. Of these, 15 were editorials or opinion pieces, 9 addressed methods, 8 were cross-sectional or mixed-methods studies, 4 were journal guidance documents, and 1 was a systematic review. Twenty-seven records met the quality criteria of the appraisal tool relevant to their study design or publication type, while 10 records, comprising 1 systematic review, 2 editorials or opinion pieces, and 7 cross-sectional studies, did not. Relevant methodological approaches to evidence synthesis included utilization of uncertainty intervals and their integration with various statistical measures (15/37, 41%), Bayes factors (6/37, 16%), likelihood ratios (3/37, 8%), effect conversion measures (2/37, 5%), equivalence testing (2/37, 5%), modified Fisher's test (1/37, 3%), and reverse fragility index (1/37, 3%). Reporting practices included problematic "null acceptance" language (14/37, 38%), with some records discouraging the inappropriate claim of no effect based on

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nonsignificant findings (9/37, 24%). None of the proposed methods were empirically tested with interest holders.

Conclusion

Although various approaches have been proposed to improve the presentation and interpretation of statistically nonsignificant findings, a widely accepted consensus has not emerged, as these approaches have yet to be systematically tested for their practicality and validity. This review provides a comprehensive review of available methodological approaches spanning both the frequentist and Bayesian statistical frameworks and identifies critical gaps in empirical validation of some approaches, namely the lack of thresholds to guide the interpretation of results. These findings highlight the need for systematic testing of proposed methods with interest holders and the development of evidence-based guidance to support appropriate interpretation of nonsignificant results in evidence synthesis.

Registration: CRD42025644578

Keywords: Evidence-Based Practice; Statistical Data Interpretation; Probability; Research Design; Scholarly Communication; Meta-Research

Running title: Interpreting nonsignificant findings in evidence synthesis

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Plain Language Summary

This review looked at how to best report results that are not statistically significant because some of these findings can still be important to inform clinical care or health policy. We searched databases for studies published between 2000 and 2025. Out of more than 5,000 records, 37 studies were relevant. These studies showed that there is no single best way to report nonsignificant findings.

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What is new?

Key findings

- Best practices have not been established for interpreting and reporting nonsignificant findings.
- The extent to which proposed methodologies for the interpretation of nonsignificant findings have been adopted in evidence synthesis is unclear.

What this adds to what is known?

- Several statistical approaches can help with the interpretation of such findings, but they expose a critical disconnect between methodological innovation and real-world adoption across the research community.
- There are knowledge gaps in the empirical validation of methods for interpreting nonsignificant findings and the absence of standardized interpretive thresholds, which highlight priority areas for methodological research.

What is the implication and what should change now?

- We advocate the need for coordinated efforts between evidence synthesis software developers, journal editors, and institutions involved in evidence synthesis to bridge the persistent evidence-practice gap in biomedical research.

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1 Introduction

Uncertainty is inherent in medicine.[1–4] Statistical methods and methodological frameworks help quantify and interpret this uncertainty in clinical decision-making and medical research.[5–7] Among various statistical frameworks, the frequentist approach predominates the field,[8] often leading researchers to interpret findings through a binary lens of statistical significance.[9] This approach has faced criticism for oversimplifying complex data and obscuring the clinical relevance of research findings.[10] Consequently, statistically significant (hereafter referred to as significant) findings may be overemphasized, regardless of their clinical importance, whereas statistically nonsignificant (hereafter referred to as nonsignificant) findings are disregarded, even when they have a signal of clinical relevance. This issue is particularly problematic in studies with rare events, small sample sizes, or high participant variability, where nonsignificant findings are common.[11] Selective reporting further aggravates such problems by favoring significant over nonsignificant findings.[12–15] This approach distorts the scientific literature through publication and data availability biases that may influence clinical guidelines, health care policies, and research directions.

The challenges in interpreting nonsignificant findings extend beyond primary research into evidence synthesis and meta-analysis.[16,17] When findings are categorized merely as significant or not, readers can misinterpret findings in ways similar to those in primary studies.[18] The complexity of interpreting nonsignificant findings often leads to their undervaluation in evidence synthesis,[19] risking a skewed understanding of evidence and undermining appropriate application to clinical practice. Furthermore, the interpretation and reporting of nonsignificant findings pose additional challenges by potentially introducing a distorted presentation of findings, which can mislead readers.[20]

Even though nonsignificant findings may hold clinically important insights,[21] no studies have comprehensively examined how they should be interpreted and reported in clinical medicine. This work aimed to systematically review approaches for reporting and interpreting statistically nonsignificant findings with clinical relevance in evidence synthesis, and to assess their methodological quality and the extent of their empirical validation.

