# Meta-IMU: A R Shiny App to Conduct Meta-Analysis in Systematic Review and Umbrella Reviews

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Many tools exist for conducting meta-analyses in systematic reviews, but they are often expensive or difficult for beginners to use. This challenge arises because most tools either fail to address all aspects of meta-analysis comprehensively or lack sufficient guidance for navigating their features. To address these limitations, we developed Meta-IMU, a free R-based Shiny application tailored specifically for beginners. Unlike many existing tools that focus solely on standard systematic reviews, Meta-IMU supports both systematic reviews and umbrella reviews, offering a more versatile approach. To ensure accessibility, Meta-IMU includes built-in instructional videos that guide users step by step, from navigating the application to interpreting the results produced. This guidance ensures users can confidently perform analyses without prior expertise. Meta-IMU encompasses a comprehensive range of features covering key aspects of meta-analysis, such as defining review questions, developing search terms, retrieving studies from various databases, assessing risk of bias, creating tables and plots, analysing small-study effects, performing meta-regression and subgroup analyses, conducting sensitivity analyses, assessing the certainty of evidence, summarizing findings, and generating PRISMA checklist reports. By integrating these functionalities into a single platform, Meta-IMU provides a user-friendly, all-in-one solution. In summary, Meta-IMU is a comprehensive, free application designed to simplify the process of meta-analysis for both systematic reviews and umbrella reviews, making advanced analytical techniques accessible to researchers at any level of experience.

***Keywords:*** *Systematic review, umbrella review, meta-analysis, R, Shiny*

## Introduction

Systematic reviews aim to comprehensively identify, evaluate, and summarise all available studies addressing a specific research question, whereas Umbrella review (also known as overviews of reviews) aims to summarise evidence across multiple systematic reviews on related topics. Both approaches employ meta-analysis, a statistical technique that integrates the results of multiple studies to generate a comprehensive conclusion. Conducting meta-analyses efficiently requires specialised software. Researchers are offered a wide range of tools, each with its own advantages, challenges, and limitations. However, these tools often vary significantly in terms of ease of use, features, and statistical capabilities, which can impact the accuracy and efficiency of the meta-analytic process. A brief overview of the most prominent existing tools used in meta-analytic research is provided below.

## 1.0 A Brief Overview of Existing Tools in Systematic Review and Meta-analysis

### *(a) RevMan*

RevMan, developed by the Cochrane Collaboration, is one of the most widely used software tools for conducting systematic reviews and meta-analyses. It offers a comprehensive environment for managing the entire review process, including data extraction, statistical analysis, and manuscript preparation.[1]

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Despite its popularity, RevMan's statistical functionality is relatively limited, as it mainly supports standard fixed-effect and random-effects models. More advanced methods, such as meta-regression or multivariate meta-analysis, are not easily accommodated. Furthermore, RevMan is primarily designed for systematic reviews of primary studies and therefore does not natively support umbrella reviews, which require the synthesis of results from multiple systematic reviews. Its design is also largely tailored to the structure of Cochrane reviews, which may limit flexibility for non-Cochrane applications.

***(b) R***

R is a powerful statistical computing environment that offers several valuable packages for meta-analysis, such as meta and metafor. These packages support various effect size measures, subgroup analyses, sensitivity analyses, and produce graphical outputs like forest and funnel plots. Their high level of customisation and flexibility makes them popular among statisticians and researchers experienced with R.[2,3] However, effective use of R requires a solid understanding of statistical methods and proficiency in R programming, which can be a significant hurdle for beginners. While R does not offer packages specifically designed for Umbrella review, its versatility allows researchers to generate the necessary outputs, such as credibility plot by using other general-purpose packages such as ggplot2.

***(c) Comprehensive Meta-Analysis (CMA)***

Comprehensive Meta-Analysis (CMA) is a widely used standalone software that offers an intuitive, graphical user interface to facilitate the meta-analysis process. It supports a wide range of study types and effect size calculations, making it a versatile choice for meta-analysts.[4] One of its key advantages is its ease of use, requiring little to no programming knowledge. However, CMA is a proprietary tool, requiring paid licenses, which may limit access for some researchers, particularly those in resource-constrained settings. Besides, CMA does not integrate well with other software tools (eg, R, Stata), thus it is difficult to extend or automate outside of the CMA environment.

***(d) Microsoft Excel***

Several Excel-based tools (eg Meta-Essentials, MetaXL and MetaEasy) have been developed to perform meta-analyses, leveraging the familiarity and accessibility of Excel as a platform. These tools support a variety of effect size measures and models, providing users with a simple, yet powerful tool for basic meta-analytic calculations.[5-8] However, these tools lack the advanced statistical features of more specialised software.

***(e) Statistical Package for the Social Sciences (SPSS)***

SPSS, a general-purpose statistical software, includes meta-analysis functionalities as part of its broader suite of statistical tools. It is particularly popular in the social sciences, where SPSS is widely used for data analysis.[9] SPSS's meta-analysis capabilities are somewhat limited compared to specialised software, and conducting meta-analyses within SPSS requires a solid understanding of both meta-analytic methods and SPSS syntax.[10] While it can handle basic tasks, more advanced features like meta-regression are not as fully developed. Besides, SPSS does not have the flexibility to easily integrate with other open-source meta-analysis libraries, such as R's metafor, restricting its extensibility.

### *(f) Stata*

Stata is a powerful statistical software package that offers extensive support for meta-analysis through built-in commands and user-contributed packages.[11] Stata is particularly known for its flexibility and ability to handle complex data structures, making it an excellent choice for advanced meta-analyses and meta-regressions. It is favored by economists and medical researchers who require high-level statistical tools. However, its steep learning curve and the need for licensing fees can be barriers for new users or those working in resource-limited settings.[12] The interface and coding-based analysis may be overwhelming for users new to statistical analysis, requiring significant time to learn and apply effectively.

### *(g) MetaWin*

MetaWin is another tool for meta-analysis, often used in ecological and environmental sciences. It provides a wide range of options for conducting meta-analyses, including different statistical models, permutation tests, and resampling techniques.[13] Although MetaWin is less commonly used in medical and social science fields, its application to ecological data sets and flexibility in handling non-parametric data make it a valuable tool for researchers in these domains. As MetaWin is tailored for ecological and environmental sciences, its applicability to other research fields, such as medicine or social sciences is limited. The software does not support advanced techniques such as multivariate meta-analysis or network meta-analysis, making it unsuitable for complex data structures.

### *(h) R-based App*

Several free, R-based applications for meta-analysis are available, such as JASP and jamovi. While these tools are open-source and provide robust statistical analysis capabilities, they function primarily as statistical software rather than comprehensive systematic review workflow managers. Consequently, they do not guide researchers through the full review process. Users are expected to already possess knowledge of systematic review and meta-analysis methodology, including the ability to formulate research questions using the PICOS framework (Population, Intervention, Comparator, Outcomes, Setting) and to develop appropriate search strategies. Additional software is required to complement JASP and jamovi, as they lack features such as automated preparation of PRISMA flow diagrams or implementation of GRADE assessments. Moreover, they do not support umbrella reviews; therefore, outputs such as redundancy tables and credibility plots cannot be generated natively within these platforms.

The pros and cons of the above-mentioned tools are summarised in Table I. Given the limitations of previously mentioned meta-analysis tools, there is a clear need for a free, comprehensive platform that provides a one-stop solution for meta-analysis, particularly for beginners. To address this gap, we developed Meta-IMU, a new R Shiny application designed to simplify the process of conducting meta-analyses for both systematic and umbrella reviews.

