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An Individual Participant Data Meta-Analysis Method Primer for Psychology

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Abstract: Individual participant data (IPD) meta-analysis (MA) is an advanced method for synthesizing research by using raw data from individual studies rather than using aggregated statistics. IPD-MA offers higher statistical power and flexibility, thereby enabling researchers to standardize measures, explore subgroup effects, and examine sources of variability often inaccessible in traditional MA. While common in clinical fields, IPD-MA remains less prevalent in psychology, partly due to challenges in data access and perceived complexity. This primer provides a nonmathematical introduction to IPD-MA, outlining its core concepts (the *what*), the main phases of implementation (the *how*), and its potential to address the credibility crisis in psychological science and offer novel insights through diverse applications (the *why*). We conclude with guidance on data sharing practice and infrastructure. We aim to promote IPD-MA as a transformative tool for improving cumulative knowledge consolidation, replicability, open science practices, as well as theoretical and methodological development in psychology.

Keywords: individual participant data, meta-analysis, integrative data, research synthesis, methods primer

Individual participant data (IPD) meta-analysis (MA), often described as the gold standard of meta-analysis (Tierney et al., 2020), is a key advancement in research synthesis science (Cooper & Patall, 2009) and is part of the newest generation of systematic review methods (Ioannidis, 2017). By utilizing primary data rather than aggregated statistics, IPD-MA offers greater statistical power and enables more sophisticated and flexible analyses compared to traditional aggregate data meta-analysis (AD-MA).

Despite these advantages, IPD-MA remains concentrated in clinical science, where it was first established (Stewart & Cochrane Working Group on Meta-Analysis Using Individual Patient Data, 1995). In contrast to the hundreds of IPD meta-analyses documented across medicine (Riley et al., 2021), psychology and the broader social sciences have seen comparatively few such studies. A Scopus review in 2016 (Crocetti, 2016) reported 476 IPD-MAs in the health sciences compared to just 13 in the social sciences (of which only two actually applied the IPD approach to social scientific topics). To update these estimates, we checked publications within psychological research fields excluding clinical psychology listed in the Web of Science (as of August 2025) for IPD-MAs and found only 63 records in total, with the first three appearing in 2015 and numbers only slowly increasing thereafter (2022: 8, 2023: 7, 2024: 13).

The adoption of new research methodologies hinges on the interplay of barriers and incentives (Cooper & Patall, 2009). While barriers to methodological advancement stemming from outdated scientific training, research practices, or funding and publishing standards require long-term reforms, other obstacles, such as conceptual unfamiliarity, can be addressed more directly through accessible guidelines and practical examples. Existing methodological resources on IPD-MA are predominantly clinical (Debray et al., 2015; Riley et al., 2021), with comparatively few contributions from psychology. Early publications in psychology gave overviews of integrative data analysis (Curran & Hussong, 2009) and IPD-MA (Cooper & Patall, 2009), and more recent work has provided more specific guidance such as tutorials for complex survey designs (Brunner, Keller et al., 2023; Campos et al., 2023). Subfield-specific studies highlight applications in developmental (Bainter & Curran, 2015) and educational psychology (Kaufmann et al., 2016), yet resources remain fragmented or dated. Given repeated calls for IPD-MA to improve replication, generalizability, and cumulative evidence across psychology (e.g., Burgard & Holzberger, 2024; Iliescu et al., 2022; Koile & Cristia, 2021; Roisman & van IJzendoorn, 2018; Schuengel et al., 2019), a concise, accessible method primer remains timely.

The aim of this primer is therefore to offer a nonmathematical, conceptual introduction to IPD-MA tailored to psychological research, rather than a comprehensive technical handbook. Foundational and up-to-date

methodological references are provided throughout to guide readers seeking more in-depth coverage. We begin by defining IPD-MA and distinguishing it from AD-MA. The second section outlines the key steps in conducting an IPD-MA, covering data acquisition, harmonization, and statistical modeling, with a focus on issues particularly relevant to psychology. The third section illustrates applications and impact, demonstrating how IPD-MA can address challenges of replication efforts and contribute to theoretical and measurement advances. Finally, we discuss the importance of data sharing, highlighting infrastructures and practices to support it. This primer, while focused on psychology, offers considerations equally relevant across the social sciences. Clarifying the conceptual and methodological foundations of IPD-MA may help extend its application beyond clinical research, strengthening cumulative knowledge consolidation, reducing research redundancy (Ioannidis, 2016), and uncovering nuances of effects and mechanisms that might otherwise remain undetected.

What Is Individual Participant Data Meta-Analysis? Conceptual Foundations and Key Distinctions

Definition and Scope

To contrast IPD-MA with AD-MA, it is useful to start with brief definitions. Both approaches aim to synthesize evidence across comparable studies and are grounded in a systematic review framework to ensure comprehensive inclusion and minimize bias (Riley et al., 2021). In AD-MA, researchers combine effect sizes derived from published summary statistics (e.g., mean differences, correlations, odds ratios), typically using multilevel models for nested data (i.e., effect sizes nested within studies) and random-effects models to model between-study heterogeneity (Chen et al., 2020). IPD-MA, by contrast, pools raw participant-level data, allowing more precise estimation and the modeling of heterogeneity at both the participant and study levels, as well as accommodating complex structures such as cross-classified or repeated-measures designs (Campos et al., 2023). IPD-MA can be implemented via a two-stage approach, where study-level estimates are first derived and then combined meta-analytically, or a one-stage approach, modeling all data simultaneously (Debray et al., 2015; Riley et al., 2021; see next section for detail).