2 Methods

We sought to answer three key questions (KQ):

- KQ1: What are the current best practices and rationales for interpreting nonsignificant findings that suggest potential clinical effects in health care research, including reporting considerations?
- KQ2: What statistical approaches are recommended for evaluating whether signals of clinical relevance warrant reporting despite not being significant?
- KQ3: What specific terminology and stylistic conventions are recommended for accurately and transparently communicating nonsignificant findings with potential clinical relevance?

We also conceptualized the following contextual questions (CQ):

- CQ1: What recommendations exist for reporting nonsignificant findings with a signal of clinical effect in the handbooks and guidance documents from reputable organizations or institutions?
- CQ2: What specific vocabulary, phrases, and stylistic guidelines do organizations or institutions suggest for accurately and transparently communicating nonsignificant findings that are clinically meaningful?

We conducted this review following the Cochrane guidelines for methodology reviews,[22] and prospectively registered it with the International Prospective Register of Systematic Reviews (CRD42025644578). This report is in line with the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) 2020 statement.[23]

2.1 Eligibility criteria

The inclusion criteria followed the Studies, Data, Methods, and Outcomes (SDMO) framework (Table S1).[24] We included documents that guided the interpretation and reporting of nonsignificant findings in health care.

2.2 Information sources

We searched MEDLINE ALL (Ovid), Scopus (Elsevier), PsycInfo (Ebsco), Library of Guidance for Health Scientists (LIGHTS),[25] and MathSciNet (American Mathematical Society) to identify publications between January 1, 2000, and January 30, 2025 (see supplementary material for search strategies). This timeframe captured recent advancements in the field following the highlight of p-value shortcomings and a call for evidence-based medical statistics.[26] A reviewer familiar with the topic (AS) developed the initial search strategy, which an information specialist (IK) refined. An information specialist reviewed the strategy using the Peer Review of Electronic Search Strategies (PRESS) guidelines.[27] We used the Deduplicator tool,[28] then EndNote, to remove duplicate search results, and we uploaded them to Covidence for screening.

We also searched the Enhancing the QUAlity and Transparency Of health Research Network (EQUATOR) network up to February 6, 2025, for relevant reporting guidelines by choosing "statistical analysis plan-whole report" and "statistical methods and analyses" under the filter "section of the report" within the EQUATOR library.

2.3 Selection process

The screening team (YTX, EN, AYO) completed calibration to standardize procedures for title/abstract screening (30 records) and full-text screening (5 records).[29] One reviewer (AS) developed the calibration, which a senior reviewer (GG) validated for accuracy. Following the pilots, four independent reviewers (AS, YTX, EN, AYO) screened the records. A senior reviewer (GG) resolved conflicts.

2.4 Data collection process

We extracted concepts aligned with our key questions, including proposed statistical methods for interpreting nonsignificant findings, approaches to reporting such findings, barriers associated with each method, and contextual applicability. One reviewer (AS) extracted data and verified accuracy using Claude 3.7 Sonnet configured in extended-thinking mode with a formal style. The choice of including artificial intelligence was driven by enhancing data-extraction efficiency.[30–32] Two other reviewers

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(AYO, EN) cross-checked the large language model's output. There were no missing or unclear information issues during data extraction.

2.5 Methodological quality appraisal

We tailored our quality appraisal process to accommodate the diverse publications included in this review and to prioritize tools designed to assess methodological quality rather than to judge risk of bias[33] since most did not have an experimental or epidemiological design. For cross-sectional studies, we used the Appraisal tool for Cross-Sectional Studies (AXIS) tool[34]; for opinion-based articles or editorials, we applied the Joanna Briggs Institute's (JBI) checklist for expert opinion[35]; for mixed-methods analyses, we used the Mixed Methods Appraisal Tool[36]; and for systematic reviews and research syntheses, we relied on the JBI checklist for systematic reviews.[37] We selected these tools based on their capacity to address methodological nuances specific to each study design. Risk of bias due to missing results and certainty of evidence evaluation did not apply to this study.