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***Table I: Pros and Cons of Existing Tools for Systematic Review and Meta-Analysis.***

| Tool | Pros | Cons |
|---|---|---|
| **RevMan** | • Widely used, especially within Cochrane.<br>• Comprehensive platform for managing systematic reviews (data extraction, analysis, manuscript preparation). | • Limited statistical methods.<br>• Not suitable for Umbrella reviews.<br>• Less flexible for non-Cochrane work. |
| **R (meta, metafor, etc)** | • Highly flexible and customisable.<br>• Supports advanced analyses.<br>• Strong graphical capabilities.<br>• Open-source and free. | • Steep learning curve, requires R programming skills.<br>• No dedicated umbrella review packages (requires custom coding).<br>• Not user-friendly for beginners. |
| **Comprehensive Meta-Analysis (CMA)** | • Intuitive GUI, easy to learn.<br>• Supports wide range of study types and effect sizes.<br>• Does not require programming. | • Proprietary licenses.<br>• Poor integration with other tools (R, Stata).<br>• Limited automation and extensibility. |
| **Microsoft Excel (Meta-Essentials, MetaXL, MetaEasy)** | • Widely available and familiar interface.<br>• Free or low-cost add-ins.<br>• Useful for basic meta-analytic calculations. | • Limited advanced statistical functions.<br>• Dependent on Excel environment.<br>• Less intuitive user interface. |
| **SPSS** | • Popular and widely used in social sciences.<br>• Provides some built-in meta-analysis capabilities.<br>• Familiar interface for existing SPSS users. | • Proprietary licenses.<br>• Limited meta-analysis functions compared to specialised tools.<br>• Requires good knowledge of SPSS syntax. |
| **Stata** | • Powerful statistical package.<br>• Extensive support for advanced meta-analysis and meta-regression.<br>• Flexible and suitable for complex data structures.<br>• Strong academic/clinical reputation. | • Proprietary licenses.<br>• Steep learning curve (code-based workflow).<br>• May overwhelm new users. |

| | | |
|---|---|---|
| **MetaWin** | • Specialised for ecological and environmental sciences.<br>• Supports permutation tests and resampling methods.<br>• Flexible for non-parametric data. | • Less applicable outside ecology/environmental fields.<br>• Limited adoption in medicine and social sciences. |
| **R-based Apps (JASP, jamovi)** | • Free, open-source, and user-friendly.<br>• GUI-based, lowering entry barrier vs R.<br>• Good for basic statistical meta-analysis.<br>• Cross-platform support. | • Not a full systematic review manager.<br>• Users must already know PICOS/ search strategy design.<br>• Lack PRISMA flowchart, GRADE, umbrella review support.<br>• Cannot produce redundancy tables or credibility plots natively. |

**2.0 Meta-IMU**

Meta-IMU is an R-based Shiny app developed by IMU University, Malaysia, and is available as freeware to the public (Copyright number: LY2024W05922). Shiny provides an interactive and user-friendly web interface while R provides computational and flexibility in data analysis. This combination ensures that complex analysis can be performed while still being accessible for users who are not proficient in R programming. Besides, as Meta-IMU is developed in line with internationally recognised standards and guidelines such as Cochrane Handbook, it ensures that the workflows and outputs produced are robust, transparent and adhere to global standards.

**2.1 Software Development**

Meta-IMU was written in R, using various packages such as shiny, shinythemes, dplyr, tidyverse, ggplot2, gridExtra, readxl, shinyscreenshot, meta, iNZightTools, metasens, syn, robvis, shinyjs, shinycssloaders, etc.

**2.2 System Requirement**

Meta-IMU can be used on both Microsoft Windows and macOS. Even though it may function on other operating systems supported by R and RStudio as well, this has not been verified. Besides, it is preferable that the computer has at least 16GB of RAM (random access memory). While a system with 8GB of RAM may run the application, some tasks may be slow or unresponsive.

### 2.3 Installation

The installation of Meta-IMU requires several preparatory steps. R and RStudio (available at https://posit.co/download/rstudio-desktop/) must first be installed as the computational environment. A spreadsheet programme such as Microsoft Excel, capable of editing .csv, .xlsm, and .xlsx files, is also necessary. Access to the Meta-IMU package is obtained by completing a registration form on the IMU University IRDI website (https://imu.edu.my/irdi/meta-analysis). Following registration, an email containing the download link to the Meta-IMU zip file is provided. Because the software is continuously updated, the most current version should be used whenever a new project is initiated.

Once the required files and software are prepared, a new RStudio project is created to establish a working directory, which functions as the default folder for reading and saving files. The Meta-IMU zip file is then extracted, and its contents placed in this directory. Opening the app.R file in RStudio loads the application code into the source panel (Figure I). To enable the full range of functionalities, the application should be executed by selecting the "Run external" option in RStudio. Thereafter, clicking "Run app" launches Meta-IMU in the web browser.

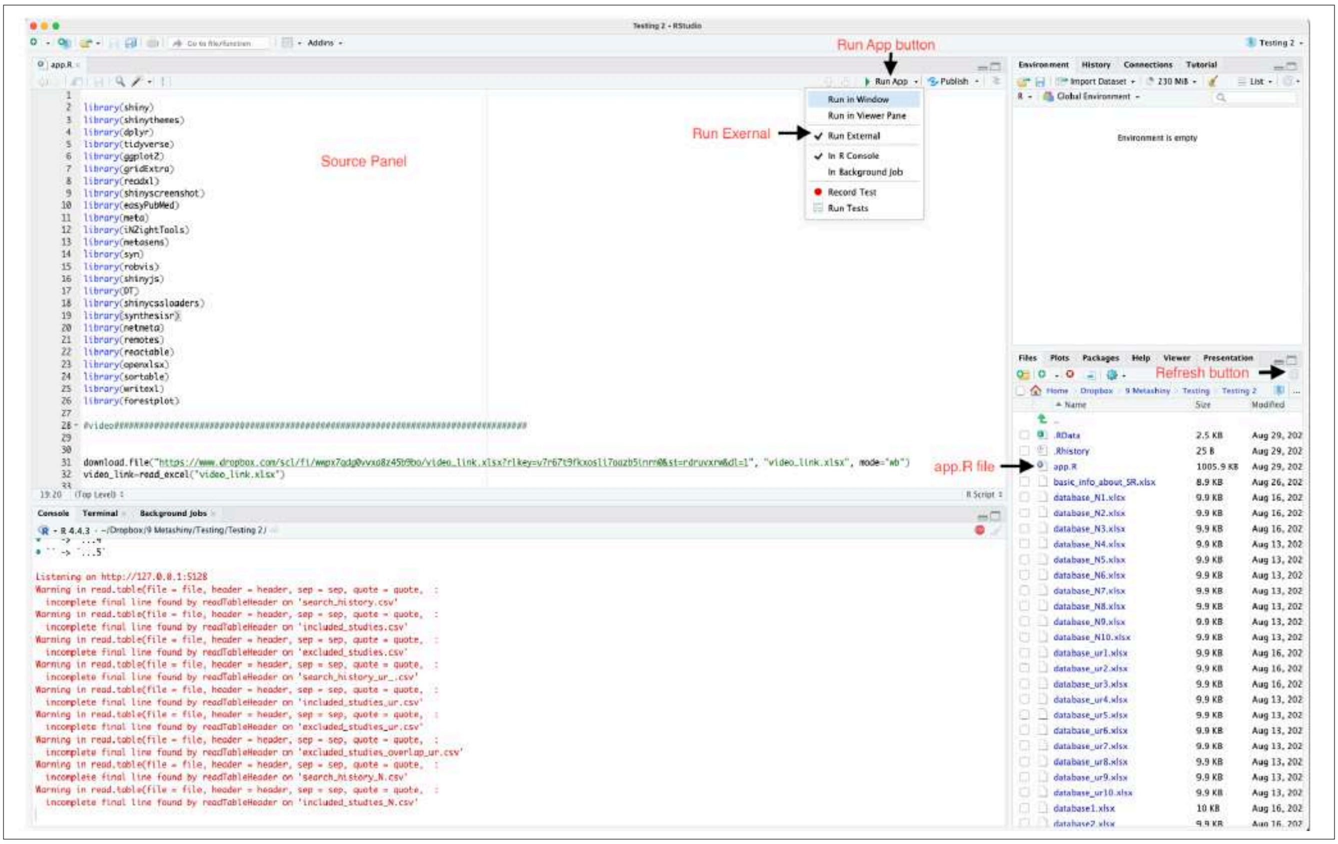


*Figure I: RStudio interface highlighting the key buttons relevant to the installation process.*