It is also helpful to distinguish IPD-MA from related approaches that combine individual-level data across studies and are sometimes used interchangeably (Beck et al., 2024, see Table 1 for an overview). *Integrative data analysis* (IDA) broadly refers to statistical analysis of a combined dataset, often leveraging between-study heterogeneity to address theoretical questions (Bainter & Curran, 2015; Curran & Hussong, 2009). *Mega-analysis* typically pools raw data from studies conducted under comparable conditions and may treat data as stemming from a single study (Eisenhauer, 2021). Both IDA and mega-analysis may not follow a systematic review process. *Pooled data analysis* is a general term for combining participant-level data, while *multisite analysis* refers to coordinated data collection under a single protocol rather than post hoc synthesis. IPD-MA is distinguished by its grounding in systematic review and meta-analytic logic, where studies are identified systematically and analyzed to synthesize evidence across the study corpus.

Two-Stage Versus One-Stage Approach

IPD-MA can be conducted using two main approaches (Debray et al., 2015; Riley et al., 2021). In the two-stage approach, raw data from each study are first analyzed separately to generate study-level summary statistics, which are then combined in a conventional meta-analysis.

Table 1. Definitions of approaches related to the synthesis of individual-level data

Term	Definition
Individual participant data meta-analysis (IPD-MA)	A systematic research synthesis approach that collects, harmonizes, and reanalyzes raw participant-level datasets from multiple studies to obtain combined results. It is considered the most rigorous form of raw data synthesis due to its systematic review foundation.
Integrative data analysis (IDA)	The statistical analysis of a single dataset created from two or more pooled samples. Often used interchangeably with IPD-MA, especially when emphasizing cumulative knowledge building and leveraging heterogeneity.
Mega-analysis	The pooling of raw data from multiple studies conducted under comparable conditions into a single, large dataset for analysis, sometimes analyzed as stemming from a single study (i.e., no multilevel modeling).
Pooled data analysis	A broad descriptive term for the statistical analysis of data combined or aggregated from two or more studies or samples. It describes the foundational step underlying IPD-MA, IDA, and mega-analysis.
Multisite analysis	A study design in which data are collected across different sites under a consistent protocol. While not an analytical method itself, it generates data that are highly suitable for IPD-MA and other integrative approaches to explore heterogeneity.

Summary statistics from studies without available IPD can optionally be included at this second stage. This approach is conceptually intuitive, uses familiar meta-analytic methods, and maximizes sample size by combining IPD and AD. Differences between IPD and AD studies can be examined as a study-level moderator (Campos et al., 2023; Cooper & Patall, 2009). However, this hybrid approach is constrained by the limitations of summary-level data, restricting the complexity of within-participant modeling and the flexibility of moderator analyses.

In the one-stage approach, IPD from all relevant studies are pooled into a single dataset and analyzed in a unified statistical model, typically using multilevel regression to account for hierarchical structures. Choices regarding fixed or random effects depend on whether effects are assumed constant, systematically varying, or randomly varying across studies (Riley et al., 2021). This approach increases statistical precision and power, particularly in small samples, by modeling all parameters simultaneously. It also accommodates more complex data structures, such as cross-classified designs, which can occur in panel data (participants contributing to multiple studies, e.g., Göritz & Fritz, 2026) or multinational research (Campos et al., 2023).

Although statistically more precise, the one-stage approach is particularly recommended when dealing with a limited number of outcome events, small samples, or with more complex data structures like the mentioned cross-classified effects or single-case experimental designs (Declercq et al., 2022; Riley, Ensor, et al., 2023). In most other cases, a well-specified two-stage approach is sufficient and easier to implement. Comparison studies in fact mostly agree that differences in results between one-stage and two-stage analyses are generally driven by model assumptions and specifications rather than the framework itself (Burke et al., 2017; Riley et al., 2021).

Advantages of Individual Participant Data Meta-Analysis

The benefits of using primary data for research syntheses become evident when considering common challenges in AD-MA, particularly regarding study comparability. Relevant studies often report different summary statistics (e.g., mean differences vs. correlation coefficients), forcing meta-analysts either to restrict inclusion to studies using a common metric – potentially excluding relevant evidence – or to convert effect sizes using formulas that often rely on rarely tested assumptions and may yield biased estimates (Poom & Af Wåhlberg, 2022). An even greater challenge arises when reported statistics differ for instance in participant groupings (e.g., varying age ranges), measurement instruments, or outcome definitions (e.g., different cut-offs). In AD-MA, these discrepancies require separate analyses, reducing sample size and increasing uncertainty. Working with primary data overcomes both problems: variables can be calculated or reanalyzed consistently across studies, standardizing analyses and improving comparability. Moreover, primary data enable the creation of entirely new variables or analyses not originally considered by primary researchers, including subgroup or moderator investigations (Bauer & Hussong, 2009; Cooper & Patall, 2009; Riley et al., 2021).

Primary data also offer advantages regarding data quality and preprocessing. Unlike in AD-MA, with raw data available, researchers can directly verify statistical assumptions (e.g., normality) and adjust inclusion or exclusion criteria, such as redefining outliers. Risk-of-bias can be assessed directly, for example, via group balance, baseline differences, or missing data diagnostics, rather than relying solely on qualitative reports (Riley et al., 2021). In AD-MA, such preprocessing is rarely documented, leaving analysts to work with the provided sample and assume the original analyses were correct.