2.6 Data analysis and synthesis

Due to the inherent lack of quantifiable data within this methodological topic, we synthesized findings descriptively. We organized data using Microsoft Excel (version 2408, Microsoft Corp., Redmond, WA, USA), conducted the analyses using R (version 4.4.2, R Core Team, Vienna, Austria), and created the flow diagram with the PRISMA2020 Shiny app.[38]

3 Results

3.1 Study characteristics

Of the 5332 records identified, 37 were included in the analysis (Figure 1). Among these, 15 were editorials or opinion articles,[39–53] 9 were method articles,[54–62] 7 were cross-sectional studies,[63–69] 4 were journal guideline documents,[70–73] 1 was a mixed-method study,[74] and 1 was a systematic review.[75] Details regarding excluded records in the full-text phase are available in Table S2.

Of the included studies, 27 (73%) met the quality criteria of the appraisal tool relevant to their study design or publication type,[39–50,52–62,70,71,73,74] while 10 (27%) did not meet these criteria.[51,63–69,72,75] Among

those that did not meet quality criteria, 7 were cross-sectional studies, 2 were editorials or opinion pieces, and 1 was a systematic review. The most common (5/7, 71%) methodological limitations among cross-sectional studies that failed to meet quality criteria included inadequate justification of sample size. For editorials and opinion pieces, limitations primarily related to insufficient acknowledgment of evidence sources. The systematic review that did not meet quality criteria lacked transparency in risk of bias assessment procedures. Despite these methodological shortcomings, we included all eligible studies to provide a comprehensive overview of the existing literature on this topic, while acknowledging that the quality of evidence supporting different approaches varies.

Other than editorials, opinion pieces, method articles, and journal recommendation papers, a small proportion of publications adhered to their respective reporting guidelines (3/10, 30%),[66,74,75] namely the STrengthening the Reporting of OBservational studies in Epidemiology statement for cross-sectional studies (STROBE) and only one reported having a protocol (1/10, 10%).[63] No articles incorporated perspectives from interest holders, comprising individuals with interests in health care issues.[76] Furthermore, the articles addressed nonsignificance in a range of study designs, including experimental and observational studies and systematic reviews. Among these, randomized controlled trials were the most frequently discussed (11/37, 30%).[41,45,49,57,60,62,65,66,68,69,75] Further details regarding the characteristics of eligible publications and quality assessment can be found in Tables 1, S3-S8.

3.2 KQ1: Best practices for interpreting nonsignificant findings

We did not identify any eligible publications that addressed best practices for interpreting nonsignificant findings.

3.3 KQ2: Approaches for interpreting nonsignificant findings

Publications have emphasized that nonsignificant findings require careful interpretation to avoid misinforming research and clinical decisions. Key arguments raised concerns about the limitations of hypothesis testing in supporting the null hypothesis,[50] cautioning against interpreting nonsignificant findings as proof of no effect,[39,40,42,45,57,58] and criticizing the dichotomization of findings by statistical significance, which can overlook clinically important findings.[48] Additionally, some publications

criticized the practice of labeling nonsignificant findings as "negative" or "useless."[49,61] Given these challenges, the following approaches were proposed for the proper interpretation of nonsignificant findings.

3.3.1 Utilizing uncertainty intervals

Focusing on confidence interval interpretation was the most frequently recommended method for KQ2 (15/37, 41%), either alone (8/37, 22%),[39,44,45,48,52,71,72,75] or in combination with other approaches, including the use of a minimal clinically important difference (3/37, 8%),[40,47,57] effect sizes (2/37, 5%),[50,67] reverse Bayesian methods (1/37, 3%),[59] or area under the curve (1/37, 3%).[74] Publications consistently endorsed confidence intervals but provided limited threshold guidance beyond prespecified minimal clinically important differences, which reflects the smallest difference considered important from a clinical perspective. One source emphasized interpreting both the point estimates and the bounds of intervals,[39] while another elaborated on the notion that the true effect is more likely around the point estimate as opposed to interval limits.[45] In the latter scenario, the line of no effect and the minimal clinically important difference may be used as the thresholds.[40,7542,48]