### 2.4 General User Interface (UI)

The Meta-IMU user interface is organised into four main components (Figure II). The *side panel* provides access to key functionalities, including options to save user inputs with or without refreshing the application, capture screenshots, and specify the type of review (systematic or Umbrella). It also contains advanced settings for defining summary measures in forest plots and adjusting plot dimensions when large numbers of studies are included, as well as a reference section. The *step selection panel* adapts dynamically to the chosen review type, displaying 13 steps for systematic reviews and 12 steps for Umbrella reviews. Each step is supported by an *instructional video* that guides users through the relevant procedures. Finally, the *main panel* serves as the primary workspace, where analyses are conducted and results are reviewed.

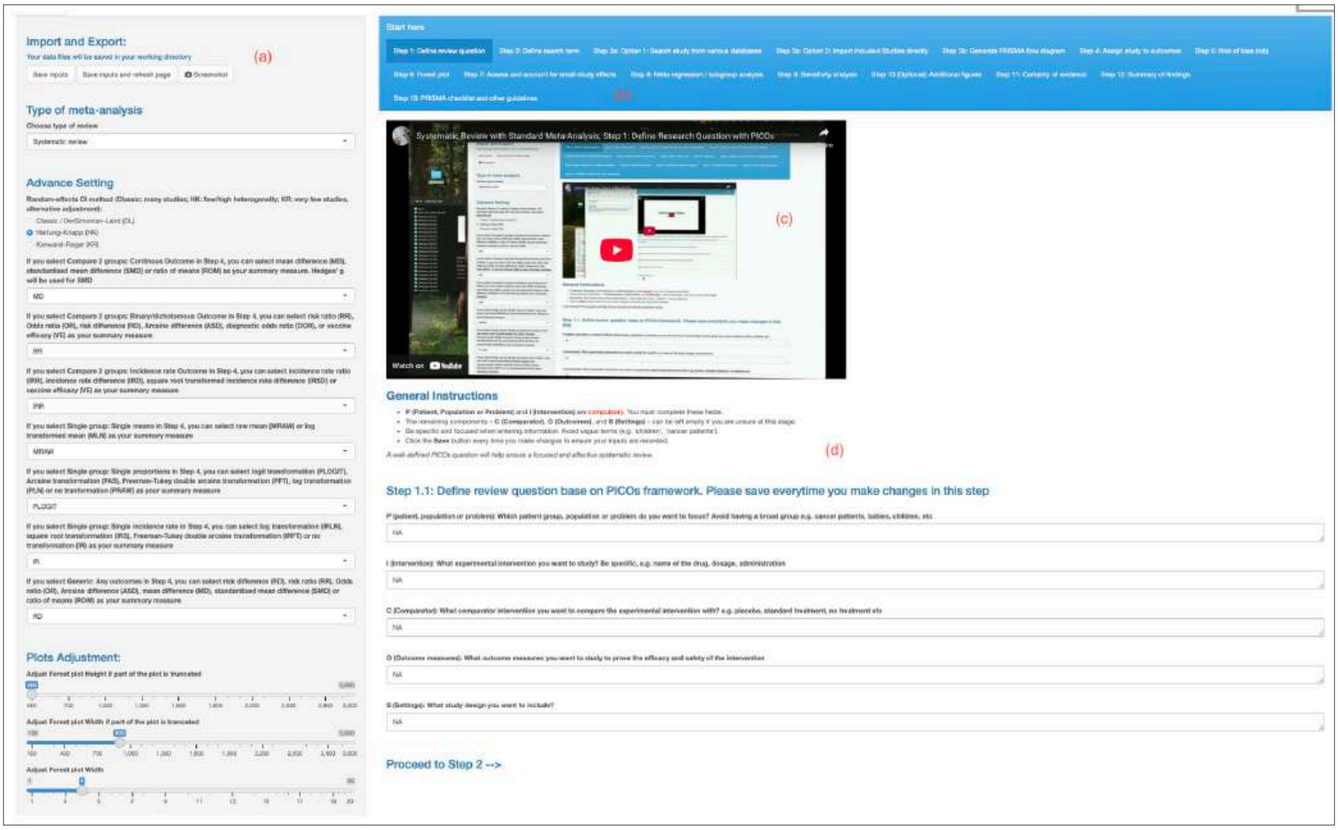


*Figure II: General User Interface (UI) for Meta-IMU.*
*(a) Side Panel (b) Step Selection Panel (c) Instructional Video (d) Main Panel*

**2.5 Data Input for Systematic Review**

Meta-IMU structures the conduct of a systematic review into sequential, interdependent steps, with each stage building on the preceding one. The process requires users to complete the following steps:

**Step 1: Define Review Question**

The review question is formulated using the PICOs framework, in which 'P' denotes the patients, population, or problem; 'I' the intervention; 'C' the comparator; 'O' the outcome; and 'S' the setting.

**Step 2: Define Search Term**

Relevant MeSH terms, serving as synonyms for the PICOs elements, are identified using the NCBI MeSH database (https://www.ncbi.nlm.nih.gov/mesh). These terms are then entered into the corresponding fields in Meta-IMU to generate search terms.

**Step 3a: Option 1 – Search Study from Various Databases**

Users should choose Option 1 if they are yet to finalise the list of included studies and plan to search across multiple databases. In Meta-IMU, database searching can be performed using one of two methods. Method 1 is suitable for most databases including Scopus, Cochrane library and ClinicalTrials. The search term generated in Step 2 is entered into the database, and the results are exported in *.ris* format with abstracts included. The downloaded *.ris* file is then processed within Meta-IMU using the appropriate upload option, which generates a processed .xlsx file. The resulting data are copied, excluding the header, into the designated database spreadsheet (eg, *database1.xlsx*).

Method 2 applies to databases such as PubMed, Semantic Scholar, and OpenAlex. This approach requires the installation of the Publish or Perish software (https://harzing.com/resources/publish-or-perish), which enables searches across a wide range of databases. The search term is entered into the software, and results are exported in *.ris* format. As Publish or Perish imposes a limit of 1,000 records per search, broad queries may need to be refined to remain within this threshold. The *.ris* file is then processed to generate an *.xlsx* file, which is transferred into the corresponding database spreadsheet (eg, *database2.xlsx*).

Once database-specific files have been prepared, Meta-IMU needs to be reloaded to integrate the data. The platform supports up to ten databases simultaneously. Duplicate records are automatically identified, and a summary table indicates both the total number of duplicates and the databases from which they were removed. This information may be requested by journal editors and is retained for transparency. A consolidated dataset of de-duplicated studies is subsequently generated.

