Meta-Analyzing Individual Participant Data From Studies With Complex Survey Designs: A Tutorial on Using the Two-Stage Approach for Data From Educational Large-Scale Assessments

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This paper has been accepted for publication at *Research Synthesis Methods* (June 8, 2022). Please cite as:

Brunner, M., Keller, L., Stallasch, S. E., Kretschmann, J., Hasl, A., Preckel, F., Lüdtke, O., & Hedges, L. V. (2022). Meta-Analyzing Individual Participant Data From Studies With Complex Survey Designs: A Tutorial on Using the Two-Stage Approach for Data From Educational Large-Scale Assessments. *Research Synthesis Methods*. Advance online publication. <https://doi.org/10.1002/jrsm.1584>

Author Note

The R syntax for reproducing all results, figures, and tables as well as the data with effect sizes used in the present paper can be accessed via the Open Science Framework at [Link]. The raw PISA data used in this article to estimate effect sizes can be downloaded from

<https://www.oecd.org/pisa/data/>. We made a preprint of our tutorial available on PsyArXiv at <https://psyarxiv.com/t79vk/>.

We have no conflicts of interests to disclose. This work was supported by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under [Grant 442358899].

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Abstract

Descriptive analyses of socially important or theoretically interesting phenomena and trends are a vital component of research in the behavioral, social, economic, and health sciences. Such analyses yield reliable results when using representative individual participant data (IPD) from studies with complex survey designs, including educational large-scale assessments (ELSAs) or social, health, and economic survey and panel studies. The meta-analytic integration of these results offers unique and novel research opportunities to provide strong empirical evidence of the consistency and generalizability of important phenomena and trends. Using ELSAs as an example, this tutorial offers methodological guidance on how to use the two-stage approach to IPD meta-analysis to account for the statistical challenges of complex survey designs (e.g., sampling weights, clustered and missing IPD), first, to conduct descriptive analyses (Stage 1), and second, to integrate results with three-level meta-analytic and meta-regression models to take into account dependencies among effect sizes (Stage 2). The two-stage approach is illustrated with IPD on reading achievement from the Programme for International Student Assessment (PISA). We demonstrate how to analyze and integrate standardized mean differences (e.g., gender differences), correlations (e.g., with students' socioeconomic status [SES]), and interactions between individual characteristics at the participant level (e.g., the interaction between gender and SES) across several PISA cycles. All the datafiles and R scripts we used are available online. Because complex social, health, or economic survey and panel studies share many methodological features with ELSAs, the guidance offered in this tutorial is also helpful for synthesizing research evidence from these studies.

Keywords: meta-analysis, individual participant data, complex survey designs, educational large-scale assessments, Programme for International Student Assessment (PISA)

1 | INTRODUCTION

Quantitative descriptive analyses are a vital component of research in the behavioral and social sciences (e.g., education, psychology, sociology, and economics) and many other disciplines (e.g., health sciences). Such analyses help to “characterize the world” or a “phenomenon” because they answer questions “about who, what, where, when, and to what extent”.¹ Quantitative descriptive analyses provide robust results when being based on representative individual participant data (IPD) from studies with complex survey designs, such as educational large-scale assessments (ELSAs)² or social, health, and economic survey and panel studies. Many studies with complex survey designs have been conducted at both international and national levels*, involving the World Health Surveys, the European Health Interview Survey, the European Values Study, the Household Finance and Consumption Survey, or the US National Longitudinal Surveys of the Youth. Well-known examples for ELSAs are the Programme for International Student Assessment (PISA), the Trends in International Mathematics and Science Study (TIMSS), the Progress in International Reading Literacy Study (PIRLS), the Programme for the International Assessment of Adult Competencies (PIAAC), and the National Assessment of Educational Progress (NAEP). Since studies with complex survey designs have been carried out for several decades, it is now possible to answer research questions not only with IPD from one study cycle or sample (e.g., PISA 2018) but by integrating results from multiple sets of IPD (e.g., PISA 2000–2018). Given the methodological complexities (e.g., sampling weights, clustered and missing IPD, dependent effect sizes) of studies with complex survey designs in general, and ELSAs in specific, a key question is how to do this. IPD meta-analysis may be a powerful tool for this purpose as it offers unique and novel opportunities to synthesize evidence from descriptive analyses.³ In this tutorial, we use the example of ELSAs to offer methodological guidance on

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* An overview can found at: <https://www.gesis.org/en/services/finding-and-accessing-data/overviews/overview-of-comparative-surveys-worldwide>

how to conduct IPD meta-analyses with studies using complex survey designs to contribute to the cumulative body of knowledge on socially important or theoretically interesting phenomena and trends. Notably, because complex health, social, or economic surveys and panel studies share many methodological features with ELSAs (e.g., sampling weights, clustered and missing IPD, dependent effect sizes), the guidance offered in this tutorial may also be helpful to use IPD meta-analyses to synthesize research evidence from these studies.⁴

2 | ADVANTAGES OF COMBINING META-ANALYTIC TECHNIQUES AND IPD FROM ELSAS

IPD meta-analyses of ELSAs may significantly enrich the extant body of knowledge with reliable and widely generalizable evidence for many research topics, for example, (temporal trends in) gender differences in achievement,^{5–7} or the relationship between students' socioeconomic status (SES) and achievement.⁸ Perhaps even more importantly, IPD meta-analyses of ELSAs open up new and unique research opportunities to synthesize evidence. Such research opportunities involve in-depth meta-analyses of policy-relevant subgroups, for example, to provide reliable empirical evidence of the consistency and generalizability of the magnitude of gender differences among top-performing students (i.e., the top 5%) in mathematics.⁹ Likewise, IPD meta-analyses of ELSAs allow researchers to examine the generalizability of (novel) theoretical propositions across countries, for example, to test predictions about nonlinear relationships between achievement and academic self-concepts,¹⁰ relationships between innovative school environments and teaching practices,¹¹ relationships between epistemic beliefs and educational outcomes in science,¹² year-in-school effects on academic self-concept,¹³ or, as we illustrate in the present paper, intersectional research questions¹⁴, such as how gender differences in students' achievement are moderated by their socioeconomic status (SES).

2.1 | Advantages of IPD From ELSAs

The wealth of data collected in ELSAs yields manifold insights into (a) the distributions of important individual characteristics involving achievement and skills in various domains (e.g., reading, mathematics), socioemotional characteristics (e.g., achievement motivation, academic self-concept, personality), well-being and health (e.g., satisfaction with life, body mass index), or sociodemographic background, (b) learning and home environments, and (c) the relational patterns between these variables. The measures applied in ELSAs are very high in quality because they are based on expert review panels, pilot-tested in large field trials, and thoroughly examined to ensure that they provide unbiased assessments of key constructs.¹⁵ Using such measures, ELSAs allow researchers to describe distributions and patterns of relationships in a certain target population or subpopulation. ELSA data are therefore obtained from large, representative probability samples,¹⁶ thus implying that descriptive analyses of these data meet the gold standard for obtaining reliable knowledge about vital research topics that can be generalized to well-defined populations.^{17,18} More specifically, the random sampling process effectively responds to threats of sample selection bias because it ensures the representativeness of the sample on observable and unobservable dimensions of a certain well-defined population.^{17,18} Further, given their large sample sizes, ELSAs provide very precise estimates of effect sizes for these populations¹⁶ with “effect size” broadly defined as any quantitative estimate used to address a certain research question.¹⁹

2.2 | Advantages of IPD meta-analyses of ELSAs

Because ELSAs have been conducted regularly at both international and national levels for many years, they provide a very large volume of data—Big Data—for carrying out descriptive analyses. For example, PISA provides IPD from over 400 independent samples with almost three million students taking part in one of seven PISA cycles across a time span of 18 years (see Figure 1). When descriptive analyses from several samples from the same or related ELSAs are available, important questions arise concerning the consistency,

replicability, and generalizability of the results.²⁰ Such questions can be tackled with IPD meta-analyses.

IPD meta-analysis is a specific type of meta-analysis that was developed primarily in biomedical research.²¹ Instead of extracting summary, aggregate data (AD) from published or unpublished studies,^{22,23} researchers search for original data that can be re-analyzed and then integrated in meta-analyses.²⁴ IPD meta-analyses can improve the generalizability of results because IPD from previously unpublished studies may become available.³ Access to IPD also allows the meta-analyst to apply a standardized analysis protocol to control the quality of the data and statistical analyses to estimate effect sizes.^{3,25} Such advantages of IPD meta-analyses help mitigate bias and unwanted heterogeneity in effect sizes, and as a consequence, they help improve the precision of the meta-analytic results.^{3,25} Furthermore, IPD allow for the application of types of analyses that would not be possible with aggregate data.²⁴ For these reasons, IPD meta-analyses are considered the “gold standard” of evidence synthesis.^{21,24}

To sum up, IPD meta-analyses that integrate the results of descriptive analyses of ELSA data draw on the strengths of two gold-standard methods: meta-analyses of (a) representative probability samples and (b) the raw data recorded for each participant. However, meta-analytic models have only rarely been applied to results from ELSAs in general^{5,7} and to IPD from ELSAs in particular.^{6,9–11,26*} Why? One reason may be that there is ample guidance available for either conducting descriptive analyses of studies with complex survey designs^{16,27–29} or carrying out IPD meta-analyses^{25,30}. But only a single guidance paper is available that describes important steps to meta-analytically integrate descriptive analyses from health surveys.⁴ This paper, however, does not focus on IPD meta-analyses of studies with complex survey designs.