3.3.2 Bayesian methods

Bayesian methods and Bayes factors were recommended for interpreting nonsignificant findings (6/37, 16%) and demonstrated greater standardization compared to others.[48,55,56,58,63,65]

3.3.3 Likelihood ratios

Three publications recommended likelihood ratios.[49,60,69] This approach quantifies the relative strength of evidence between competing hypotheses and may be preferable when uniform prior distributions render Bayes factors inapplicable or undefined, as likelihood ratios are not bound to priors. The interpretation follows the thresholds corresponding to Bayes factors.[69]

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3.3.4 Equivalence testing

Two publications recommended equivalence testing using predefined margins based on the minimal clinically meaningful differences.[56,58] The approach employs two one-sided tests or 90% confidence intervals to establish whether effects fall within equivalence bounds. However, acquiring evidence-based equivalence margins can be challenging, limiting the practical utility of evidence synthesis. Additionally, the available tool for equivalence testing in meta-analysis requires standardized mean difference metrics,[77] which necessitates converting various statistical measures under the assumption of normally distributed data in evidence synthesis.

3.3.5 Effect size conversion methods

Absolute risk reduction and numbers needed to treat or harm were recommended as intuitive measures for dichotomous outcomes (2/37, 5%).[51,61] However, the latter might be perceived as unsuitable for nonsignificant findings or those with zero difference between groups, as such data fail to yield clinically meaningful values.[51] Numbers needed to treat or harm can be obtained from either absolute or relative effects, with the latter providing a more constant effect among various baseline risks across primary studies.[61] Both methods must be implemented on pooled effect estimates in meta-analyses.

3.3.6 Modified Fisher's test

One publication proposed a method for identifying potential false negatives among sets of nonsignificant findings.[64] The approach aggregates nonsignificant p-values; if the resulting p-value is lower than the threshold of 0.1, as proposed by the authors, at least one false negative is likely present. The method's reliability increases with larger result sets, although it cannot identify specific false negatives.[64] Therefore, its application in studies with a low number of endpoints and evidence synthesis might be limited.

3.3.7 Reverse fragility index

One publication recommended assessing robustness by determining the minimum events needed to shift nonsignificant findings to significant.[66] This method is applicable to dichotomous outcomes only. While

providing a fragility measure for nonsignificant findings can help evaluate their robustness, the practical utility is uncertain. No specific thresholds have been proposed for this method; however, a similar approach using the reciprocal interpretation of values applied to the fragility index of meta-analyses[78] could be adapted here, although its applicability remains to be tested.

It is worth noting that among the identified approaches for the proper interpretation of nonsignificant findings, two were tailored for randomized controlled trials.[41,59] One approach, which focuses on power calculations and risk of type II errors,[41] is not directly applicable to evidence synthesis. The second, Analysis of Credibility, is based on reverse Bayes methods and requires adaptation to account for between-study heterogeneity when applied to meta-analyses.[59] Further details on interpretation approaches are provided in Table S9.

3.4 KQ3: Proposed terminologies for reporting nonsignificant findings

Publications identified two categories of problematic terminology: "Null acceptance" statements inappropriately supporting the null hypothesis, namely "there was no difference between the groups" (14/37, 38%),[39,42,44,45,47–49,53,55–58,63,70] and "trend" statements suggesting interpretation of p-values near significance thresholds using qualifying terminologies, e.g., "the results trended toward significance" (10/37, 27%).[40,43,46,53,62,64,67,68,70,73] Recommended alternatives included precise language acknowledging uncertainty: "Study results do not support a recommendation in favor of the intervention" (1/37, 3%),[41] and describing effect ranges compatible with confidence intervals (1/37, 3%).[39] Bayesian approaches offered additional precision with phrases like "data are insensitive" for inconclusive evidence (1/37, 3%).[55] Several publications recommended incorporating contextual considerations beyond statistical measures, including costs, interest holders' perspectives, and potential harms (9/37, 24%).[39–41,44,56,57,61,65,75] On the other hand, while some publications stressed the importance of correctly reporting a nonsignificant p-value as "statistically nonsignificant" (1/37, 3%),[44] others discouraged highlighting the quoted term and p-values altogether, advocating instead for the use of alternative metrics, namely confidence intervals, to convey the results more meaningfully (2/37, 5%).[39,57] Further details on encouraged and discouraged reporting of nonsignificant results are available in Table 2 and Table S10.