Titles and abstracts of de-duplicated studies are screened to identify potentially eligible studies. These records are transferred into a "potential studies" table. Full-text articles for these studies should then be obtained and assessed in detail. Following this review, eligible studies are moved into the "included studies" table, while those deemed unsuitable are recorded in the "excluded studies" table along with reasons for exclusion.

To ensure rigor, lists of included and excluded studies generated by independent authors are compared, and discrepancies are resolved by consensus. Authors may add or remove studies from either list during this reconciliation process.

**Step 3a: Option 2 – Import Included Studies Directly**

Option 3 is intended for cases in which the list of included studies has already been finalised, particularly when other software such as Covidence has been used for screening. In this approach, the study title, year of publication, and first author's last name are entered into the *included_studies.csv* file within the working directory. After refreshing Meta-IMU, Step 3b can be bypassed, and the process continues directly with Step 4.

**Step 3b: Generate PRISMA Flow Diagram**

A PRISMA flow diagram can be generated within Meta-IMU through an embedded online application developed by Haddaway, *et al.*[14]

**Step 4: Assigning Studies to Outcomes**

Once the list of included studies has been established, the next step involves determining which outcomes each study contributes to. Individual studies may contribute to one or more outcomes. Meta-IMU accommodates up to six outcomes per project; additional outcomes require the initiation of a new project.

Meta-IMU supports eight types of meta-analyses depending on the number of groups and data structure: (i) compare two groups-continuous outcomes, (ii) compare two groups – binary/dichotomous outcomes, (iii) compare two groups-incidence rate outcomes, (iv) single group – correlation, (v) single group – mean, (vi) single group – proportion, (vii) single group – incidence rate, and (viii) generic outcomes. Each type of analysis requires extraction of different data elements from the studies.

For each outcome, studies are assigned by entering their index number, as listed in the included studies table. Meta-IMU then generates a *data_outcome.csv* file for each outcome, which is saved in the working directory. These files are automatically populated with the study label and publication year, while the remaining columns must be completed with data extracted from the studies. Once populated, these files form the basis for subsequent analyses.

**Step 5: Risk of Bias Assessment**

The reliability of evidence in a systematic review can be influenced by the risk of bias in the included studies. To account for this, Meta-IMU provides six risk-of-bias assessment tools tailored to different study designs: ROB-1, ROB-2, ROB-2-Cluster (for cluster randomised trials), ROB-2-Crossover (for crossover trials), ROBIN-I (for non-randomised interventions), and ROBINS-E (for non-randomised exposure studies). Once the appropriate risk-of-bias tool is assigned to each outcome, Meta-IMU will generate a corresponding *rob_outcome.xlsm* file for each outcome.

Risk-of-bias assessment requires independent evaluation by at least two authors. Following independent assessments, reviewers compare results, discuss discrepancies, and resolve disagreements through consensus or, if necessary, consultation with a third reviewer. Once the risk of bias for all outcomes have been assessed, the *rob_outcome.xlsm* file should be filled up.

**Step 6: Forest Plot**

Figure III shows a sample of Forest plot generated by Meta-IMU. Users can customise various features, including the names of the treatment and control groups, the lower and upper limits of the x-axis, and the measures of effect. For details about the interpretation of Forest plot, please refer to the article from Chang, *et al* (2022).[15]

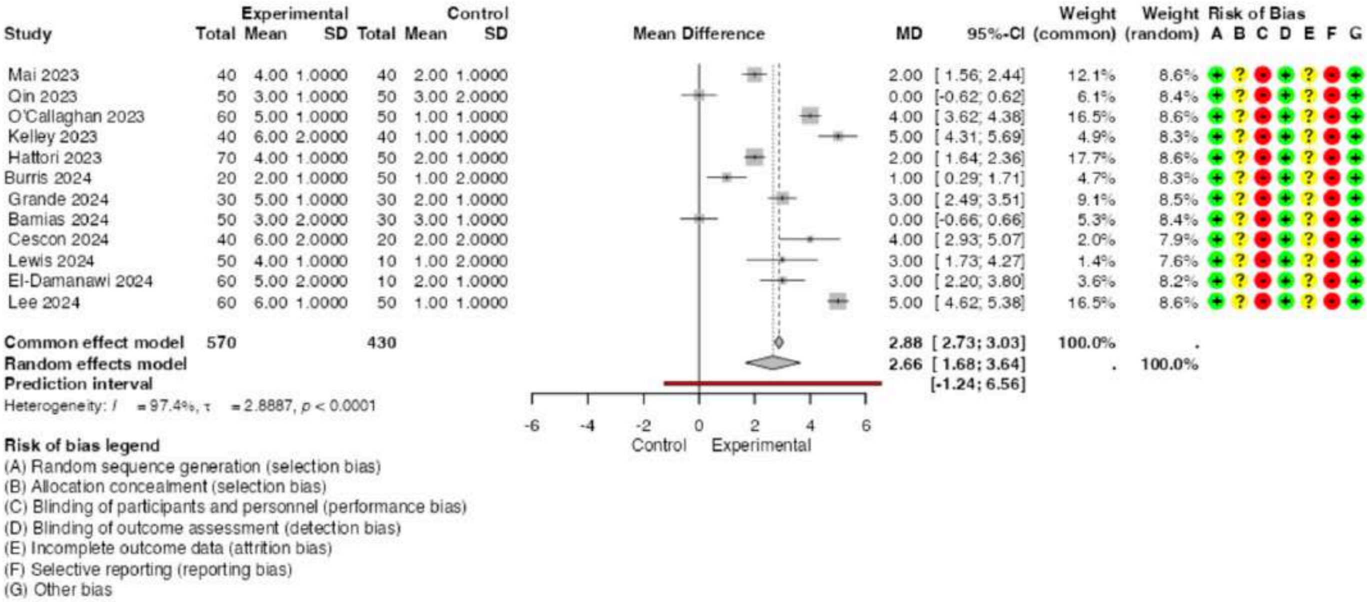


*Figure III: Forest plot with risk of bias.*

**Step 7: Small-Study Effects**

Small-study effects refer to the phenomenon where smaller studies tend to report larger effects (or stronger associations) than larger studies, which can bias the overall meta-analysis and lead to an overestimation of the true effect size. To assess and mitigate these potential biases, Meta-IMU provides Funnel plots, trim-and-fill adjusted Funnel plots, and Radial plots for each outcome (examples shown in Figure IV). Statistical tests for Funnel plot asymmetry are also available, including the Begg, Egger, Thompson, Harbord, Macaskill, Peters, Schwarzer, and Pustejovsky tests, which can only be performed if at least ten studies are included for a given outcome.[16]