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* This also became evident from a literature review in which we searched the ERIC and PsycINFO databases for records that were relevant to four major ELSA programs: NAEP, PISA, TIMSS, and PIRLS. Our review showed that only 59 out of 15,923 identified records (0.4%) relevant to these ELSAs were classified as meta-analyses (for details, see Online Supplement [OSM.1]). Given that we focused on four major ELSA programs, this result provides a plausible estimate of the application of meta-analytic models to results from ELSAs.

3 | THE PRESENT TUTORIAL

To address this gap in the literature, we aim to provide researchers with methodological guidance on how to take advantage of IPD meta-analyses to synthesize the empirical evidence obtained from descriptive analyses of studies with complex survey designs. These studies share several central methodological features (e.g., sampling weights, clustered and missing IPD, dependent effect sizes) that need to be taken into account when analyzing the IPD and integrating the results.⁴ To this end, we use ELSAs as an example to offer a robust and versatile work flow that can be applied to (a) carry out quantitative descriptive analyses with IPD from studies with complex survey designs, which are then (b) integrated by means of meta-analytic models. Specifically, we first discuss general characteristics of IPD meta-analyses of ELSAs. We then elaborate on how the two-stage approach of IPD meta-analysis^{31,32} can be tailored to account for the methodological complexities of ELSAs when estimating effect sizes in Stage 1 and integrating the results by means of meta-analytic models in Stage 2. We illustrate the potential of the two-stage approach for integrating results of descriptive analyses of ELSA data by drawing on PISA public use files encompassing data from over 400 independent samples with about 3 million students (see Figure 1)*. Particularly, we show how to estimate effect sizes that are often synthesized in meta-analyses in Stage 1²²: standardized mean differences between groups (i.e., gender differences in reading achievement) and bivariate correlations (i.e., the correlation of students' SES with reading achievement). Further, we discuss and illustrate a key strength of IPD meta-analysis—the analysis of heterogeneity in effect sizes at the participant level (i.e., how the size of gender differences in reading achievement is moderated by students' SES). We also elaborate on and showcase Stage 2 in which meta-analytic and meta-regression models are applied to integrate the (dependent) effect sizes as estimated in Stage 1. Finally, we discuss the opportunities,

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* The raw PISA data used in this article to estimate effect sizes can be downloaded from <https://www.oecd.org/pisa/data/>.

challenges, and limitations that come from using IPD meta-analyses for descriptive analyses of ELSA data. We also offer extensive online supplementary material (OSM) where we provide details on the applied methods. Further, we share the syntax for reproducing all results on the Open Science Framework ([Link]). In doing so, we want to facilitate other researchers' use of IPD meta-analyses of studies with complex survey designs.

4 | IPD META-ANALYSES OF ELSAS: GENERAL CHARACTERISTICS

4.1 | IPD meta-analyses of ELSAs and systematic reviews

We begin our discussion of IPD meta-analyses of ELSAs by distinguishing meta-analyses from systematic reviews (also known as research syntheses) because these terms have often been used synonymously even though they refer to different methodological concepts.³³ Specifically, the term meta-analysis concerns the statistical analysis (e.g., of IPD from ELSAs or AD from published and unpublished studies) with the aim of integrating the findings.^{33(p532)} The term systematic review, on the other hand, refers to the entire process of using systematic methods to identify, select, collect, analyze, integrate, and critically appraise relevant research. In systematic reviews, meta-analytic models might or might not be applied to integrate the results.^{33(p535)} Importantly, systematic reviews aim to cover the complete body of empirical data and results that are relevant to a certain research question.³⁴ On the other hand, IPD meta-analyses of descriptive analyses of ELSA data are aimed at covering relevant—but not the complete body of—empirical evidence. They may therefore significantly contribute to the cumulative evidence in the behavioral and social sciences and become an important component, but they are not a substitute for systematic reviews (see Discussion).

4.2 | One-stage and two-stage approaches to IPD meta-analyses of ELSAs

IPD from ELSAs are typically hierarchically structured. For example, in PISA and other international ELSAs (e.g., TIMSS and PIRLS), IPD from several independent student samples are available for most countries (see Figure 2a). This data structure needs to be taken into

account when conducting an IPD meta-analysis of ELSA data. There are two major approaches that can accomplish this goal: the two-stage and the one-stage approach. In Stage 1 of a two-stage IPD meta-analysis, the IPD for each sample from an ELSA are used to estimate effect sizes and corresponding sampling variances or their square roots, the standard errors (see Figure 2b). In many applications of the two-stage approach, the estimation of effect sizes (and their sampling variances) draws on statistical models from the large family of generalized linear models that are specified at the participant level, for example, regression models for continuous, binary, ordinal, or count data.^{27,28} In Stage 2 of a two-stage IPD meta-analysis, the effect sizes are integrated with meta-analytic models that are also applied in AD meta-analyses, involving common-effect models (fixed-effect models) or random-effects models.^{35,36} In these models, more precise effect size estimates (in terms of their sampling variances) obtain larger weights (inverse variance weighting).

The one-stage approach, on the other hand, combines the two stages of the two-stage approach into a single statistical model to meta-analyze the data. To this end, the IPD from all samples of one specific or several related ELSAs are combined in a single large data set and analyzed simultaneously in this model. For example, using all IPD from PISA, a one-stage approach would involve creating a data set with about three million students (see Figure 2b). Given the hierarchical nature of these IPD, the statistical model is typically a multilevel model taken from the family of generalized linear mixed models.²⁵

Both one-stage and two-stage approaches can be used to fit statistical models that draw on the same set of assumptions for the same set of IPD. So which approach should be used for IPD meta-analyses of ELSAs? The major difference between the two approaches lies in the procedures they use to estimate the meta-analytic parameters, and the largest differences can be expected for sparse data.^{32,37} For example, when studying differences between independent groups (e.g., male and female students), the most notable differences in meta-analytic estimates between these approaches can be expected for IPD meta-analyses of

ELSAs when most samples have IPD from (a) only a few participants (e.g., < 30 per group) or (b) only a few events (e.g., < 10 per group) demonstrating a rare experience (e.g., winning an international math Olympiad).^{37(p216)} Further, when examining moderating effects at the participant level (e.g., how gender differences are moderated by students' SES), differences between these approaches can be expected to be largest, particularly for binary outcomes (e.g., obtaining a college degree or not), with only a few samples (e.g., 5) and only a few participants per sample (e.g., < 50).^{38(p11)} In such applications, the one-stage approach is preferred because it will likely give more precise and less biased meta-analytic estimates.^{25,31,37}

Sparse data occur more often when synthesizing evidence, for example, in the biomedical sciences,³⁹ than when drawing on ELSAs (and other complex survey data) because key characteristics of these studies are large sample sizes and a large number of available samples (see Figure 1). Drawing on such an ensemble of IPD, empirical, theoretical, and simulation studies have shown that the one- and two-stage approaches provide very similar results when statistical models that draw on the same set of assumptions are fit to these data.^{31,32} In the present tutorial, we therefore focus on and recommend the two-stage approach that also offers several additional advantages.

First, the one-stage approach requires a commensurable metric for the applied measures, whereas the two-stage approach requires a commensurable metric for the effect sizes. In this respect, the two-stage approach is easier to apply. For example, different ELSAs (e.g., PISA and PIRLS) typically measure the same target construct (e.g., reading achievement) with different instruments. To allow for comparison of results across ELSAs, the two-stage approach draws on standardized effect sizes that are estimated in Stage 1 and meta-analytically integrated in Stage 2. The one-stage approach, however, requires to first establish a commensurable metric for the applied measures to allow for the meta-analytic integration of results within a single model. To this end, researchers need to harmonize the

target measures, for example by using advanced psychometric models or missing data procedures.^{40,41} The success of these harmonization procedures depends strongly on the availability and quality of the applied measures (e.g., a large number of common items that are psychometrically equivalent across ELSAs), which may even preclude the application of the one-stage approach.^{40,41}

Second, the two-stage approach requires considerably less expertise to account for the statistical complexities that are inherent to IPD from ELSAs (e.g., sample weights, clustered and missing IPD, dependent effect sizes) than the one-stage approach, which requires all these complexities to be incorporated in the specification of a single model.^{31,32,37} This advantage becomes even more valuable when the applied survey methodologies vary across ELSAs (e.g., number of plausible values provided for students' achievement [see Section 5.1.4 on "Plausible Values"], methods used to estimate sampling variances for effect sizes).