Another potent benefit of IPD-MA is increased statistical power, particularly for small effect sizes, limited samples, few studies, or low moderator variance (Lambert et al., 2002). IPD provides greater granularity, which is critical for moderator analyses as the typical core interest of research syntheses. In AD-MA, moderator analyses are often underpowered, as only a subset of studies report relevant moderators (Cooper & Patall, 2009; Dagne et al., 2016; Debray et al., 2015). Pooling IPD also increases the frequency of low base-rate events, stabilizing estimates and reducing the influence of extreme values (Curran & Hussong, 2009), and allows sufficiently large samples to address questions that single studies cannot, such as latent variable modeling or mediation effects (Campos et al., 2023).

A central strength of IPD-MA is its ability to model heterogeneity and moderators at the individual level, allowing tests of differential effects across participant characteristics. Beyond treatment specificity in clinical research (Debray et al., 2015; Riley et al., 2021), this can inform targeted interventions, study design, and theory development. For example, IPD-MAs on depression treatments identified moderators such as age and baseline severity, guiding tailored recommendations (Cuijpers et al., 2022), and helped derive design parameters for early childhood interventions, showing how individual covariates affect power and outcomes (Brunner et al., 2025). Wolff and Möller (2022) illustrate how high-resolution subgroup analyses can refine theoretical models by specifying conditional effects. These cases demonstrate how IPD-MA provides greater specificity regarding the circumstances, beneficiaries, and mechanisms of effects.

Beyond moderator analysis, the granularity of IPD expands analytical possibilities. It allows disentangling within- and between-person variability and addressing the ecological fallacy, a form of aggregation bias where group-level relationships may not hold, or even reverse, at the individual level (Curran & Hussong, 2009; Kievit et al., 2013). This aligns with calls for a return to more idiographic, person-centered approaches in psychology (Beck & Jackson, 2020; Lee & Gates, 2024). IPD-MA also enables analyses that are difficult or infeasible in AD-MA, such as time-to-event models, multivariate techniques, and cross-classified dependencies (Campos et al., 2023), while allowing flexible integration of individual- and aggregate-level data within a single framework. Importantly, its capacity to model nonlinear relationships addresses long-standing criticisms that psychological research often relies on overly simplistic linear models, which fail to capture the complexity of human behavior (Brown, 1975).

In summary, IPD-MA overcomes key limitations of AD-MA by improving comparability, statistical power, and analytical flexibility. By integrating primary and aggregate data, it provides a versatile framework for meta-analytic synthesis. Modeling heterogeneity across study- and individual-level factors allows IPD-MA to reveal previously unrecognized effect modifiers and address the full spectrum of evidence synthesis, replicability, and generalizability (Graham et al., 2022).

Challenges and Limitations of Individual Participant Data Meta-Analysis

While these advantages make IPD-MA a powerful tool for evidence synthesis, its implementation presents challenges that merit careful consideration.

First, although IPD-MA reduces publication and reporting bias by using raw data rather than published summaries, it introduces the complementary issue of selective data availability (Cooper & Patall, 2009; Debray et al., 2015). This may manifest as recency bias, where newer studies are more likely to provide data; funding bias, favoring funded research requiring published data; or availability bias, in which accessible datasets tend to report significant effects or larger effect sizes (Cooper & Patall, 2009). Open science practices can help mitigate these biases, but their impact depends on overcoming persistent barriers to data sharing, which remain substantial in many fields (Dewidar et al., 2021).

Second, IPD-MA requires sufficiently comparable measures and outcomes to enable meaningful harmonization (Campos et al., 2023). When measures show substantial heterogeneity (e.g., minimal item overlap or differing assessment modes), harmonization may be compromised. Similarly, variation in sampling approaches can threaten the internal validity of pooled data (Campos et al., 2023).

Third, IPD-MA can be time- and resource-intensive (Riley et al., 2021). In contrast to the rather straightforward process of extracting summary statistics of studies for AD-MA, obtaining raw data for IPD-MA often requires extensive coordination, locating data across various platforms, contacting study authors, and negotiating formal data-sharing agreements. Hróbjartsson (2013), recounting a 19-month odyssey to retrieve clinical trial data, illustrates some of the obstacles that can arise in this process. Practical estimates suggest an IPD-MA of 20 studies may cost around US$187,000 for a seven-person team (Maxwell et al., 2024), and the average project takes roughly two years to complete (Riley et al., 2021). These considerations highlight that while IPD-MAs provide unique advantages, they demand substantial time, resources, and coordination.

Beyond data access and coordination, a considerable share of effort is dedicated to data harmonization. The anecdotal claim that 80% of statistical analysis involves data preparation (Kelleher & Tierney, 2018) is particularly true for IPD-MA. Even with codebooks available, harmonizing datasets from diverse teams often requires collaboration with original authors to resolve discrepancies. Key challenges include aligning outcomes and covariates, establishing measurement equivalency, addressing heterogeneity in populations and study designs, and managing missing or selectively available data (Levis et al., 2021). Furthermore, pooled datasets can reach tens of thousands of observations, creating computational demands that necessitate efficient model specification and optimized code to avoid convergence issues.

Taken together, IPD-MA introduces its own potential biases related to primary data availability and cannot fully resolve comparability issues when underlying measurements are too heterogeneous. As long as data sharing is not the norm in scientific practice, retrieving and integrating primary data consumes a large portion of an IPD-MA project. Adequate resources – in terms of time, personnel, and data science expertise – are essential to address data retrieval, harmonization, and analysis.

Choosing Between Aggregate Data and Individual Participant Data Meta-Analysis: When Are Individual-Level Data Worth the Effort?