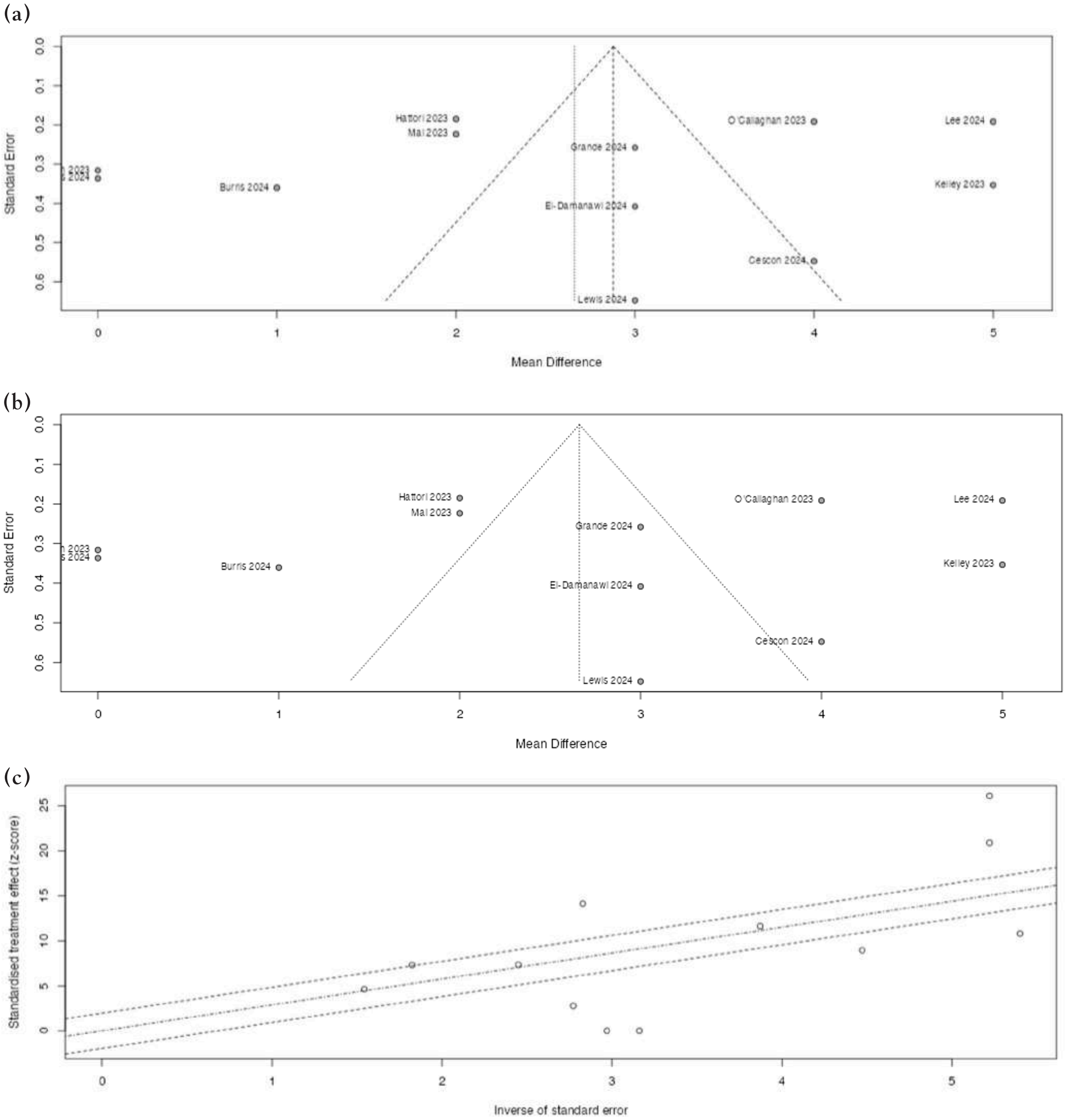


*Figure IV: Small-study Effects. (a) Funnel Plot (b) Trim-and-fill Funnel Plot (c) Radial Plot.*

**Step 8: Meta-regression/Subgroup Analysis**

Meta-regression is a statistical technique used in meta-analysis to examine the relationship between study-level characteristics – such as participant demographics, intervention features, or study design – and the observed effect sizes across individual studies. Subgroup analysis represents a specific form of meta-regression, allowing the exploration of whether particular groups respond differently to an intervention. For example, while a Forest plot may show no overall intervention effect, subgroup analysis may reveal that a specific age group benefits significantly.

In Meta-IMU, users can conduct meta-regression and subgroup analyses with up to two covariates. For each outcome, the process begins by generating the corresponding *data_regression_outcome.csv* files, which are then populated with covariate data. Covariates can represent categorical or continuous variables. For instance, studies may be grouped by patient age (eg, Age 1, Age 2, Age 3) or by sex (eg, male = 1, female = 2). Once covariates are entered, the files are saved and the application is refreshed to proceed.

Meta-IMU supports several estimation methods for meta-regression, including restricted maximum likelihood (REML), DerSimonian–Laird (DL), maximum likelihood (ML), Hunter–Schmidt (HS), Sidik–Jonkman (SJ), Hedges (HE), and empirical Bayes (EB). The fitted model provides estimates of residual heterogeneity ($\tau^2$), the proportion of unexplained variability between studies ($I^2$), and the proportion of variance explained by the included predictors ($R^2$). A test of moderators is also provided; a statistically significant p-value ($p < 0.05$) indicates that the covariate meaningfully influences effect sizes.

Outputs also include Forest plots stratified by subgroups, and bubble plots that visualise regression slopes. In bubble plots, each bubble represents a study, with size proportional to its weight in the analysis. Subgroup Forest plots allow visual comparison of intervention effects across predefined categories, and their display can be adjusted within the application for clarity. Examples of meta-regression results, including bubble plots and subgroup Forest plots, are presented in Figure V.[17]