Third, IPD meta-analyses of ELSAs often require analyses of complex, hierarchical data structures with IPD from several million individuals (see Figures 1 and 2). This may result in an inability to analyze the data due to the insufficient random-access memory of regular computers—a typical problem with Big Data analyses.⁴² In such cases, the two-stage approach may be the only feasible approach because it takes advantage of an analytic strategy that has been developed for these Big Data problems. This strategy entails first splitting a single large data set (e.g., a data set comprising about 3,000,000 IPD points from students from PISA) into considerably smaller subsets (e.g., 424 data sets comprising student samples from a certain country and PISA cycle). A standardized protocol for managing and analyzing the data is subsequently applied to each subset. Then, the results obtained for each subset are combined, for example, by using meta-analytic methods.⁴²

Finally, the two-stage approach can be used to integrate a broader spectrum of effect sizes, involving effect sizes that are typically applied in meta-analyses (e.g., standardized mean differences, e.g., Cohen's *d* or correlations)^{22,43} as well as less commonly used ones. For

example, Keller et al.⁹ used the two-stage approach to meta-analyze the overlap between the distribution of achievement profile scores as obtained from female and male students belonging to the group of top-performing math students in their respective countries. This kind of effect size cannot be specified in generalized linear mixed models that are typically applied in the one-stage approach.

4.3 | Explaining heterogeneity in effect sizes in IPD meta-analyses of ELSAs

4.3.1 | Heterogeneity in effect sizes at multiple levels

A major goal of a meta-analysis is to estimate the extent to which the magnitude of an effect size depends on further moderator variables.^{36,44,45} In IPD meta-analyses of ELSAs, heterogeneity in effect sizes can be investigated at different levels by applying regression and meta-regression models. These models help to examine the extent to which one or more categorical or continuous moderators explain differences in effect sizes (a) across countries (Level 3 in Figure 2a), (b) across assessment cycles within countries (Level 2 in Figure 2a), or (c) at the participant level (Level 1 in Figure 2a). For example, a moderator analysis at the country level may explain heterogeneity in gender differences in reading achievement between countries by country-level characteristics, involving socioeconomic, educational, cultural, or political factors.^{5,9} A moderator analysis at the cycle level may explain heterogeneity in gender differences in reading achievement across time.^{6,7} Finally, a moderator analysis at the participant level may examine how gender differences in reading achievement are moderated by students' SES within countries.

4.3.2 | Ecological fallacies

Compared with AD meta-analyses, IPD meta-analyses offer one major advantage: moderator analyses at the participant level. IPD meta-analyses of ELSAs may therefore provide unique insights into important phenomena that cannot (or can hardly) be provided with AD meta-analyses because the effect sizes that depict interactions between individual characteristics at

the participant level are often not reported at all or are available in only a small subset of the relevant primary studies. Yet, unless data on these effect sizes are available, it is impossible to learn about moderating effects at the participant level. Intuitively, one might expect that moderating effects as observed at higher hierarchical levels (e.g., the country level)—which is possible with AD meta-analyses—would allow for valid inferences about participant-level moderating effects. However, this intuition is wrong and has been referred to by different terms, such as, *ecological fallacy*,⁴⁶ *ecological bias*, or *aggregation bias*.⁴⁷ We illustrate this problem in Figure 3 with artificial ELSA data from 30 countries. Figure 3 displays how the magnitude of gender differences in students' reading achievement may be moderated by (a) students' SES at the participant level and (b) students' SES aggregated on the country level. Figures 3a and 3b show that the magnitude of gender differences is related to average SES at the country level ($r_{between} = .70$) with larger gender differences observed in countries with higher average SES. Further, with increasing levels of students' SES at the participant level within each country, the magnitude of gender differences increases ($r_{within} = .50$) in Figure 3a, whereas it decreases in Figure 3b ($r_{within} = -.50$). Taken together, these examples emphasize that moderating effects may have different sizes and even directions at the participant and country levels. Thus, it is not possible to draw valid conclusions about moderating effects at the participant level from results obtained at higher hierarchical levels (and vice versa).

4.3.3 | Some guidance for examining the heterogeneity of effect sizes at various levels

The examples of ecological fallacies highlight that the two-stage approach to IPD meta-analyses of ELSAs requires researchers to pay special attention to several key issues when specifying, estimating, and interpreting moderating effects to explain heterogeneity in effect sizes.^{25,38,48,49} Arguably the most important issue here is that it is important to match the substantive research question on the one hand with the appropriate level of analysis and form of centering of the moderating variables on the other.^{48–52}

First, when the research goal is to learn about heterogeneity in effect sizes at the participant level, it is essential to directly model the interaction between individual characteristics at this level in Stage 1. In particular, when the research goal is to study moderating effects for the populations represented by each sample (see Model Set 3 in Section 5.1.5), the regression models that need to be specified for each sample must include the target interaction effect(s) between the predictor variables depicted as multiplicative terms (e.g., Gender x SES) in addition to the main effects of these predictors (e.g., Gender and SES).^{25,48,49,53,54} In Stage 2, the multiplicative terms are integrated with meta-analytic and meta-regression models.^{25,48,49,53,54} Of note, the regression models used in Stage 1 can be extended (e.g., by using cubic spline functions) to explore the extent to which the magnitude of the moderating effect varies along the distribution of a certain predictor variable at the participant level.⁴⁸ Integrating the results of these extended models may require multivariate meta-analytic and meta-regression models in Stage 2.^{48,55}

Second, for regression analyses involving interactions as described above, it is recommended that the predictor variables in these models are centered or z-standardized to reduce collinearity and ill-conditioning in the data.^{51,52} Further, to facilitate the interpretation of regression coefficients for interaction effects, each predictor variable should have a meaningful zero point. Such zero points can be achieved, for example, by dummy-coding nominal variables (e.g., gender) or z-standardizing or centering continuous variables (e.g., occupational status as a measure of SES).⁵² Of note, dichotomizing continuous predictor or outcome variables when examining interaction effects (e.g., with the goal of improving the interpretation of results) is not recommended because doing so decreases the precision with which the interaction term can be estimated.⁴⁸

Third, when applying the two-stage approach to IPD meta-analyses of ELSAs to examine the heterogeneity of effect sizes, we strongly recommend that researchers use the analytic strategies (e.g., meta-analyzing interaction terms) as described above because these

strategies can help researchers avoid the statistical pitfalls that are likely to occur when using alternative approaches.^{48,49,53} In particular, when examining how effect sizes vary across participant subgroups (e.g., male and female students), it might be tempting to estimate effect sizes for each subgroup separately for each sample in Stage 1, meta-analytically combine these effect sizes within these subgroups in Stage 2, and then compare the meta-analytic results across subgroups. However, this strategy should not be used because it is prone to ecological biases as it combines moderating effects that may be observed within samples with moderating effects that may be observed across samples (e.g., across countries).^{48,49}

Fourth, many ELSAs apply stratified multistage random sampling schemes (see Section 5.1.1), for example, by first drawing random samples of schools within a country and then sampling students within schools. This sampling process leads to clustered data at the sample level (e.g., students nested in schools). It is important to always consider the clustered data when estimating the standard errors of the effect sizes in Stage 1 (see Section 5.1.2). However, depending on the substantive research question, the clustered nature of the data might or might not be considered when estimating the effect size. For example, when the research goal is to study the extent to which the magnitude of gender differences is moderated by students' SES in the total population that is represented by a certain sample, it is sufficient to specify a linear regression model for each sample as described above in Stage 1. Notably, the resulting effect size represents an amalgam of the within-cluster interaction between gender and SES (e.g., within schools) and the between-cluster interaction between these variables aggregated to the cluster level (e.g., the proportion of female students in schools and the average SES at school level). Thus, when the research goal is to disentangle within-cluster relationships from between-cluster relationships in Stage 1, statistical models (e.g., multilevel models) that provide separate effect sizes for each hierarchical level in each sample need to be specified. To this end, it is necessary to center all variables (including dummy-coded variables, e.g., gender) within clusters within each sample, for example, by subtracting the

school-specific proportion of female students from each student's value on the gender variable or subtracting the average SES at the school level from each student's value on the SES variable.⁵⁰ The interaction term is then computed by multiplying the predictor variables after centering them within clusters. When using this approach, it is important to (a) use appropriate approaches (e.g., weights at the participant and cluster levels) that take into account the sampling process of the ELSA when estimating the effect sizes at the participant and cluster levels in Stage 1 (see also Section 5.1.1)^{56,57} and (b) consider the possibility that the magnitude of effect sizes may vary between clusters (e.g., by specifying a multilevel model in Stage 1 that includes a random effect for the interaction term).⁴⁸