While IPD-MA offers higher statistical power and the capacity for sophisticated analyses, it also requires significant investment. Thus, the decision of whether to

conduct an IPD-MA or a traditional AD-MA is pivotal. This section outlines a decision framework, visually summarized in Figure 1, to guide researchers in determining when the unique advantages of IPD-MA justify the effort.

Three primary considerations drive the decision for conducting an IPD-MA:

1. *Research aim.* The choice between AD-MA and IPD-MA depends on the complexity of the research question. For straightforward questions, such as estimating an overall effect or examining a few study-level moderators, AD-MA often suffices. IPD-MA becomes essential when questions require participant-level detail, for instance exploring subgroup differences (Belias et al., 2019), modeling developmental trajectories across the lifespan (McArdle et al., 2009), or analyzing rare or nonlinear outcomes that aggregate data cannot capture (Hattle et al., 2024).
2. *Feasibility and resources.* Even for complex questions, IPD-MA requires careful consideration of practical constraints. Researchers must assess whether enough individual datasets can be obtained and harmonized (Griffith et al., 2014). Resources like those listed in the section on data infrastructure can aid this process. Second, it is crucial to determine if the necessary resources are available to handle the additional demands of data acquisition, harmonization, and complex statistical modeling of an IPD-MA project (Dewidar et al., 2021; Levis et al., 2021).
3. *Necessity and added value.* Researchers should consider whether the question could be adequately addressed with AD-MA, especially when published studies already provide comparable, detailed data. Since there is no universally agreed minimum number of datasets for IPD-MA, the key criterion is whether IPD offers added value (Higgins et al., 2019) – insights, precision, or validity unattainable with AD alone.

To further guide decisions on whether to conduct an AD- or IPD-MA, it is useful to consider how results from both approaches compare. Evidence from medical research indicates that conclusions between the two methods tend to align only when analyses use the same or comparable studies (Smith et al., 2016), when AD-MAs draw on a larger evidence base (Tierney et al., 2020), or when estimating simple overall effects (Lambert et al., 2002). For other cases, substantial discrepancies between

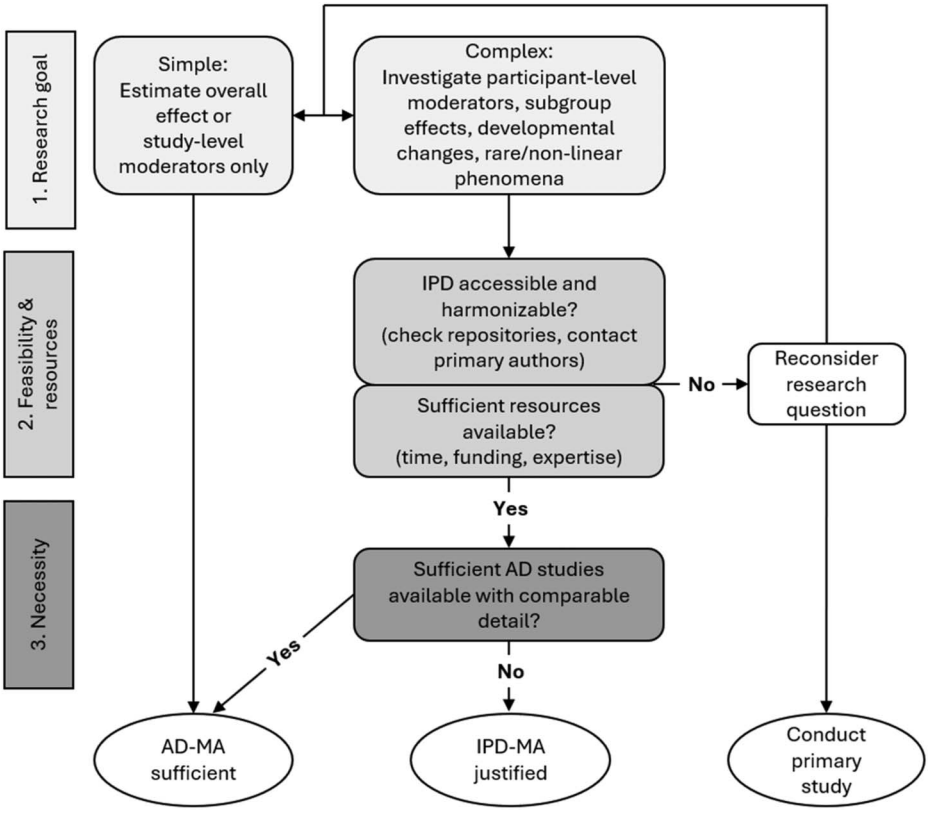

Figure 1. Decision framework for choosing between aggregate data (AD) and individual participant data (IPD) meta-analysis (MA).

AD- and IPD-MA have been observed, sometimes leading to different clinical conclusions (Smith et al., 2016) or systematic over- or underestimation of effects (Riley et al., 2019; Stewart & Parmar, 1993; Tierney et al., 2020). Simulation studies further suggest that AD-MAs may show greater effect variation and reduced power (Lambert et al., 2002). Just as IPD-MAs in medicine have identified clinically relevant subgroups inaccessible through AD-MA (van der Worp et al., 2023), similar results have been reported in psychology. For instance, IPD-MA has revealed aggregation biases in studies of children's equivalence understanding (Hornburg et al., 2018), whereas in PTSD pharmacotherapy trials, IPD-MA enabled identification of individual-level dropout predictors that AD-MAs could not capture (Wright et al., 2025). These cases highlight that IPD-MA becomes increasingly sensible the more nuanced and subtle effects of interest are.