**(a)**

```
Mixed-Effects Model (k = 12; tau^2 estimator: REML)

tau^2 (estimated amount of residual heterogeneity):     3.3890 (SE = 1.7587)
tau (square root of estimated tau^2 value):             1.8409
I^2 (residual heterogeneity / unaccounted variability): 97.39%
H^2 (unaccounted variability / sampling variability):   38.25
R^2 (amount of heterogeneity accounted for):            0.00%

Test for Residual Heterogeneity:
QE(df = 8) = 290.6939, p-val < .0001

Test of Moderators (coefficients 2:4):
QM(df = 3) = 1.3711, p-val = 0.7123

Model Results:

                          estimate      se     zval    pval    ci.lb   ci.ub
intrcpt                     3.6986  1.0939   3.3811  0.0007   1.5546  5.8426  ***
.subgrouplight smoking     -1.0370  1.5357  -0.6753  0.4995  -4.0468  1.9728
.subgroupmoderate smoking  -1.3907  1.5423  -0.9017  0.3672  -4.4136  1.6321
.subgroupno smoking        -1.6864  1.5320  -1.1008  0.2710  -4.6891  1.3162

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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
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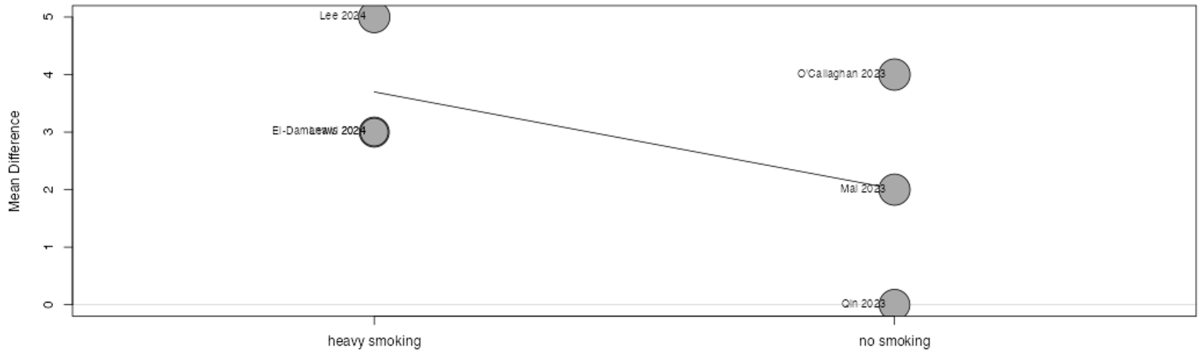
(b)




(c)

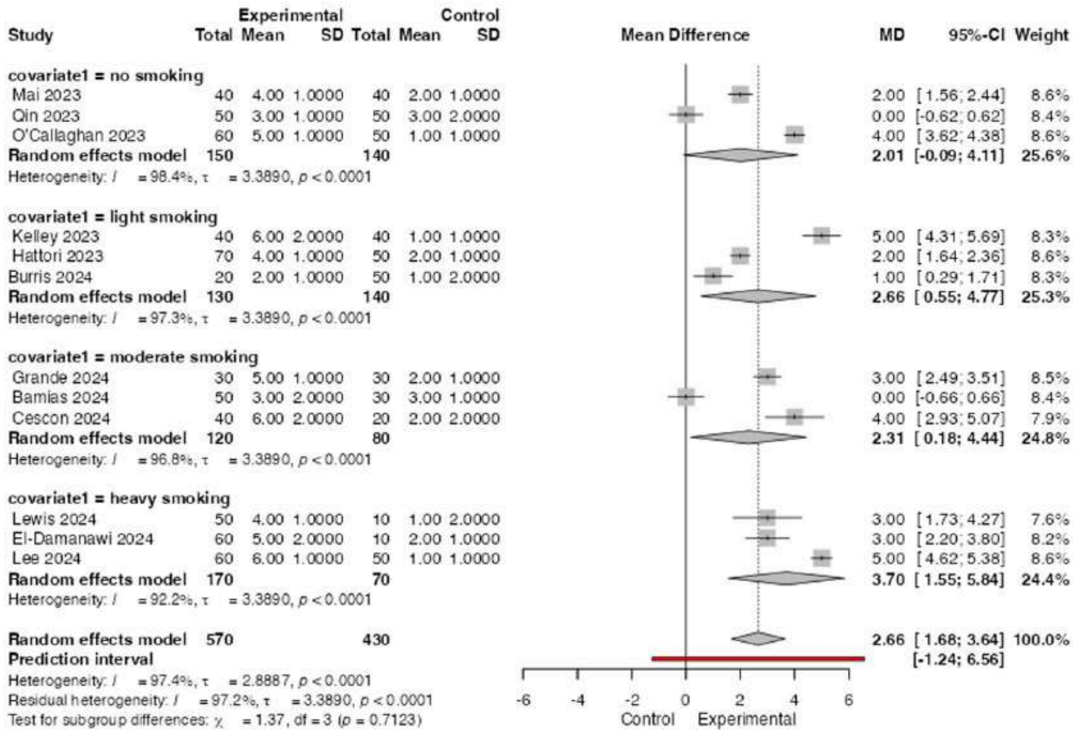



*Figure V: Meta-regression. (a) Meta-regression Based on REML (b) Bubble Plot (c) Forest Plot with Subgroup Analysis.*

**Step 9: Sensitivity analysis**

Sensitivity analysis in a systematic review is a method used to evaluate the robustness and reliability of the results by examining how changes in the analysis influence the conclusions drawn from the data. Additionally, by conducting sensitivity analysis, researchers can identify whether specific studies have a disproportionate impact on the overall results. Meta-IMU conducts sensitivity analysis using leave-one-out and cumulative meta-analysis methods (sample shown in Figure VI).

In the leave-one-out approach, each study is removed individually from the analysis, and the remaining studies are synthesised to estimate the effect size. This process is repeated for each study, yielding a series of effect size estimates that can be compared to the original estimate, which includes all studies. If the effect size remains relatively consistent across all iterations, it suggests that the results of the meta-analysis are robust and not heavily influenced by any single study. Conversely, if the effect size varies significantly when individual studies are excluded, it may indicate that the results are sensitive to those specific studies.

Cumulative method is used to assess how evidence evolves over time. In a cumulative meta-analysis, studies are added in chronological order, and the cumulative effect size is recalculated after each addition. This method helps visualise how the results of the meta-analysis change as more evidence becomes available.

**(a)**

```
Influential analysis (common effect model)

                              MD          95%-CI  p-value   tau^2    tau    I^2
Omitting  Mai 2023        3.0009 [2.8381; 3.1637] < 0.0001  3.1437  1.7731  97.5%
Omitting  Qin 2023        3.0654 [2.9079; 3.2228]        0  2.4143  1.5538  97.0%
Omitting  O'Callaghan 2023 2.6576 [2.4905; 2.8246] < 0.0001  2.9877  1.7285  97.4%
Omitting  Kelley 2023     2.7714 [2.6150; 2.9279] < 0.0001  2.5962  1.6113  97.4%
Omitting  Hattori 2023    3.0685 [2.9003; 3.2367] < 0.0001  3.1447  1.7733  97.4%
Omitting Burris 2024      2.9715 [2.8152; 3.1278] < 0.0001  2.8908  1.7002  97.4%
Omitting  Grande 2024     2.8675 [2.7074; 3.0275] < 0.0001  3.1783  1.7828  97.6%
Omitting  Bamias 2024     3.0423 [2.8854; 3.1991]        0  2.4220  1.5563  97.1%
Omitting  Cescon 2024     2.8564 [2.7022; 3.0106] < 0.0001  2.9988  1.7317  97.6%
Omitting  Lewis 2024      2.8778 [2.7240; 3.0315] < 0.0001  3.1510  1.7751  97.6%
Omitting  El-Damanawi 2024 2.8750 [2.7195; 3.0304] < 0.0001  3.1701  1.7805  97.6%
Omitting  Lee 2024        2.4595 [2.2924; 2.6265] < 0.0001  2.5598  1.5999  96.3%

Pooled estimate           2.8795 [2.7269; 3.0321] < 0.0001  2.8887  1.6996  97.4%

Details of meta-analysis methods:
- Inverse variance method
- Restricted maximum-likelihood estimator for tau^2
- Calculation of I^2 based on Q
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**(b)**

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Cumulative meta-analysis (common effect model)

                                   MD          95%-CI  p-value   tau^2    tau    I^2
Adding  Mai 2023 (k=1)         2.0000 [1.5617; 2.4383] < 0.0001
Adding  Qin 2023 (k=2)         1.3333 [0.9755; 1.6912] < 0.0001  1.9250  1.3874  96.2%
Adding  O'Callaghan 2023 (k=3) 2.6032 [2.3442; 2.8622] < 0.0001  3.9257  1.9813  98.4%
Adding  Kelley 2023 (k=4)      2.8969 [2.6543; 3.1395] < 0.0001  4.7948  2.1897  98.2%
Adding  Hattori 2023 (k=5)     2.6199 [2.4182; 2.8216] < 0.0001  3.6723  1.9163  97.8%
Adding Burris 2024 (k=6)       2.4979 [2.3040; 2.6919] < 0.0001  3.3415  1.8280  97.5%
Adding  Grande 2024 (k=7)      2.5622 [2.3811; 2.7433] < 0.0001  2.8260  1.6811  97.1%
Adding  Bamias 2024 (k=8)      2.3827 [2.2081; 2.5574] < 0.0001  3.1454  1.7735  97.3%
Adding  Cescon 2024 (k=9)      2.4244 [2.2520; 2.5968] < 0.0001  3.1078  1.7629  97.0%
Adding  Lewis 2024 (k=10)      2.4348 [2.2640; 2.6056] < 0.0001  2.8153  1.6779  96.7%
Adding  El-Damanawi 2024 (k=11) 2.4595 [2.2924; 2.6265] < 0.0001  2.5598  1.5999  96.3%
Adding  Lee 2024 (k=12)        2.8795 [2.7269; 3.0321] < 0.0001  2.8887  1.6996  97.4%

Pooled estimate                2.8795 [2.7269; 3.0321] < 0.0001  2.8887  1.6996  97.4%