Fifth, in IPD meta-analyses of international ELSAs, some moderator variables may vary within and between countries when meta-regression models are used to examine the heterogeneity of effect sizes in Stage 2. For example, some studies have found that gender differences in mathematics achievement are moderated by gender equality indicators at the country level (e.g., the percentage of women in tertiary education in a country).^{5,9} These factors may vary within countries across time (e.g., because of political initiatives to reduce gender disparities in a certain country) or between countries (e.g., because of stable between-country differences in the educational and economic opportunities offered to men and women). Because moderating effects may vary in magnitude and direction within and between countries, including a certain moderator as a single variable in the meta-regression model yields a meta-regression coefficient that comprises a mixture of the within- and between-country relationships.^{58,59} To disentangle these within- and between-country relationships, the meta-regression model should contain (a) the aggregated country-specific mean of the moderator (e.g., the country-specific value of a certain gender equality indicator averaged across time) to estimate the moderating effect at the country level and (b) the centered value of the moderator (e.g., the deviation of a gender equality indicator as observed

at a certain point in time from the country-specific average) to estimate the moderating effect within countries.⁵⁹

4.4 | Missing data in ELSAs

4.4.1 | Sporadically and systematically missing data

All empirical analyses face the problem that missing values reduce the information available on effect sizes, moderator variables, or both. Missing data can take different forms in IPD meta-analyses of ELSAs: (a) sporadically, (b) planned systematically, and (c) unplanned systematically missing data.⁶⁰ Sporadically missing data occur at the participant level (Figure 2a) and refer to missing data for those participants who were included in a certain sample and who were administered a certain instrument (e.g., a test booklet or questionnaire). For example, such missing data may result when participants intentionally ignore or forget to answer certain questions or test items. By contrast, planned systematically missing data occur in ELSAs at the participant level because planned missing designs (also called booklet designs) are applied (see section 5.1.4 on “Plausible Values”), thus implying that some data are missing for random subsamples of participants. Finally, unplanned systematically missing data may occur in ELSAs at the cycle level (see Figure 2a) when data are not available for all individuals in a certain sample.⁶⁰ For example, in PISA 2006, all students in the US had (unplanned) systematically missing data on reading achievement because the applied paper-pencil test contained severe printing errors.^{61(p281)} Thus, it was not possible to estimate, for example, gender differences in reading achievement for that cycle in the US. Moreover, unplanned systematically missing data may also occur at the cycle or country level when information on a certain moderator variable is not available for a specific cycle or country (e.g., information on country-specific socioeconomic or political factors).

4.4.2 | Missingness mechanisms

Fortunately, (most) missing data in ELSAs can be handled effectively. The possibility of imputation and the choice of imputation method depends on the type of missing values. Three different missingness mechanisms can be distinguished: missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR).^{62,63} For example, if students happen by chance to be ill on the day of testing, their achievement data can be considered to be MCAR. Missing data in ELSAs are MAR when missingness on a target variable X can be explained by other observed data in the data set but does not depend on unobserved data, including unobserved values of X itself. For example, MAR occurs for achievement data if school personnel discourage students with lower SES from taking the tests. However, when students' SES is observed and taken into account, missingness does not depend on the unobserved achievement scores. Finally, missing data in ELSAs are MNAR when the missingness on X depends on unobserved data (e.g., unobserved values of X itself). For example, MNAR occurs for achievement data if school personnel discourage students they know will perform poorly on the test from coming to school on testing days. If the school personnel's knowledge is not observed, and can thereby not be taken into account, the missingness of the achievement data depends on an unobserved variable.

The missingness mechanism describes the conditions under which a certain missing data method works best to provide unbiased and precise estimates of statistical parameters.^{62,63(p526)} Most modern missing data methods, involving multiple imputation or full information maximum likelihood, were developed for situations in which MAR or MCAR is assumed.^{60,63} These methods substantially outperform traditional methods (e.g., listwise deletion) or work at least equally well.^{62–64} In Section 5.1.4, we explain how modern missing data methods can be applied in the context of the two-stage approach to IPD meta-analysis of ELSAs to deal with sporadically and planned systematically missing data in Stage 1. In Section 5.2.4, we discuss how to treat unplanned systematically missing data in Stage 2.

5 | INTRODUCING THE TWO-STAGE APPROACH TO IPD META-ANALYSIS TAILORED TO ELSAS

In the following, we discuss and illustrate how to tailor the two-stage approach to IPD meta-analysis to the methodological complexities of ELSAs. In Stage 1, the tailoring involves addressing the statistical challenges of using IPD from complex survey designs (e.g., sampling weights, clustered and missing IPD) when estimating effect sizes for descriptive analyses. Because ELSAs have been conducted regularly at both international and national levels for many years, several effect sizes may be available for the same country. These country-specific effect sizes are likely to be correlated (i.e., dependent); that is, they are more similar to each other than to effect sizes from other countries. In Stage 2, the tailoring therefore involves taking the dependent structure among effect sizes into account when integrating the results with meta-analytic and meta-regression models.

5.1 | Stage 1: Effect size estimation for IPD from ELSAs

ELSAs implement various methodological state-of-the-art features, for example, to ensure that data are representative at the population level and to cover as much content as possible with surveys that are as brief as possible. In addition, as in any other study, missing values occur in ELSA data. These features and characteristics need to be taken into account when estimating effect sizes and their sampling variances in IPD meta-analyses.

5.1.1 | Stratified multistage random sampling and (final) sample weights

Stratified multistage random sampling

ELSAs are designed to obtain precise estimates of effect sizes for a well-defined population. The sampling processes in ELSAs achieve this by two means: representative, random selection of study participants and large sample sizes.¹⁶ To this end, ELSAs often apply stratified multistage sampling procedures. For example, using two-stage sampling, the

primary sampling units (PSUs; e.g., schools) are randomly selected within strata (e.g., geographic regions, types of schools) in the first stage of sampling. In the second stage, a random sample of individuals (e.g., students) are selected from a certain PSU. Stratification offers at least two advantages. First, it guarantees that a prespecified number of individuals who belong to a certain (policy-relevant) subgroup (i.e., the stratum) is included in the sample. Second, stratified sampling helps to substantially improve the precision needed to estimate statistical parameters when the strata variables are related to the key target outcomes (e.g., student achievement).^{28,65}

Stratified multistage random sampling as applied in PISA

To illustrate the stratified multistage random sampling process that is typically applied in ELSAs, we use PISA as an example. PISA is aimed at evaluating education systems worldwide at the end of compulsory education by assessing skills and knowledge in the target population of 15-year-old students. PISA sets high-quality standards for collecting representative probability samples and obtaining precise estimates of effect sizes.¹⁵

Specifically, at least 4,500 students in each country participate in each PISA cycle, or the full student population is included if it is smaller than 4,500. To this end, most countries apply a stratified two-stage sampling design. In the first sampling stage, individual schools with 15-year-old students are systematically sampled from a stratified list of all schools with sampling probabilities proportional to the number of 15-year-old students enrolled. Strata are specific for each country and include characteristics that explain performance differences between schools, for example, geographic regions or school types. In each country, a minimum of 150 schools have to be selected; if a country has fewer than 150 schools, all schools are selected. Also, in most countries, 35 students who are 15 years old are randomly selected within schools; if a school has fewer than 35 students at age 15, all students in this age group are selected.

(Final) sample weights

After drawing a stratified sample of participants, the next step is to weight the data to be able to calculate unbiased estimates of effect sizes for the target population (i.e., a well-defined finite population). A well-defined finite population is a population for which the number of members is known. For inferences to finite populations, each member of the population has a non-zero probability of being selected into the sample. To this end, a sampling frame is required to estimate the total number of population members. Based on the sampling frame, the data from the individuals selected from the sample are weighted when estimating the effect size. The weight can then be interpreted as the number of people in the population who are represented by a certain individual who was selected from the sample. OSM.2 provides a didactic example for the computation of weights in stratified two-stage random sampling. Specifically, the weights are computed such that they reflect the joint (i.e., multiplied) probabilities of the inclusion of the PSUs (e.g., schools) as well as of the individuals in the PSUs (e.g., students). Notably, weights in multistage probability samples often require some adjustments to obtain participants' final weights. Adjustments involve accounting/correcting for (a) the over- or undersampling of some strata of the population (e.g., when a larger number of minority students were sampled to obtain more precise effect sizes for this subpopulation), (b) issues in the sampling frame because of inaccuracies in estimating the total number of population members (e.g., because the sampling frame was determined 2 years before the data were collected), (c) nonresponse at the level of PSUs (e.g., a school selected for the sample did not participate), and (d) nonresponse at the individual participant level (e.g., a selected student did unexpectedly not take part in the assessment).^{66,67} The final weights to which such adjustments are applied are then used to estimate the effect size.*

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* For some types of analyses, the final weights are linearly transformed to obtain different sets of weights.⁶⁷ Normalized weights (also called house weights) are transformed such that the sum of the weights is equal to the sample size. Normalized weights are often used in structural equation modeling.⁶⁸ Further, for some research questions, it is of interest to obtain pooled results by using a single data set encompassing the IPD from all samples (e.g., all country-specific samples) where each sample contributes equally to the pooled results. To this