Planning and Conducting Individual Participant Meta-Analysis: Methodological Overview

This section outlines the key phases of IPD-MA (Figure 2), highlighting its unique challenges in data retrieval, harmonization, and modeling that extend beyond standard AD-MA procedures. The planning is supported by established guidance: The *Cochrane Handbook* (Higgins et al., 2019) and the Campbell Collaboration standards for nonclinical fields (Aloe et al., 2024) provide foundational frameworks for conducting systematic research syntheses, while the PRISMA-IPD guideline (Stewart, 1995) informs protocol development and reporting. Comprehensive methodological options are described in medical literature (Debray et al., 2015; Riley et al., 2021; Veroniki et al., 2023), with practical resources for project management, data agreements, and budgeting available from Maxwell et al. (2024). Contributions from psychology-specific IDAs further illustrate applications and adaptation of the general principles (Curran & Hussong, 2009; Graham et al., 2022).

Phase 1: Planning and Protocol Development

An IPD-MA begins with a comprehensive protocol to define the research question, scope, and methods, ensuring reproducibility and minimizing bias. Core elements include:

- *Research questions.* IPD-MA is ideal for nuanced questions such as individual-level moderators, subgroup effects, or complex relationships not accessible via AD-MA (Cooper & Patall, 2009; Veroniki et al., 2023). Specify outcomes, predictors, moderators, target population, and relationships of interest.

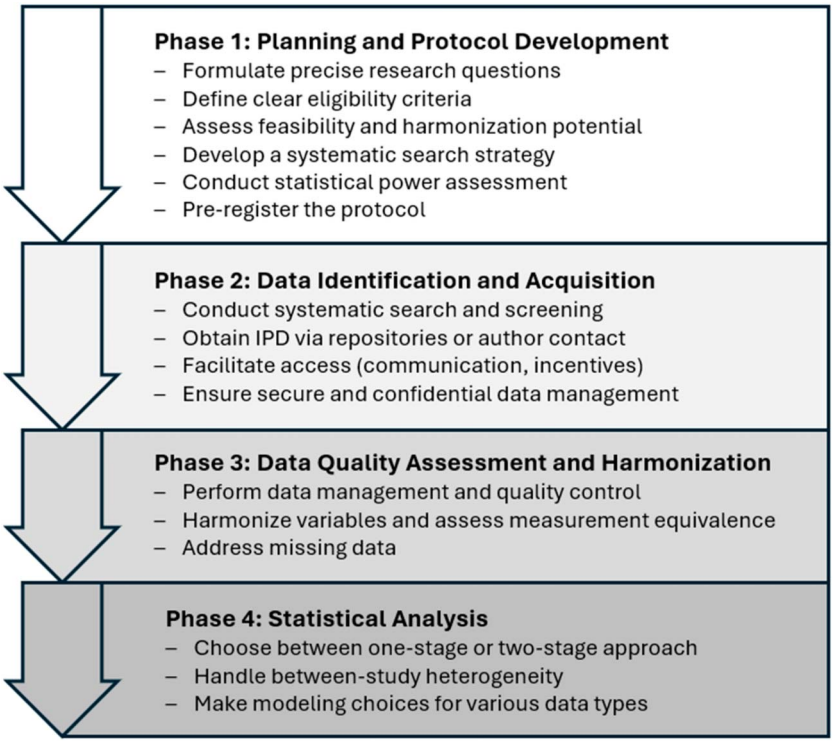

Figure 2. Key phases of conducting an individual participant data meta-analysis.

- *Eligibility criteria.* Translate research questions into clear inclusion/exclusion rules. Frameworks such as NIRO-SR adapt intervention-focused PICO principles for behavioral and cognitive research, covering outcomes, independent variables, populations, designs, and covariates (Topor et al., 2020).
- *Feasibility and harmonization.* Evaluate whether IPD are available and whether variables can be harmonized, given the measurement diversity in psychology (Beck et al., 2024).
- *Systematic search strategy.* Develop a reproducible approach for identifying eligible studies, including databases, search terms (e.g., MeSH and text words), and documentation procedures (Clark et al., 2021; Ventresca et al., 2020).
- *Statistical power.* Given resource investment of an IPD-MA, a priori statistical power assessment is advised. Methods exist for various scenarios, such as binary outcomes (Riley et al., 2022; Whittle et al., 2024), time-to-event outcomes (Riley, Collins, et al., 2023), preschool interventions (Brunner et al., 2025), two-stage IPD-MA (Ensor et al., 2018; Kontopantelis et al., 2016), or Bayesian approaches (Qi et al., 2023).
- *Pre-registration.* Register the protocol in an open repository (e.g., PROSPERO) to enhance transparency and reduce selective reporting.

Phase 2: Data Identification and Acquisition

After protocol development, the next step is to systematically identify eligible studies and obtain the IPD. This process marks a significant distinction from traditional AD-MA, which rely on published summary statistics. Key elements of this phase include:

- *Study identification and screening.* Conduct the planned systematic search and screen records against the predefined eligibility criteria.
- *Data acquisition routes.* IPD can be obtained either through existing repositories (see section Data Infrastructure and Repositories in Psychology below) or by directly contacting study authors. The latter often entails extensive coordination and formal data sharing agreements (templates available for instance in Polanin & Williams, 2016, or Maxwell et al., 2024).
- *Facilitating access.* Effective strategies include clear communication with authors, offering authorship or collaboration incentives, and leveraging repository or funder policies (Ventresca et al., 2020).
- *Data management*. Retrieved datasets must be checked against study protocols, stored securely, and handled in line with confidentiality and data protection standards. Compliance with local laws and funder policies ensures rigorous protection of participant privacy (Levis et al., 2021; Ventresca et al., 2020).