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3.5 Exploratory questions

3.5.1 Ethical considerations

Some publications emphasized the ethical importance of reporting nonsignificant findings, highlighting how publication and reporting biases can undermine research integrity and lead to research waste (7/37, 19%).[40,53–56,63,67] One publication highlighted the critical consequences of false negatives in diseases with high mortality or limited treatment options.[66]

3.5.2 Barriers to adopting alternative statistical methods

Most publications suggested that the frequentist approach remains deeply ingrained in the field, creating barriers to adopting alternative statistical methods (14/37, 38%).[39,40,42,47–50,53,55,61,66–68,74] They also noted that alternative statistical methods often require additional training and familiarity among researchers (5/37, 14%).[48,56,58,60,63] Nevertheless, most sources (28/37, 76%) showed unclear adoption status, suggesting limited systematic implementation across biomedical literature. Further details are available in Table S11.

3.6 Contextual questions

Major institutions involved with clinical trials or evidence syntheses provided minimal to no guidance on interpreting and reporting nonsignificant findings (see Table S12).

4 Discussion

4.1 Overview

This systematic review identified multiple approaches for interpreting and reporting nonsignificant findings, but no single evidence-based approach with broad agreement among researchers, statisticians, methodologists, and journal editors exists. While the presentation and interpretation of confidence intervals emerged as the most endorsed approach for incorporating nonsignificant results into evidence synthesis, substantial heterogeneity exists in implementation recommendations, and most methods lack empirical validation or clear adoption pathways.

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4.2 Nonsignificant findings in meta-analysis and evidence synthesis

Meta-analysis constitutes the cornerstone of quantitative evidence synthesis and provides a framework for combining results from multiple methodologically similar individual studies with appropriate statistical heterogeneity.[17,79] The output of a meta-analysis is a pooled effect estimate along with associated measures of precision, such as confidence intervals in frequentist frameworks or credible intervals in Bayesian approaches.[80] When pooled effect estimates are nonsignificant, the interpretation becomes challenging. The Cochrane Handbook emphasizes interpreting the magnitude and precision of pooled effects rather than relying on binary significance testing, but lacks concrete guidance for authors.[81] Importantly, nonsignificant results in evidence synthesis reflect uncertainty rather than the absence of effect.[82] Prediction intervals, which capture effect size variability,[83] provide additional context for interpreting nonsignificant pooled estimates by illustrating the scope of uncertainty in the evidence base. Despite these established principles, our review demonstrates that standardized implementation approaches for these interpretive principles in evidence synthesis remain lacking.

4.3 Clinical and research implications

The variety of approaches to interpreting nonsignificant findings highlights the absence of a single best practice and reflects the complexity of the problem. Misinterpretation of nonsignificant findings, whether through inappropriate acceptance of the null hypothesis or misleading trend language, can lead to suboptimal clinical decisions and research waste. The common recommendation to focus on the interpretation of confidence intervals suggests emerging consensus; however, researchers sometimes misinterpret confidence intervals similar to p-values, incorrectly claiming “no difference” when intervals include the value of no effect rather than acknowledging the full range of plausible values.[84]

In response to this issue, recent proposals for decision threshold guidance in interpreting the results in evidence synthesis may enhance the practical implementation of confidence intervals.[85,86] On the other hand, Bayesian approaches, with the established threshold classification schemes,[87] offer a promising standardized framework that could facilitate adoption in clinical guideline development.[88] Multiple sources referenced Jeffreys’ classification scheme for the Bayes factor (BF_{10}), which quantifies the

relative evidence for the alternative hypothesis (H_1) versus the null hypothesis (H_0). In this scheme, BF_{10} values between 1/3 and 3 are considered anecdotal evidence and are generally regarded as barely worth mentioning. Moderate or substantial evidence in favor of the alternative hypothesis is indicated by values between 3 and 10, while values from 10 to 30 suggest strong evidence. Values between 30 and 100 are interpreted as very strong evidence, and those exceeding 100 provide decisive support for the alternative hypothesis. The same strength of evidence in favor of the null hypothesis is given by the reciprocal of these thresholds (i.e., a BF_{10} below 1/10 for strong evidence, below 1/30 for very strong, and below 1/100 for decisive evidence).[55,58,63] However, the additional statistical expertise required may constrain widespread implementation. Alternatively, methods such as the reverse fragility index may help decision makers more objectively assess the imprecision of findings.