5.1.2 | Clustered data and the estimation of sampling variances

Clustered data

The multistage random sampling procedure makes the computation of sampling variances more complex than in studies with simple random sampling. In simple random sampling, individuals are selected independently of each other. Thus, in standard methods for computing sampling variances of effect sizes, selected individuals are treated as independent observations.⁶⁹ By contrast, in multistage sampling, individuals selected from the same PSU do not represent independent observations. Instead, the multistage sampling process induces dependencies among the selected individuals, thus leading to so-called clustered data.^{65,66,69} In particular, students in the same school are often found to be (much) more similar to each other than to students from other schools.⁷⁰ These similarities may result from, for example, performance-based tracking into a certain school (or type of school) or sharing the same teachers. Importantly, the dependencies resulting from multistage sampling need to be taken into account because they substantially increase the sizes of the sampling variances of the effect sizes.⁶⁹

Estimation of sampling variance

Several methods have been developed to account for the estimation of the sampling variance of clustered data, involving sandwich estimators, multilevel models, linearization methods, and replication techniques.^{65,68,71} For IPD from ELSAs, we recommend replication techniques because they (a) are asymptotically consistent for the true sampling variance with increasing sample size, (b) provide sampling variance estimates that are very similar to those obtained from using more complex procedures, (c) are robust and can be flexibly applied to estimate

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end, so-called Senate weights are computed by using a linear transformation of the final weights to ensure that the sum of the Senate weights equals a constant (say 500) in each sample.⁶⁷ Notably, these linear transformations of the final weights do not affect the values obtained for effect sizes as applied in the two-stage IPD meta-analyses when the IPD for each sample are analyzed separately.

sampling variances for a very large variety of effect sizes (e.g., mean differences, correlations, and regression coefficients), and (d) are well supported by relevant information (i.e., replicate weights) in public use files because they are the standard method applied in ELSAs.^{65,67,71}

Notably, sometimes only replication techniques can take full advantage of the stratified sampling design because the explicit information on strata membership needed to obtain better (i.e., smaller) sampling variances with sandwich estimators, multilevel models, or linearization methods is not provided, or details are left out to guarantee the confidentiality and anonymity of individuals (e.g., students or teachers).^{15(p198)}

Two replication techniques are commonly applied in ELSAs for which replicate weights are provided in public use files⁷²: the Jackknife (JK) method, which is used (with different modifications, e.g., JK2) to estimate sampling variances (e.g., in TIMSS, PIRLS, and NAEP), and the Balanced Repeated Replication (BRR) method, which is applied in a modified form (i.e., Fay BRR), for example, in PISA.^{66,67} The common idea behind all replication techniques is to use computational intensity to tackle the problem that an analytical technique for estimating the sampling variance of a certain effect size T is not available (for a certain statistical model) or has not yet been developed.^{29,71} Each replication approach therefore estimates the sampling variance $v(T)$ by using a large number of somewhat different subsamples of PSUs—the replicates—taken from the original sample. The subsamples are derived from applying the replicate weights to the original data. The variability of the resulting effect size estimates around T (as obtained from the original sample) is then used as an estimate of $v(T)$.^{29,66,71} OSM.3 provides details on how the replicate weights are derived for JK2, BRR, and Fay BRR and how these weights are used to obtain the sampling variance.

5.1.3 | Estimating effect sizes

Unstandardized and standardized effect sizes

A key feature of ELSAs is that many of the applied measures provide a metric that is commensurable across time or countries (e.g., achievement measures). Thus, meta-analysts can compute unstandardized effect sizes that are based on this original or raw metric, involving mean differences between groups or unstandardized regression coefficients. Alternatively, the meta-analyst can compute standardized effect sizes, involving Cohen's d or Hedges' g , correlations (r), and standardized regression coefficients (β). Both the standardized and unstandardized options have advantages and disadvantages.^{73,74}

One advantage of unstandardized effect sizes is that their sampling variance can be expected to be somewhat smaller than that of standardized effect sizes. This implies that unstandardized effect sizes can be estimated more precisely because standardized effect sizes are computed as ratios where both the numerator and the denominator are subject to sampling variability.^{75(p175)} For example, d is the mean difference between two groups divided by an estimate of the population standard deviation. Further, measures with a commensurable metric are also necessary to compute unstandardized effect sizes that address research questions that focus on a comparison of effect sizes in absolute terms (e.g., To what extent has the mean level of the reading achievement of a certain country changed over time?). Finally, if the raw metric is intuitive (e.g., number of days absent in school, income in Euro or US dollars) or well-established (e.g., body mass index), unstandardized effect sizes are advantageous because their meaning can be conveyed much more easily to a broader audience comprising researchers as well as practitioners and policy makers.^{73,74}

A major advantage of standardized effect sizes is that they allow results to be compared across studies even when different measures were used because the results are converted to a standardized scale.⁷³ For example, PIRLS and PISA use different reading achievement tests. Nevertheless, gender differences in terms of standardized mean differences (e.g., d or g) can be compared and combined across studies because they are expressed in terms of standard deviation units. Further, standardized effect sizes are well-established in the

behavioral and social sciences.^{22,73} Hence, when standardized effect sizes are computed for ELSAs, their magnitudes can be compared with relevant prior research as well as with established benchmarks that are expressed in terms of standard deviations. Such benchmarks involve typical intervention effects, learning gains, differences between policy-relevant subgroups (e.g., gender, ethnicity), or differences between low-achieving and average-achieving schools.⁷⁶ Because of these advantages, we focus on standardized effect size measures in the present tutorial. Notably, when the research goal is to meta-analyze effect sizes that are based on measures with a commensurable metric, meta-analysts can capitalize on the advantages of both unstandardized and standardized effect sizes.

Linear regression models to estimate standardized effect sizes

When estimating effect sizes for IPD meta-analyses of ELSAs, it is important that researchers specify a statistical model that matches the substantive research question. Many substantive research questions (e.g., for ELSAs and other complex surveys) require researchers to estimate effect sizes for the total population that is represented by a certain sample. Such effect sizes (and their sampling variances) can often be estimated by drawing on the large family of generalized linear models. In particular, linear regression models provide a versatile statistical framework for estimating the key standardized effect size measures that are applied in many meta-analyses,²² involving standardized mean differences between two independent groups and correlations. Moreover, linear regression models can also be applied to estimate standardized effect sizes that depict moderating effects at the participant level. Figure 4 illustrates the model specifications that we used in our empirical examples.

When using linear regression models, obtaining standardized effect sizes requires the standardization of some or all of the variables that are involved in estimating the effect sizes. First, computing standardized mean differences between independent groups requires the outcome (e.g., reading achievement) to be *z*-standardized ($M = 0$ and $SD = 1$) by using

estimates of the population mean and standard deviation. The indicator variable that provides information about group membership should be dummy-coded (e.g., 0 = male students, 1 = female students). The standardized regression coefficient (e.g., β_{Gender}) then depicts a standardized mean difference (equivalent to d). Second, a bivariate regression model where both the outcome (e.g., reading achievement) and the predictor variable (e.g., the SES measure) are z -standardized is needed to compute correlations. The bivariate standardized regression coefficient (e.g., β_{SES}) is identical in size and interpretation to the correlation between the outcome and predictor.⁴³ Third, examining moderating effects at the participant level requires a multiplicative term between the predictor variables to represent their interaction (e.g., $Gender \times SES$; see Section 4.3.3). To standardize regression coefficients for interaction terms, nominal variables (e.g., gender) can be dummy-coded, and continuous predictor variables (e.g., SES) can be z -standardized.

The models illustrated in Figure 4 do not provide separate effect sizes to disentangle relationships within and between clusters within a certain sample. However, for some substantive research questions researchers may need to obtain effect sizes that depict relationships at different hierarchical levels within a certain sample (e.g., separating gender differences in reading achievement as observed within and between schools within a certain country). To this end, researchers can, for example, apply a two-stage approach to IPD meta-analysis in which multilevel models are used to estimate effect sizes for the within-cluster and between-cluster relationships in each sample in Stage 1. These effect sizes can then be integrated with separate meta-analytic models in Stage 2 (see also Section 4.3.3).

5.1.4 | Missing data in ELSAs

Missing data can take different forms in IPD meta-analyses of ELSAs. In the following, we discuss how to handle planned systematically and sporadically missing data.