Phase 3: Data Quality Assessment and Harmonization

Once individual datasets are acquired, careful quality checks and harmonization are essential to enable joint analyses. This step is a defining feature of IPD-MA and often the most resource-intensive, particularly in psychology where studies use diverse instruments (Beck et al., 2024; Levis et al., 2021). Frameworks such as the PRIME-IPD (Dewidar et al., 2021) or Maelstrom Research guidelines (Fortier et al., 2016) provide structured guidance for these steps. Key tasks include:

- *Data quality checks.* Each dataset should be scrutinized for errors, inconsistencies, and logical impossibilities. IPD allows more thorough assessment than AD, including detailed exploration of missingness and group imbalances.
- *Variable harmonization and measurement equivalence.* Full harmonization across complex psychological constructs is rarely feasible; conceptual harmonization (i.e., defining a common denominator across convergent measures) is often more practical (Bauer & Hussong, 2009; Beck et al., 2024; Verhage et al., 2022). Scale validation work can guide harmonization approaches (Beck et al., 2024; Howe et al., 2019). Statistical approaches for harmonization include *standardization methods* (e.g., *z*-transformations) to create a common metric, although they may mask heterogeneity (Griffith et al., 2014); *latent variable models* (e.g., factor analysis (FA), item response theory (IRT)) to align constructs, assess measurement equivalence, detect differential item functioning, and establish shared latent metrics (Bainter & Curran, 2015; Bauer & Hussong, 2009; Chan et al., 2015; Curran et al., 2008; Gibbons et al., 2014), as well as advanced variants such as multivariate or higher-order IRT that support complex or longitudinal constructs (Jiao et al., 2020; Mun et al., 2019); and finally, *incomplete data approaches* (multiple imputation, maximum likelihood), addressing missing or nonoverlapping items (Siddique et al., 2018).
- *Handling missing and sparse data.* In addition to typical missingness within studies, IPD-MA missingness can also stem from non-overlapping measures. Multiple imputation handles within-study gaps well (Debray et al., 2015), although cross-study methods may underestimate variability when overlap is limited

(Siddique et al., 2018). Sparse datasets worsen these issues (Griffith et al., 2014; Howe et al., 2024). Sensitivity analyses are recommended given unverifiable missing-at-random assumptions (Kunkel & Kaizar, 2017).

Phase 4: Statistical Analysis

Once IPD are harmonized and quality-checked, the statistical analysis can proceed. IPD-MA is not a unique statistical method but rather applies established single-study and meta-analytic techniques to pooled IPD. One-stage models use multilevel modeling to simultaneously estimate participant- and study-level effects while accounting for dependencies in nested or cross-classified data (Campos et al., 2023; Van Aert, 2022), and two-stage models first estimate study-specific effects according to variable scales and study design before applying conventional meta-analytic methods similar to the one-stage approach (Donegan et al., 2012; Jansen, 2012; Pigott et al., 2012). Below we highlight key considerations for the analyses in IPD-MA, while referring to more in-depth methodological resources such as Debray et al. (2015), Fisher (2015), Tierney et al. (2015), or Riley et al. (2021). For worked application within psychology, see the application examples section below. Key analytical considerations include:

- *Account for heterogeneity.* Heterogeneity in IPD-MA may stem from study-level differences such as sampling strategies, participant demographics, geographic regions, designs, measurement variation (Campos et al., 2023; Curran & Hussong, 2009; Jiao et al., 2020), or participant-level differences or subgroups (Belias et al., 2019; Debray et al., 2015). Strategies to address heterogeneity include random intercepts and slopes for study effects (Chen et al., 2020; Cooper & Patall, 2009) and subgroup analyses (Belias et al., 2019). Guidance also exists to combine heterogeneous outcomes from diverse studies (Jiao et al., 2020).
- *Choose modeling approach depending on data type.* IPD-MA offers flexibility to handle diverse outcomes and complex data structures (see Table 1 in Debray et al., 2015, for model types, and Wilcox & Wang, 2023, for simulations on fixed-, random-, and multilevel models with pooled data). Specialized approaches include multivariate models for correlated outcomes (Frosi, 2017), Bayesian hierarchical models for small or complex datasets (Berkhout et al., 2023; Huh et al., 2019), network or nonlinear meta-analyses integrating IPD and AD (Debray et al., 2016; Jansen, 2012), models for count, zero-inflated, time-to-event, or survival outcomes (De Jong et al., 2020; Huh et al., 2023); longitudinal or repeated-measures data (Campos et al., 2023), single-case experimental designs (Baek & Luo, 2023; Declercq et al., 2022; Moeyaert et al., 2023), IPD-SEM (Groot et al., 2024, 2025; Huh et al., 2021); longitudinal IRT models (McArdle et al., 2009), and linear or nonlinear treatment–covariate interactions across time points (Hattle et al., 2024).
- *Statistical software.* IPD-MA can be conducted in standard statistical environments supporting multilevel modeling (Van Aert, 2022), although specialized packages in R and Stata – the two most widely used platforms – facilitate one- and two-stage approaches (Table 2). Debray et al. (2015) report further software