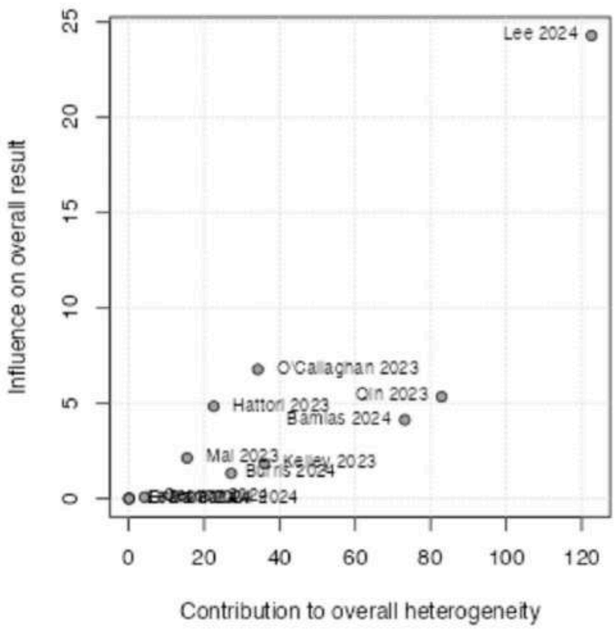
Details of meta-analysis methods:
- Inverse variance method
- Restricted maximum-likelihood estimator for tau^2
- Calculation of I^2 based on Q
```

*Figure VI: Sensitivity Analysis. (a) Leave-one-out Method (b) Cumulative Method.*

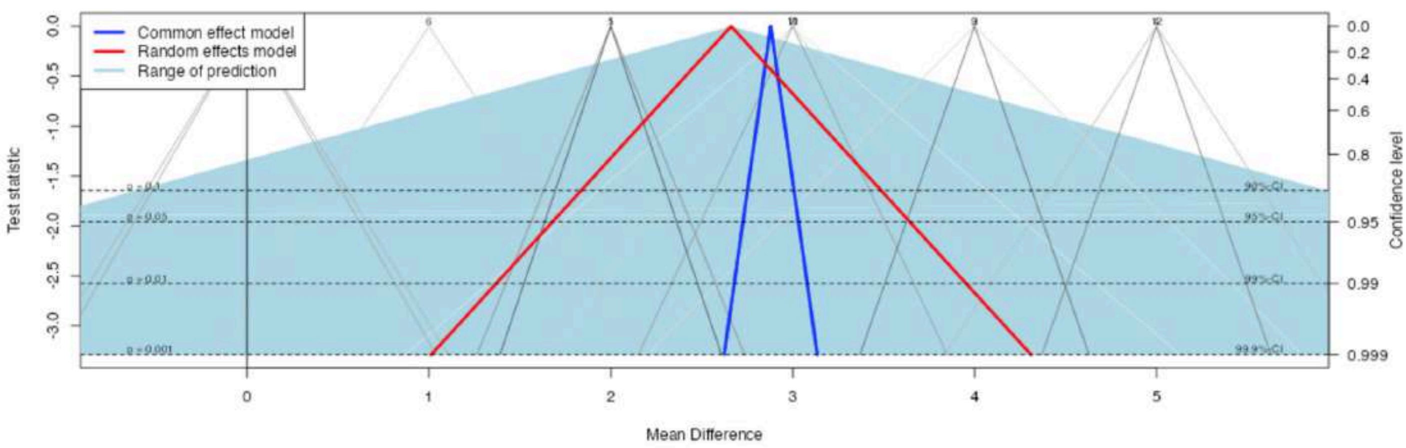
**Step 10: (Additional figures)**

Meta-IMU offers several types of plots that are less commonly used in meta-analysis but can still be quite useful. Figure VII shows Baujat plots, drapery plots and L'Abbé plot. Baujat plot is a visualisation tool to assess heterogeneity, special attention should be paid to studies located at the far right or at the top of the plot, as these may skew the results of the meta-analysis. The drapery plot can complement the forest plot. One advantage of the drapery plot is that confidence intervals for individual studies and pooled estimates can be directly read for any confidence level, whereas the forest plot displays only one confidence level at a time. However, a limitation of the drapery plot is that it may be difficult to identify individual studies if the number of studies is large. L'Abbé plot is only applicable for binary data. The points on the solid diagonal line represent studies where the event rates did not differ between the intervention and control groups. Points below this line indicate studies where the event rates were lower in the treated group compared to the control group. The dashed line represents the estimated effect based on the fitted model, and larger points correspond to more precise estimates.

(a)




(b)



(c)

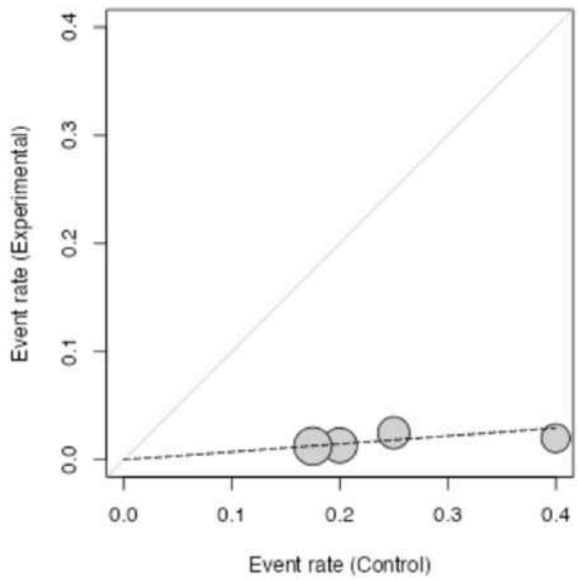



*Figure VII: (a) Baujat Plot (b) Drapery Plot (c) L'Abbé plot.*

**Step 11: Certainty of Evidence**

In the final stage of evidence synthesis, the effect size for each outcome is categorised as "trivial or no effect," "small but important," "moderate," or "large." This assessment is followed by a series of structured "yes" or "no" questions that evaluate the certainty of the evidence. These judgments are then integrated to generate concise, one-sentence conclusions summarising the findings for each outcome. The process ensures that both the magnitude of effect and the strength of supporting evidence are explicitly considered, thereby enhancing the interpretability and applicability of results. Ultimately, these outcome-specific conclusions are incorporated into a summary of findings table, providing a transparent and accessible synthesis to support decision-making in clinical and policy contexts.

**Step 12: Summary of Findings**

A sample of the summary of findings is displayed in Figure VIII. Please note that this table is quite generic, and it should be further tailored to the specific study.

| Outcomes | Plain language statement | Number of studies | Estimated overall effect (Common model) | Standard error of overall effect (Common model) | P value for overall effect (Common model) | Lower confidence limit (Common model) | Upper confidence limit (Common model) | Estimated overall effect (Random model) | Standard error of overall effect (Random model) | P value for overall effect (Random model) | Lower confidence limit (Random model) | Upper confidence limit (Random model) | Certainty of the evidence |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| incident rate | The evidence is very uncertain about the effect of treatment on outcome1 | 3 | -0.03 | 0.03 | 0.35 | -0.09 | 0.03 | -0.08 | 0.08 | 0.30 | -0.24 | 0.07 | very low |

*Figure VIII: Summary of Findings.*

**Step 13: PRISMA Checklist**

A PRISMA checklist report can be generated via an embedded online app developed by Page, *et al* (2021).[18]

**2.6 Data Input for Umbrella Review**

Meta-IMU breaks down the procedures for Umbrella review into sequential steps. Each step is interrelated and builds upon the previous one. Users need to perform the following steps:

**Step 1: Suitability of Umbrella Review**

This step helps users confirm whether their research question is best addressed by an Umbrella review rather than a systematic review. Users need to answer a series of questions. After completing this, a response will be given by Meta-IMU. If it says "Do not carry out an umbrella review", users should perform a standard meta-analysis instead. But if it says "Proceed to step 2", then the umbrella review is the right approach.

**Step 2 – Step 4b**

These procedures are identical to those described in Steps 1–3b of the systematic review process outlined above, with the distinction that all files requiring modification in the working directory carry the suffix _ur, which indicates Umbrella review.

**Step 5: Redundancy Table**

Overlapping studies occur when different systematic reviews include the same primary studies, which may lead to redundancy and potential bias in evidence synthesis. To address this, Pollock, *et al*, provides a decision tool to guide whether overlapping reviews should be retained or excluded, based on factors such as recency, quality, relevance, and comprehensiveness.[19] A *primary_study_list.csv* file can be generated, where study labels for each primary study are entered by replacing placeholder values. This allows identification of shared primary studies across systematic reviews. This allows the generation of a redundancy table, which facilitates cross-referencing to determine which reviews overlap. Where overlap is identified, a specific review can be excluded by entering the corresponding index number and providing justification (eg, removal of an older or redundant review due to overlapping primary studies). Excluded reviews remain documented in a separate table and can be reinstated if necessary. Importantly, all subsequent analyses (Step 6 onwards) are based solely on the updated set of included studies, ensuring that the synthesis reflects deliberate and transparent decisions regarding study overlap.