Plausible values

To cover a broad range of content, ELSAs often assess participants' characteristics by applying a planned missing design (so-called booklet designs) where each participant is randomly assigned to a booklet that comprises a selected subset of test items or questions taken out of a pool of several hundred test items or questions. To handle the resulting systematically missing data to estimate unbiased group-level effect sizes, ELSAs draw on a methodology that is referred to as plausible values (PVs).⁶⁷ PVs reflect the idea that individual characteristics (e.g., achievement) are latent variables that cannot be observed directly with the applied measures but need to be estimated.^{66,77} To reflect the uncertainty underlying the estimation process, a range of possible values, the PVs, are estimated for each individual rather than a single point estimate (e.g., sum score). Specifically, PVs are derived as random draws from a distribution that is estimated for each individual. These distributions are typically estimated by using item response theory (IRT) based on individuals' responses (e.g., to the test items) and further background information (e.g., individuals' socio-demographic background).⁷⁷ Using these procedures, for each participant between $5 \leq N \leq 20$ PVs are typically provided in public use files from ELSAs. Applying these PVs in descriptive analyses yields unbiased group-level estimates of effect sizes in a certain population (e.g., a country's total student population) or subpopulation (e.g., male or female students). However, PVs do not allow researchers to reliably assess each individual's characteristics.⁶⁷

The substantive-model-compatible sequential modeling (SMC-SM) approach

ELSAs may also contain planned, systematically missing values for which PVs are not provided in public use files or are only available for a subsample of participants (e.g., mathematics achievement in PISA 2000). Further, many items or scales in ELSAs have unplanned, sporadically missing values (e.g., the SES measure that we applied in the empirical examples). There is on-going research on how to best handle such missing data in IPD meta-analyses.^{60,78,79} On the basis of the logic of the two-stage approach, we suggest that

missing data be imputed separately for each student sample at the participant level (see Figure 2). In using this approach, it is possible to impute (a) sporadically and (b) planned systematically missing data that occur within a certain sample in Stage 1. This imputation strategy is well-suited for examining moderating effects at the participant level,⁸⁰ and it does not require any assumptions about how the effect sizes vary across samples.^{78(pp509-510)} Further, this approach draws on the strength of Big Data analytic strategies⁴² to avoid plausible convergence problems when using a large volume of IPD demonstrating a complex hierarchical data structure (see Figure 2).

However, because missing values are imputed separately for each sample, in this approach, strength in the imputation process cannot be borrowed from the results obtained from other samples to impute unplanned systematically missing values that are missing for whole samples.^{60,78,79,81–83} For example, it would not be possible to impute the unplanned systematically missing data on students' reading achievement for the US in PISA 2006 (see Section 4.4.1). Further, it is not possible to incorporate higher level covariates at the cycle or country level into the imputation model (see Figure 2). Hence, the imputation strategy that we present here may somewhat underestimate moderating effects at these levels in meta-regression models.^{60,78,79,81–83}

To implement the imputation strategy separately for each sample, we suggest that researchers apply the SMC-SM approach for two reasons.^{80,84} First, the SMC-SM approach is a member of the larger family of multiple imputation procedures, which all draw on an imputation model to replace missing values with imputed values to provide complete data. Because the true values of the missing data are unknown, the imputation model uses the observed data (from participants for whom data are not missing) to create a predictive distribution from which the complete data are sampled (for participants for whom data are missing). More specifically, by using a Markov chain Monte Carlo algorithm, the predictive distribution is applied to impute the missing values in the original data M times to obtain M

complete data sets.⁸⁰ Each of these M imputed data sets is then used to estimate an effect size with a certain target model. The resulting variability in effect sizes across multiply imputed data sets reflects the uncertainty of the imputation process.^{62,85} Importantly, with these multiply imputed, complete data, it is possible to take full advantage of all standard statistical tools that take the methodological features of ELSAs into account when estimating effect sizes (e.g., applying sample weights) and their sampling variances (e.g., replication techniques) in Stage 1 of an IPD meta-analysis.

Second, it is important that the imputation model that is used to generate the imputed values is at least as general as the target model that is used to estimate the effect sizes. For example, if the target model includes interaction effects (e.g., a linear regression model with an interaction term), the imputation model needs to take into account these interaction effects. The imputation model of the SMC-SM approach is therefore specified such, that a joint predictive distribution is created that is based on a sequence of conditional models. Importantly, the target model (or a more general model) is included in this sequence. This guarantees that the imputation model is compatible with the target model (substantive-model-compatibility).⁸⁶ One particular advantage of the SMC-SM approach is that it can accommodate normally distributed and skewed continuous and binary predictor variables as well as the multilevel structure of the data in these conditional models. Hence, it is well suited for imputing missing data to estimate effect sizes in ELSAs with clustered data (see Section 5.1.2) that draw on standard regression models (e.g., to estimate mean differences and bivariate regression relations) but also regression models involving moderating effects at the participant level (with highly skewed predictor variables).

As noted above, the imputation model is needed to impute the missing values in the original data M times to obtain M complete data sets. One general rule of thumb is that the number of imputed data sets M should be at least as large as the percentage of individuals in a sample with one or more (sporadically) missing values.^{87(p388)} However, because multiple

imputations can be computationally intensive, this rule of thumb might not be feasible with a large proportion of missing values. Often, a smaller number of imputations with a reasonable number of iterations may also be sufficient for the imputation algorithm to converge.

Furthermore, it is recommended that auxiliary variables be included in the imputation model.^{80,88} Auxiliary variables are not part of the target model itself but are related to the propensity of missing data and to the variables with missing values themselves. Using auxiliary variables may (a) enhance the plausibility of the MAR assumption⁸⁰ and (b) substantially reduce bias in the parameter estimates.⁸⁸ Finally, it is strongly recommended that researchers check the quality of the imputed data by examining imputation diagnostics.⁶⁴

Applying PVs, multiple imputations, and nested multiple imputations to estimate effect sizes and their sampling variances

All multiple imputation approaches involving PVs and the SMC-SM approach comprise three steps to handle missing values. In Step 1, missing values are imputed by using some imputation model to obtain N PVs or M multiply imputed data sets. In Step 2, once the PVs or the multiply imputed data are available, the meta-analyst can apply the target model to estimate the target effect size T (by using the final weights) and its sampling variance $v(T)$ (e.g., by using JK2 or Fay BRR) from each PV or each imputed data set (e.g., when an ELSA provides 10 PVs, the target effect size is estimated 10 times). In Step 3, the average effect size and its sampling variance are computed by pooling the effect size estimates obtained in the second step. The uncertainty that results from imputing unknown missing values induces some additional variability to the results. In addition to the sampling variance for each PV or each multiply imputed data set, there is between-imputation variance of effect sizes around the average effect size. The total sampling variability for the average effect size is then computed as the sum of the average sampling variances and the between-imputation variance (see OSM.4 and OSM.5 for details). In accordance with Burgess et al.'s⁸⁹ recommendations,

the average effect size (and its sampling variance) is then used in Stage 2 of the IPD meta-analysis.

As noted above, key outcome variables in ELSAs (e.g., achievement) are often represented as a set of N PVs rather than a single variable. When using PVs, the SMC-SM approach is extended as a nested multiple imputation approach.⁹⁰ Effect size calculation with nested multiply imputed data also implies three steps. First, for each PV, a set of M imputed data sets is obtained by using the SMC-SM approach as described above. Second, the target model is run on all M imputed data sets for each of the N PVs, resulting in $N \cdot M$ effect size estimates and sampling variances (e.g., imputing a data set $M = 10$ times that provides $N = 10$ PVs would yield 100 effect size estimates and sampling variances). Third, the average effect size and its sampling variance is pooled across all $N \cdot M$ effect size estimates (see OSM.5 for details).

Finally, it is important to note that using a “shortcut” where participants’ average PV or average multiply imputed value is used rather than conducting the analyses separately for each PV or multiply imputed data set will lead to biased results and statistical inferences. The shortcut will underestimate the heterogeneity of the distribution (e.g., the distribution of students’ achievement) and the sampling variance of the resulting effect size estimate.⁶⁷

5.1.5 | Empirical examples: Estimation of effect sizes and their sampling variances

Research questions

We illustrate the potential of IPD meta-analyses of ELSAs by taking advantage of international PISA data (see Figure 1). In doing so, we demonstrate how to estimate the kind of effect sizes that are typically applied in meta-analyses.^{22,43} First, we estimate standardized mean differences to depict average gender differences in reading achievement. This analysis expands on previous research by Nowell and Hedges⁶ and Reilly et al.⁷ that also used meta-analytic models to integrate gender differences in reading achievement as observed in ELSAs

from the US. Second, we estimate correlations to depict how reading achievement and students' SES are related. This analysis extends Sirin's⁸ meta-analysis, which examined the association between achievement and SES in the US. Third, we illustrate a key strength of IPD meta-analysis by analyzing the heterogeneity in effect sizes at the participant level. To this end, we examine how the magnitude of gender differences in reading achievement is moderated by students' SES. This analysis connects to current quantitative intersectionality research that posits that each individual is simultaneously influenced by multiple social identities (e.g., gender and SES) that interact in explaining educational outcomes.¹⁴

Samples and measures

In our applications, we drew on international IPD from PISA (2000–2018) with over 400 independent student samples from 92 countries or economic regions (total $N = 2,970,892$ students; see Figure 1). To estimate the various effect sizes, we used the PISA reading achievement scores that were provided as PVs. Further, we used information on students' gender as obtained from student questionnaires (0/1 = male/female students). Finally, as a measure of students' SES, we applied parents' highest occupational status (HISEI), which corresponds to the higher occupational status of either parent or to the only available parent.¹⁵ Higher HISEI values indicate higher SES.