These considerations are particularly relevant to evidence synthesis involving safety outcomes, where reporting concerns are well-documented.[89–91] Furthermore, systematic application of these approaches could help address publication bias in evidence syntheses across scientific disciplines.[92,93]

4.4 Implementation in existing reporting guidelines

To translate these clinical and research insights into practice, it is important to consider how they align with and inform existing reporting guidelines. Current reporting guidelines, including PRISMA, provide limited direction for interpreting nonsignificant findings beyond basic effect size and confidence interval reporting. Our findings demonstrate that available guidance resources are insufficient, given the complexity of interpretation challenges identified in contemporary research.

Integration of methods that quantify evidence in favor of the null hypothesis, such as Bayesian inferences, represents a reasonable improvement for reporting standards concerned with testing hypotheses. These methodological advances warrant consideration in future updates to major reporting guidelines and their extensions so researchers have more comprehensive frameworks for interpreting and communicating nonsignificant findings.

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5 Limitations

Most identified approaches lacked empirical testing with relevant interest holders, particularly clinicians, patients, and health care policy makers, who must ultimately interpret such findings. The unclear adoption status of most recommendations suggests limited real-world validation. Furthermore, our study focused on English-language literature published between 2000 and 2025, which may exclude non-English publications and earlier foundational works. While the date frame captures recent advancements, it risks overlooking historical perspectives. Finally, the adoption of methods proposed for primary studies in the context of evidence synthesis should be approached with caution, as various factors, namely heterogeneity between studies, must be considered.

6 Conclusion

This systematic review addresses a critical gap by comprehensively evaluating available approaches for interpreting nonsignificant findings in evidence synthesis. To further advance the field, it is important to move beyond replacing one statistical tool with another and, instead, embrace a more holistic approach to interpretation and reporting of findings. Rather than emphasizing distinctions between Bayesian and frequentist paradigms, integrating these frameworks enables more nuanced evidence synthesis, which could enhance clinical decision-making, though this requires empirical validation. Authors are encouraged to adopt the methods described in this article to contextualize their findings, and journals should be more receptive to these approaches, especially for findings with potential clinical relevance. Institutions involved in evidence synthesis may also consider incorporating the methodologies identified here into their platforms, ensuring a more comprehensive, evidence-based interpretation of available data for the scientific community. Nevertheless, systematic evaluation of implementation barriers and user comprehension will be essential before broader institutional adoption of these methodologies. Finally, the formation of expert panels and guideline groups may facilitate the interpretation of findings for statistical methods without readily available thresholds.

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8 CRediT authorship contribution statement

Amin Sharifan: Conceptualization, Data curation, Methodology, Software, Formal analysis, Investigation, Writing - Original Draft, Writing - Review & Editing, Visualization, Project administration. **Andreea Dobrescu:** Conceptualization, Writing - Review & Editing, Supervision. **Curtis Harrod:** Conceptualization, Writing - Review & Editing, Supervision. **Irma Klerings:** Investigation, Writing - Review & Editing. **Etienne Ngeh:** Investigation, Writing - Review & Editing. **Ariel Yuhan Ong:** Investigation, Writing - Review & Editing**. Yu-Tian Xiao:** Investigation, Writing - Review & Editing. **Gerald Gartlehner:** Conceptualization, Methodology, Formal analysis, Validation, Investigation, Writing - Review & Editing, Supervision.

9 Declarations

9.1 Ethics statement

This study utilized only publicly available data from the scientific literature. As the research did not involve any participants or identifiable personal data, ethical approval was not applicable.

9.2 Patient and public involvement

This study did not engage patients or the public in its design, implementation, reporting, or dissemination.

9.3 Competing interests

The authors have nothing to disclose.

9.4 Funding sources

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9.5 Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article and its supplementary materials. The protocol for the study is available from the corresponding author upon request.