**Step 6: RoB Assessment Using AMSTAR2 Tool**

The reliability of an umbrella review is closely linked to the methodological quality of the systematic reviews it includes, and this is commonly evaluated through risk of bias assessment. In this study, the AMSTAR 2 tool was applied to assess the methodological quality of the included systematic reviews. Data for this evaluation were entered into a structured spreadsheet (*rob_ur.xlsx*), with items completed according to the accompanying AMSTAR 2 guidance. The completed assessments were then summarised in tabular form, providing an overview of the risk of bias across reviews. Importantly, each systematic review was assigned an overall confidence rating, which served as a critical input for subsequent stages of the analysis.[20]

**Step 7: RoB Assessment Using ROBIS Tool**

The ROBIS tool is used to evaluate the risk of bias.[21]

**Step 8: Descriptive Characteristics**

Descriptive characteristics of the included systematic reviews is documented using a structured data extraction file (*basic_info_about_SR.xlsx*). Relevant information is entered across all predefined columns, capturing key attributes of each review. The completed dataset is then processed to generate summary table, which provides an overview of the characteristics of the included systematic reviews.

**Step 9: Assign Study to Outcome**

This step involves determining the outcomes to which each study contributes. Each included study may contribute data to one or more predefined outcomes. Meta-IMU can accommodate up to six outcomes within a single project. If more than six outcomes are of interest, a new project must be initiated.

The type of effect size needs to be specified for each outcome, followed by assigning studies to outcomes. Once assignments are completed, the *data_outcome_ur.xlsx* file is generated and stored in the working directory. Each generated file already containspre-populated columns for *studlabel* and year, the remaining fields must be completed with data extracted directly from the included studies:

- *AMSTAR2* values are selected from a dropdown menu, using the table generated in Step 6 as guidance;
- *Nstudies* refers to the number of primary studies included in the systematic review;
- *Npart* denotes the total number of participants across all primary studies;
- $I^2$ indicates heterogeneity;
- *Effect* represents the pooled effect size;
- *Lower and Upper* indicate the lower and upper bounds of the confidence interval, respectively.

**Step 10: Forest Plot**

Based on the data provided in Step 9, the corresponding forest plots are automatically generated. In the event that the plots fail to appear despite completion of the preceding steps, Meta-IMU should be refreshed. The Forest plot comprises a tabulated summary of the included studies on the left and the main graphical display on the right. Users may modify the x-axis labels through the designated text box. The default plot width is relatively narrow; however, both the width and height of the plot can be adjusted using the slider controls located in the side panel.

**Step 11: Credibility Plot**

In this visualisation, each study is depicted as a bubble, with bubble size proportional to the number of participants included (Figure IX). Bubble color indicates the assigned credibility class, based on the predefined classification standards. Users may also modify the label of the X-axis if alternative terminology is preferred.

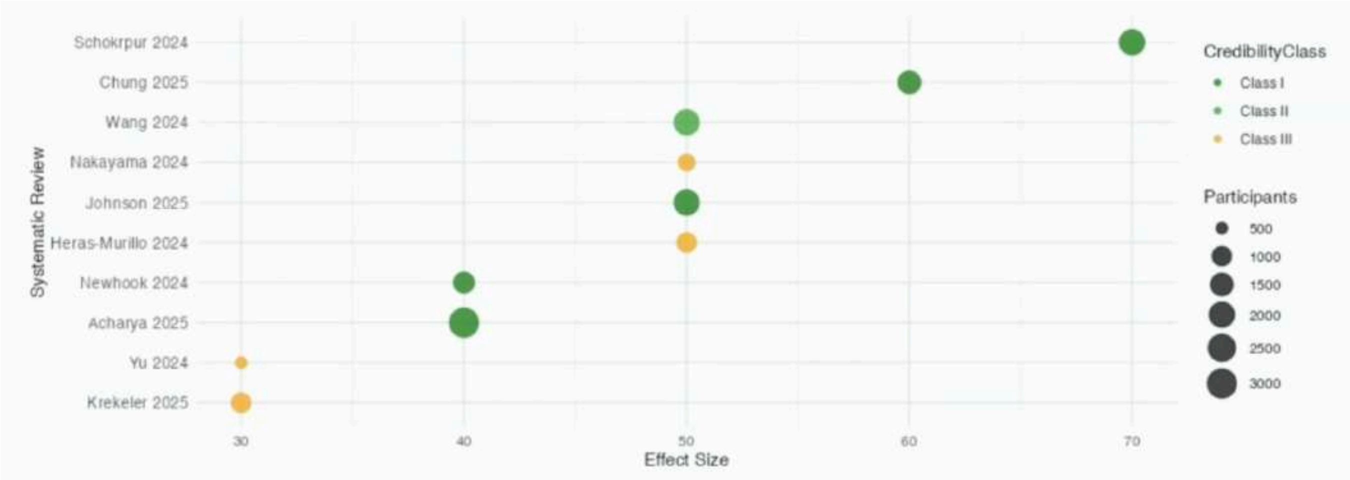



*Figure IX: Credibility Plot.*

### 3.0 Discussion and Conclusion

Meta-IMU integrates an intuitive interface with advanced statistical functionalities, offering an accessible yet powerful platform for conducting systematic reviews and meta-analyses. Its step-by-step guidance, comprehensive feature set, and embedded instructional resources make it particularly valuable for researchers with varying levels of methodological expertise. Beyond supporting conventional meta-analysis, Meta-IMU extends its functionality to umbrella reviews, thereby broadening its applicability and addressing a gap in existing tools that often lack versatility or ease of use.

The significance of Meta-IMU lies in lowering the entry barrier for novice researchers while simultaneously providing advanced options for experienced analysts, effectively bridging the gap between usability and methodological rigor. Compared with traditional software, Meta-IMU enhances transparency, learning support, and methodological flexibility, thereby contributing to improved quality and reproducibility of evidence synthesis.

Nevertheless, some limitations should be acknowledged. The current version depends on stable internet connectivity, may have computational constraints for extremely large datasets, and requires further validation across a wider range of complex analytic scenarios. Future developments will aim to optimise performance, incorporate additional statistical modules, and ensure seamless integration with external databases. Recognising these limitations provides a balanced appraisal and underscores the potential of Meta-IMU as a valuable contribution to the evolving ecosystem of evidence synthesis tools.

### Acknowledgement

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