Table 2. Overview of common statistical software and packages to conduct IPD-MA

Approach	R package	Stata module
Specific for IPD-MA	ipdmeta (Kovalchik, 2012)*	ipdmetan (Fisher, 2022)
One-stage / (G)LMM	lme4 (Bates et al. 2025) nlme (Pinheiro et al. 2025)	xt command family (in-build command, see e.g., Kaufman, 2018; Riley et al., 2021)
Two-stage / AD-MA	metafor (Viechtbauer, 2025) meta (Schwarzer, 2025)	admetan (Fisher, 2019) metan (Fisher et al., 2024) metareg (Harbord & Higgins, 2009)
Power	ipd.meta.power (function in ipdmeta)	ipdpower (Kontopantelis, 2018)
Multivariate MA	mixmeta (Gasparrini & Sera, 2021)	mvmeta (White, 2022)
Network MA	netmeta (Rücker et al. 2023)	network (White, 2018)
Bayesian (IPD-)MA	bayesmeta (Roever, 2025) bipd (Seo, 2022)	bayesmh (in-build command, see e.g., Marchenko, 2022)
Forest plots	forest (function in metafor)	ipdforest (Kontopantelis & Reeves, 2019)

Note. AD = aggregate data, (G)LMM = (generalized) linear mixed models, IPD = individual participant data, MA = meta-analysis. *The *ipdmeta* package was removed from the CRAN repository as of 2021 due to uncorrected check problems, but archived versions are still accessible.

in their review (see Table 2 and 3 there), while Riley et al. (2021) curate an online collection of packages and code for one- and two-stage approaches, power analyses, interactions, multivariate/network analyses, and missing data in R and Stata (https://www.ipdma.co.uk/software-code). General resources for multilevel modeling in R include Dewey and Viechtbauer (2024) and Bolker et al. (2025). Annotated R code and tutorials exist for example for two-stage analyses of complex survey data (Brunner, Keller et al., 2023), multiarm count data trials (Huh et al., 2019), and multilab replications (Van Aert, 2022).

Impact and Applications of Individual Participant Data Meta-Analysis in Psychology

Building on the methodological foundations outlined above, this section highlights the potential of IPD-MA for psychological science to encourage broader adoption. We first discuss how IPD-MA can support replication, advance theory development, and refine psychometric measurement, and then illustrate further potential through its application across diverse psychological domains.

Leveraging Individual Participant Data Meta-Analysis to Tackle the Replication, Theory, and Measurement Crises

IPD-MA offers a powerful methodological response to the credibility crisis facing psychological science, particularly its intertwined problems of replication, theory, and measurement (Oberauer & Lewandowsky, 2019): it enables the testing of theory under diverse conditions with regard to replicability, specificity, and generalizability, and it facilitates harmonization of measures (Graham et al., 2022).

For replication, IPD-MA goes beyond binary success–failure judgments by specifying when, where, and for whom findings replicate. In direct replications, it avoids aggregation bias, separates lab-specific effects, and detects subtle moderators. For example, reanalysis of multilab hostile priming studies showed that only IPD-MA, not AD-MA, revealed age as a within-lab moderator (Van Aert, 2022). In conceptual replications, where populations, designs, or measures differ, IPD-MA provides a framework for advanced synthesis, such as the Product Bayes Factor, to evaluate theoretical consistency across heterogeneous contexts (Van Lissa et al., 2024). For theoretical replications, IPD-MAs can test complex models' generalizability: for instance, one- and two-stage IPD-MAs across international cohorts found that additive effects of infant characteristics and parenting replicated, whereas interaction effects rarely generalized, highlighting opportunities for theory refinement (Eves et al., 2025).

Crucially, replication insights directly inform theory development by revealing underspecified models and contextual boundaries (Haeffel & Cobb, 2022; Oberauer & Lewandowsky, 2019). IPD-MA is particularly suited for this, enabling modeling of fine-grained effects often obscured in AD analyses. For instance, Wolff and Möller (2022) used IPD-MA to validate the Internal/External Frame of Reference model of academic self-concepts, identifying moderators such as age and prior achievement. Similarly, Cipora et al. (2019) showed that the SNARC effect, a robust group-level phenomenon in numerical cognition, was driven by only a minority of individuals, illustrating how IPD-MA avoids ecological fallacies and enriches person-centered theorizing.

Finally, IPD-MA provides powerful tools to address vague constructs and heterogeneous measures, key drivers of psychology's measurement crisis (Bringmann et al., 2022). Pooling IPD from diverse instruments creates a richer representation of the underlying construct, enabling "retrospective psychometrics" to detect and correct biases often missed in AD-MA (Howe & Brown, 2023). IPD-MA also strengthens psychometric properties (Bainter & Curran, 2015; Curran & Hussong, 2009; Howe & Brown, 2023) through the possibility to test differential item functioning, scale invariance, or measurement equivalence (Curran et al., 2008; Howe et al., 2019), while increasing statistical power to reduce artifacts (Bauer & Hussong, 2009; Kaufmann, 2018). For example, IPD-MA has been used to validate a widely used depression screening measure across diverse populations (Negeri et al., 2021).

In essence, IPD-MA does not solve the credibility crisis, but it provides psychologists with tools to make replication more informative, theory more precise, and measurement more robust.

Application Examples of Individual Participant Data Meta-Analysis in Psychology

IPD-MA has begun to make valuable contributions across diverse areas of psychology, yielding insights that traditional synthesis approaches often miss. In particular, it excels at uncovering heterogeneity and individual-level processes that remain hidden in aggregate analyses. For example, Korous et al. (2023) used two-stage MA-SEM on nearly half a million participants to show that the relationship between socioeconomic status and depressive

symptoms followed a curvilinear "better near the middle" pattern, visible only within specific ethnic groups and developmental periods. Barry et al. (2024) synthesized six European birth cohorts to reveal subgroup differences in the effects of childcare arrangements, reducing trial-level confounding and disentangling interactions between family socioeconomic position and child sex. Dagan et al. (2022) pooled harmonized attachment data to show how joint mother–child and father–child relationships predict socioemotional outcomes, uncovering patterns shaped by temperament that only IPD-level modeling can detect. Brunner, Preckel et al. (2023) combined IPD and AD from international educational assessments (PISA, TIMSS) to resolve conflicting findings on math anxiety and achievement, offering a more precise breakdown of moderators such as gender and prior achievement. Together, these examples illustrate how IPD-MA can refine, challenge, or strengthen conclusions in ways unattainable with AD.