Handling missing values

OSM.6 provides a detailed account of how we handled the missing data. We briefly summarize the key points here. Due to (unplanned) systematically missing values on reading achievement or the SES index, we had usable IPD from (a) 424 samples to estimate gender differences and from (b) 422 samples to estimate the relationship between reading achievement and students' SES and the interaction between gender and SES. Given that we used PVs for reading achievement as the outcome, we used a nested multiple imputation strategy combined with the SMC-SM approach and imputed each of the 422 student sample

data sets $M = 10$ times separately for each PV using the raw data provided in the public use files. To this end, we used the R package “mdmb” (version 1.5.8).⁹¹ The imputation model for the SMC-SM approach comprised a sequence of conditional models that took into account the distribution of the variables to be imputed (e.g., continuous distribution for reading achievement) and the functional form for how these variables are interrelated (e.g., multilevel regression). For example, the conditional (multilevel regression) model of reading achievement contained gender, SES, the interaction between gender and SES, as well as mathematics achievement as predictors. Mathematics achievement was used as an auxiliary variable* because of (a) the small, albeit consistent gender differences found in this achievement domain in many countries⁹ and (b) the consistent relationships found between students’ SES and achievement.⁸ Finally, to account for the fact that students were nested within schools, we added a random intercept for schools to each conditional model.⁹² Of note, we did not impute missing values for gender because the mechanism underlying missing values on gender may be MNAR, thus reflecting that students’ gender identity was not represented well by the binary response format used in the PISA student questionnaire.[†] In summary, the applied imputation model was compatible with all regression model sets that we used to estimate the target effect sizes.

Model sets to estimate effect sizes and their sampling variances

To estimate the various effect sizes and their sampling variances, we applied three sets of linear regression models—Model Sets 1, 2, and 3—to the IPD of each student sample (see

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* Mathematics achievement was used as an auxiliary variable for multiple imputations in PISA cycles 2003–2018. In PISA 2000, the proportion of missing values on the mathematics achievement variable was too high for it to serve as an auxiliary variable.

† There is no consensus on how best to handle missing data on binary measures that are aimed at capturing multidimensional constructs, such as gender. Further, in PISA, the amount of missing data on gender was very small (the largest sample-specific percentage was 2.6% for Canada in PISA 2003). When there are so few missing data, the applied procedure for missing data on gender (i.e., listwise deletion) may be a reasonable option for handling missing data.^{62(p554)} An alternative approach is to use a multiple imputation strategy to impute missing data on gender, assuming that these missing data are MCAR or MAR. We compared the results obtained from using both missing data approaches in the three countries with the largest amount of missing data on gender. The two approaches yielded very similar results for the effect sizes and their standard errors.

Figure 4 for an example). Further details on the specification and interpretation of these models are presented in OSM.6. We highlight the most important aspects of these analyses here. First, in all model sets, the regression coefficients were estimated by using the final weights, which implied that students with larger weights had a larger influence on the values of the regression parameters.^{27,28} Further, the sampling variances of all effect sizes were estimated by using Fay BRR.⁶⁶ Second, we *z*-standardized the outcome variable (i.e., reading achievement) and the continuous predictor variable (i.e., the SES measure *HISEI*) with $M = 0$ and $SD = 1$ for each multiply imputed data set as obtained for a certain student sample.⁹³ We did not *z*-standardize the indicator variable for gender. The standardized regression coefficient for gender (β_{Gender} as obtained from Model Set 1) therefore depicts gender differences as a standardized mean difference (equivalent to d), with positive values indicating that female students outperformed male students. Third, using this *z*-standardization procedure yielded a bivariate regression coefficient (β_{SES} as obtained from Model Set 2) that was identical in size and interpretation to the correlation between reading achievement and the SES index.⁹³ Fourth, to examine how gender differences in reading achievement were moderated by students' SES, we specified Model Set 3, which included gender, the *z*-standardized SES index, and a multiplicative term between gender and the *z*-standardized SES index to represent their interaction. The standardized regression coefficient $\beta_{Gender \times SES}$ indicates how gender differences in reading achievement (in terms of d) change when students' SES increases by 1 (cycle- and country-specific) *SD* (see Figure 4d). Finally, in accordance with Burgess et al.'s⁸⁹ recommendations, we computed the (pooled) average effect size (e.g., $\bar{\beta}_{Gender}$) and its sampling variance (e.g., $v(\bar{\beta}_{Gender})$) for each model set across the multiply imputed data sets as obtained for a certain student sample (using the nested multiple imputation formula; see OSM.5). These average effect sizes were then used in Stage 2 of the IPD meta-analysis.

Software

There are several software packages that can be used to take the methodological features of ELSAs into account when estimating effect sizes and their sampling variances.⁹⁴ We used the “survey” package (version 4.1.1) that is implemented in the free software environment R (version 4.1.1)⁹⁵ because it is well-documented.²⁸ Further, it allows researchers to specify many different generalized linear models (e.g., linear, logistic, Poisson, or quantile regression) to estimate effect sizes and their sampling errors for a large variety of stratified multistage sampling designs. Finally, using R allowed us to repeat the data analytic steps as required in Stage 1 for the IPD of each sample from an ELSA, and it provided a versatile interface to the applied meta-analytic models in Stage 2 of the IPD meta-analysis.

5.2 | Stage 2: Integrating effect sizes and analyzing their heterogeneity with meta-analytic models

5.2.1 | Choosing a meta-analytic model

When integrating effect sizes resulting from descriptive analyses with ELSAs in an IPD meta-analysis, researchers should choose a meta-analytic model that provides a good fit to (a) the inference population and (b) the dependent structure and distributional form of the observed effect sizes.

Inference populations in the fixed-effect model and random-effects model

There are two popular statistical models—the fixed-effect model (also known as the common-effect model) and the random-effects model—which differ in their respective inference populations.^{36,44} If the goal is to make inferences about the effect size parameters only in the observed set of ELSA samples, the fixed-effect model can be applied. However, in this case, the meta-analyst assumes that all observed effect sizes share a common population value for the true effect size.^{36,44} Observed variations between effect sizes are only expected due to

sampling errors as estimated by the sampling variances of the observed effect sizes.^{36,44} As for ELSAs, this set of assumptions seems most plausible when the effect sizes to be integrated stem from direct or very close replication studies using IPD from the same target population.⁴⁴

Given these restrictions of the fixed-effect model, the random-effects model will be a more plausible match for most meta-analyses of descriptive analyses with IPD from ELSAs.⁴⁴ Specifically, the random-effects model allows researchers to make inferences about a population of studies from which the observed ELSA samples are considered to be a random (representative) sample.^{36,44} The random-effects model therefore assumes that there is a distribution of true effect sizes ϑ rather than a single true common effect size. This assumption seems plausible, for example, when the effect sizes to be integrated stem from several cycles of an ELSA that draw on independent student samples that were observed at different points in historical time (e.g., several PISA cycles). The random-effects model can also be applied to integrate the results as obtained from related ELSAs (e.g., PISA and PIRLS) that draw on different independent student samples and that also differ in the materials that were used.^{44(p107)}

Dependencies among observed effect sizes and their distributional form

Statistical inferences from parameters in meta-analytic models are based on some assumptions about the dependencies among observed effect sizes and their distributional form.^{96,97}

Standard meta-analytic models (e.g., the two-level random-effects model) assume independent effect sizes. Is this a reasonable assumption for IPD meta-analyses of ELSAs? The two-level model can be used, for example, to meta-analyze the descriptive analyses for a certain outcome as obtained from several independent samples in the same country⁷ or from independent student samples in a single ELSA cycle,⁵ for example, when a certain target variable is assessed in this cycle only. In these examples, the effect sizes are based on independent samples, and hence, the assumptions of the two-level random-effects model

apply. OSM.7 presents an application of the two-level random-effects model for independent student samples participating in a single PISA cycle (i.e., PISA 2018).