9.6 Declaration of generative AI in scientific writing

During the preparation of this work, the authors used Claude Pro to quality-check the data extraction and quality appraisals. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Figure legend

Figure 1. PRISMA Flow diagram. The website represents records identified from the EQUATOR Network. EQUATOR, Enhancing the Quality and Transparency of Health Research; LIGHTS, Library of guidance for health scientists; PRISMA, Preferred reporting items for systematic reviews and meta-analyses.

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Table 1. Study characteristics.

Category	Characteristics	n/N (%)
Article type	Editorials and opinions	15/37[a] (41)
	Methods	9/37 (24)
	Cross-sectional and mixed methods	8/37 (22)
	Journal guide for authors	4/37 (11)
	Systematic review	1/37 (2)
Clinical area	General medicine	18/37 (49)
	Psychology	3/37 (8)
	Oncology	2/37 (5)
	Anesthesiology	2/37 (5)
	Cardiology	1/37 (2)
	Evidence-based medicine	1/37 (2)
	Biostatistics	1/37 (2)
	Gerontology	1/37 (2)
	Mental health	1/37 (2)
	Nicotine & tobacco research	1/37 (2)
	Nursing	1/37 (2)
	Orthopedic medicine	1/37 (2)
	Reproductive health	1/37 (2)
	Spinal cord medicine	1/37 (2)
	Sport medicine	1/37 (2)
	Urology	1/37 (2)
Funding	Not reported	21/37 (57)
	Government	9/37 (24)
	None	5/37 (14)
	Nonprofit organization	2/37 (5)
Geographic contributions	Europe	10/37 (27)
	North America	10/37 (27)
	Europe and North America	8/37 (22)
	Oceania	5/37 (14)
	Not reported	2/37 (5)
	Europe and Oceania	1/37 (2)
	Europe, North America, and South America	1/37 (2)
Quality assessment questions	Addressed	280/324[b] (86)
	Not addressed	14/324 (4)
	Unclear	2/324 (1)
	Not applicable	28/324 (8)

[a] The denominator represents the number of identified records.
[b] The denominator represents the number of questions.

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Table 2: Encouraged and discouraged language in the literature for reporting statistically nonsignificant findings when using the frequentist approach.

Category	**Characteristics**
Encouraged Phrasing	Results are most compatible with no important effect[39]
	We were unable to demonstrate a difference between the groups[70]
	Promising[52]
	Interesting hint[62]
	Suggestive[52]
Discouraged Phrasing	No effect[39,42,45,48,53,55,56,58,63]
	Trend toward significance/nonsignificant trend/trend[40,43,46,53,62,67,68,70,73]
	Almost statistically significant[43,53,62,67]
	No difference[39,44,57,70]
	Approaching statistical significance[46,62,70]
	Ineffective[49,70]
	Marginal significance[64,68]
	Lack of evidence[49]
	Near statistical significance[40]
	No association[47]
	Borderline significance[40]

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Identification of new studies via databases and registers

Identification of new studies via other methods

Identification

Records identified from:
Databases (n = 5,248):
MEDLINE (n = 2,781)
Scopus (n = 886)
PsycInfo (n = 1,424)
MathSciNet (n = 106)
LIGHTS (n = 51)

Records removed before screening:
Duplicate records (n = 352)
Records marked as ineligible by automation tools (n = 0)
Records removed for other reasons (n = 0)

Records identified from:
Websites (n = 84)

Screening

Records screened
(n = 4,896)

Records excluded
(n = 4,769)

Reports sought for retrieval
(n = 127)

Reports not retrieved
(n = 0)

Reports sought for retrieval
(n = 4)

Reports not retrieved
(n = 0)

Reports assessed for eligibility
(n = 127)

Reports excluded:
Did not address research question (n = 57)
Focused on statistically significant results (n = 20)
Irrelevant to healthcare (n = 10)
Focused on mathematics (n = 3)

Reports assessed for eligibility
(n = 4)

Reports excluded:
Did not address research question (n = 3)
Duplicate (n = 1)

Included

New studies included in review
(n = 37)
Reports of new included studies
(n = 37)

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Highlights

- Statistically nonsignificant findings are inaccurately interpreted and reported.
- Mapping diverse methods reveals complexity in interpreting nonsignificant findings.
- No guidelines exist for interpretation of meaningful but nonsignificant findings.
- Methods outlined herein may complement interpreting nonsignificant findings.
- Empirical validation of methods to interpret nonsignificant findings is warranted.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests.

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