A second unique strength of IPD-MA is its ability to model developmental and longitudinal trajectories as well as fine-grained temporal dynamics across multiple studies. Pooling data enables precise estimates for rare events and extensive longitudinal measurements across diverse populations (Graham et al., 2022). For example, an IPD-MA of 13 parenting intervention trials found that child age did not affect intervention effectiveness, aligning with a larger AD-MA, yet illustrating IPD-MA's precision in smaller samples (Gardner et al., 2019). Similarly, harmonized sleep data from over 200,000 participants across three countries provided detailed lifespan trajectories and identified adolescents at elevated risk (Kocevska et al., 2020). At finer time scales, pooling high-resolution temporal and daily diary data has uncovered within-person dynamics invisible to aggregate analyses: Kuehn et al. (2022) found that negative affect rose before and fell after self-injurious behavior; Dora et al. (2023) report that positive affect could more strongly predict daily alcohol use than negative affect, challenging prevailing theoretical models; and Zanesco et al. (2024) observed that mind-wandering systematically increased during task performance, a pattern obscured in AD-MA. These examples demonstrate IPD-MA's unique capacity to capture both broad developmental patterns and high-resolution psychological processes.

Guidance on and Promotion of Data Sharing for Individual Participant Data Meta-Analysis

Truly insightful and robust IPD-MAs depend on the availability of individual-level data. Data sharing practices, infrastructure, and ethical considerations therefore form the practical backbone of IPD research. This section outlines the current state of data sharing in psychology, available infrastructures, and ethical challenges.

The State and Future of Data Sharing Practices in Psychology

Retrieving datasets from published studies remains a challenge in meta-research: Fewer than half of published IPD-MAs succeed in obtaining more than 80% of eligible IPD (Nevitt et al., 2017). While medicine has a stronger culture of open data, data sharing is still the exception rather than the norm in psychology (Hardwicke & Ioannidis, 2018; Tedersoo et al., 2021; Van Aert, 2022; Vanpaemel et al., 2015). Barriers include fear of misinterpretation, the effort of preparing datasets, and a lack of recognition (Houtkoop et al., 2018). Progress is visible, however: *Psychological Science*'s adoption of open science badges in 2013 led to 69% of articles earning an open data badge by 2022 (Hardwicke & Vazire, 2024). Still, psychology lags behind fields where journals and funders mandate data availability, as seen at *Nature* or *BMJ*, whereas APA has only issued nonbinding recommendations (Houtkoop et al., 2018).

To build a sustainable culture of sharing, incentives must cut both ways: encouraging the release of new and existing data and rewarding dataset reuse through visibility and citations. It remains to be seen whether the new generation of researchers, shaped by the replication crisis and the open science debate (Open Science Collaboration, 2015; Wiggins & Christopherson, 2019), will embrace data sharing as second nature.

Data Infrastructure and Repositories in Psychology

A growing number of initiatives provide infrastructure for IPD-MA (see list in Table S1 in the online supplement available at https://osf.io/cwth9. Options range from basic platforms such as ResearchBox to comprehensive frameworks such as the Open Science Framework, or specialized tools such as DataWiz for guided data management. Re3data.org further offers a searchable registry across disciplines.

While there is no shortage of technical options, the challenge lies in changing norms, embedding best data practices into research cultures. Researchers are encouraged to establish clear data management strategies early in their careers (and teach their students likewise), aligning with FAIR principles (Wilkinson et al., 2016). For IPD-MA, this means preparing data and

metadata in structured, well-documented formats to facilitate reuse.

Ethical and Legal Considerations of Data Reuse

Consistent with the APA Ethical Code, data needed to verify findings should be shared. Yet IPD raise issues that go beyond AD, including informed consent for secondary use, participant confidentiality, and authorship rights (Cooper & Dent, 2011). Even anonymized datasets may risk reidentification, especially with AI advances, underscoring the need for careful consent and confidentiality safeguards. Data recipients share responsibilities: protecting privacy, demonstrating capability, crediting original researchers, fostering collaboration, and adhering to regulations (Hunter et al., 2023). Transparent collaboration is best ensured through early agreements on authorship, opportunities for primary researchers to publish first, and the use of clear data-sharing agreements (Polanin & Williams, 2016).

Conclusion

The advancement of research depends on our ability to move beyond fragmented findings and toward cumulative, integrative knowledge consolidation. IPD-MA represents a methodological innovation in this shift. By leveraging individual-level data, it allows researchers to capture heterogeneity, identify moderators, model nonlinear relationships, and refine measurement in ways that aggregate data cannot. Applications across psychology have shown how IPD-MA can reveal subgroup nuances, trace developmental and temporal processes, and resolve conflicting findings – demonstrating its potential to advance both theory and practice. At the same time, widespread adoption remains constrained by barriers to data sharing and reuse. Yet with emerging infrastructures, collaborative networks, and the momentum of open science, the conditions are increasingly in place for IPD-MA to reshape evidence synthesis in psychology and strengthen the credibility and generalizability of research.

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