However, in many applications of IPD meta-analyses of ELSAs, the assumption of independent effect sizes may be unrealistic. In particular, in international ELSAs (e.g., PISA, TIMSS, PIRLS), independent student samples participated in a certain cycle of an ELSA. Several such samples were nested within countries (see Figure 2a). The effect sizes within the same country can be expected to be more similar to each other (e.g., because individuals are educated in the same system) than to effect sizes from other countries. Modeling these dependencies requires researchers to account for the hierarchical structure of the observed effect sizes in the meta-analytic model. To this end, a model-based approach drawing on a three-level meta-analytic model can be used.^{35,97,98}

Importantly, following Pustejovsky and Tipton,⁹⁹ we recommend combining the model-based approach with robust variance estimation (RVE)⁹⁶ to adjust the sampling variances and the 95% confidence intervals (95% CIs) for the average true effect size and meta-regression coefficients.* Doing so safeguards statistical inferences against (a) violations of distributional assumptions, (b) small sample bias when integrating effect sizes from a small number of countries, (c) the misspecification of the structure of the dependence of observed effect sizes, and (d) the misspecification of the applied meta-analytic model, for example, when using a mixed-effects meta-regression model rather than a random-slope meta-regression model.^{36,99} Moreover, using a model-based approach in combination with RVE is a reasonable strategy when a meta-analyst cannot fully accommodate the complex structure of the dependence of observed effect sizes in a model-based approach (e.g., when combining an IPD meta-analysis of ELSAs with an AD meta-analysis). Finally, the sampling distribution

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* RVE shares vital statistical characteristics with the widely recommended^{100,101} Hartung-Knapp-Sidik-Jonkman method^{102,103} for two-level random-effects meta-analysis.⁹⁶ However, RVE makes less stringent assumptions about the weights for estimating the standard errors for meta-analytic averages or meta-regression coefficients⁹⁶ and can easily be extended to safeguard statistical inferences for meta-analytic models with three levels or even more complex random-effects structures.⁹⁹

for some effect sizes (e.g., correlations or standardized regression coefficients, such as β_{SES}) might not be well approximated by a normal distribution unless the sample size is very large.¹⁰⁴ However, the standard assumption in meta-analytic models is that the observed effect sizes are normally distributed (see Sections 5.2.2 and 5.2.4). In such situations, RVE helps to reduce potential bias in the standard errors and confidence limits of the average true effect size and meta-regression coefficients because it makes no assumptions about the specific form of the sampling distributions of the observed effect sizes.^{96,105}

5.2.2 | *Three-level random-effects model*

Model specification

Accounting for the hierarchical dependency of effect sizes as found in many ELSAs requires a three-level random-effects model³⁵ that involves three stages of sampling (see Figure 2a).

Given that sporadically missing data are the rule (and not the exception) in ELSAs, we illustrate this model for the observed, pooled effect sizes $\bar{T}_{ct}$ and their sampling variances $v(\bar{T}_{ct})$ that were obtained (e.g., by means of [nested] multiple imputation) for a certain sample in country c in cycle t . The first stage (Level 1) of the sampling process assumes that the observed effect sizes $\bar{T}_{ct}$ estimate a true effect size ϑ_{ct} with some estimation error e_{ct} .

$$\bar{T}_{ct} = \vartheta_{ct} + e_{ct} \quad (1)$$

The second stage (Level 2) of the sampling process assumes that the true effect sizes ϑ_{ct} may vary around the country-specific true mean effect size β_{0c} . The deviation of a certain true effect size ϑ_{ct} is depicted by the random effect u_{ct} .

$$\vartheta_{ct} = \beta_{0c} + u_{ct} \quad (2)$$

The third stage (Level 3) of the sampling process assumes that the true country-specific mean effect sizes β_{0c} may vary around the (grand) true mean effect size γ_{00} . The deviation for a certain true country-specific mean effect size from γ_{00} is depicted by the random effect u_{0c} .

$$\beta_{0c} = \gamma_{00} + u_{0c} \quad (3)$$

When we combine Equations 1, 2, and 3, the three-level random-effects model can be written as:³⁵

$$\bar{T}_{ct} = \gamma_{00} + u_{0c} + u_{ct} + e_{ct}. \quad (4)$$

In the three-level random-effects model, the sampling errors e_{ct} and the random effects u_{ct} and u_{0c} are assumed to be uncorrelated within and across levels and to follow normal distributions with means of zero and variances $v(\bar{T}_{ct})$, $\tau_{Level\ 2}^2$, and $\tau_{Level\ 3}^2$, respectively. Thus, three sources of variation affect the distribution of observed effect sizes: the variance of the sampling errors $v(\bar{T}_{ct})$, the variance of the true sample-specific effect sizes around the mean true effect size within countries $\tau_{Level\ 2}^2$ (which is assumed to be identical for all countries), and the variance of the country-specific true mean effect sizes around the average true effect size $\tau_{Level\ 3}^2$. The total variance of the true effect sizes is therefore $\tau^2 = \tau_{Level\ 2}^2 + \tau_{Level\ 3}^2$. When estimating the meta-analytic parameters for the true effect sizes, an inverse-variance weighting scheme is applied. The weights are based on all three sources of variance, which also implies that effect sizes that were estimated more precisely (as reflected by $v(\bar{T}_{ct})$) receive greater weight.³⁵ The computation of the weights requires estimates of the variances $\tau_{Level\ 2}^2$ and $\tau_{Level\ 3}^2$.³⁵ Veroniki et al.¹⁰⁶ recommended the restricted maximum likelihood estimator (REML) to estimate these variances. Reliable 95% CIs can then be obtained (a) by using the profile likelihood method for variances or standard deviations¹⁰⁶ and (b) by drawing on the estimates of $\tau_{Level\ 2}^2$ and $\tau_{Level\ 3}^2$ with RVE for the average true effect.⁹⁹ Model convergence can be assessed with profile likelihood plots (see OSM.8).¹⁰⁷

Evaluation of the heterogeneity of effect sizes

The three-level random-effects model provides several key meta-analytic parameters: the average true effect size and the variance estimates for describing the heterogeneity of the true effect sizes in total as well as at Levels 2 and 3. There are several approaches that can be used

to assess the heterogeneity of effect sizes.¹⁰⁸ First, the Q test statistic is computed by summing the squared deviations of each individual effect size estimate from the average true effect estimate where individual effect sizes are weighted by their sampling variance. A statistically significant value of Q is typically taken to indicate effect size heterogeneity.¹⁰⁸ Second, the I^2 statistic provides information about the proportion of observed heterogeneity that is real and not due to random noise and has a range of 0% to 100%.¹⁰⁸ The Cochrane handbook for research syntheses¹⁰⁹ offers guidelines that characterize I^2 values falling in the intervals $30\% \leq I^2 \leq 60\%$, $50\% \leq I^2 \leq 90\%$, and $75\% \leq I^2 \leq 100\%$ as representing moderate, substantial, and considerable heterogeneity. Notably, any evaluation of the size of I^2 should also take into account the sign and size of the effect sizes as well as the precision with which the heterogeneity could be estimated (e.g., the p value from the Q test statistic). Moreover, when using three-level random-effects models, the I^2 statistic can be computed for each level separately with $I^2_{Level\ 2}$ and $I^2_{Level\ 3}$ providing information about the proportions of the total variance of the effect sizes that can be explained by true effect size heterogeneity at Level 2 (e.g., between samples within countries) or Level 3 (e.g., between countries).⁹⁸ Third, the 95% prediction interval (95% PI) takes into account τ^2 as well as the uncertainty (i.e., the sampling variance) in estimating the average true effect size.¹⁰⁸ In doing so, the 95% PI gives a hint about the variation in true effect sizes by providing a plausible range of values in which the true effect sizes of about 95% of all relevant populations will fall.

5.2.3 | Applications of the three-level random-effects model

We applied three three-level random-effects models to meta-analyze the (pooled) effect sizes $\bar{\beta}_{Gender}$, $\bar{\beta}_{SES}$, and $\bar{\beta}_{Gender \times SES}$ as obtained from Model Sets 1, 2, and 3 (see Figure 5) by using the R package “metafor” (version 3.0.2).¹⁰⁷ We applied “metafor” because of its comprehensive modeling capabilities.¹¹⁰ Further, we implemented RVE by using the “clubSandwich” package (version 0.5.3).¹¹¹

Meta-analyzing gender differences in reading achievement

Our results (Table 1) indicated that, on average, female students outperformed male students in reading with an average estimated (true) effect size $\gamma_{00}(\bar{\beta}_{Gender}) = 0.37 SD$ units across 92 countries (95% CI [0.35, 0.39]). This gender difference in favor of 15-year-old female students is slightly larger than the gender gap ($d = 0.30$) reported for eighth-grade students in the US.⁷ Assessing the heterogeneity of effect sizes showed that gender differences in reading achievement varied substantially, $Q(df = 423) = 5878.4, p < .001; I^2 = 93.2\%$; 95% PI [0.13, 0.62], with larger variation observed between ($\tau_{Level\ 3} = 0.10$) than within countries ($\tau_{Level\ 2} = 0.08$). According to the benchmark ranges that Hyde¹¹² proposed for evaluating effect sizes for gender differences (negligible: $0.00 < |d| \leq 0.10$, small: $0.10 < |d| \leq 0.35$, moderate: $0.35 < |d| \leq 0.65$, large: $0.65 < |d| \leq 1.00$, and very large: $|d| > 1.00$), the average gender difference in reading achievement can be considered moderate in size. The 95% PI (Figure 5a) indicates that about half of the gender differences will likely be small, whereas the other half will probably be moderate in size.

Meta-analyzing the relationship between reading achievement and students' SES

Our results (Table 1) showed that the average (true) standardized regression coefficient between reading achievement and students' SES was $\gamma_{00}(\bar{\beta}_{SES}) = 0.30$ (95% CI [0.29, 0.31]) across 96 countries. That is, on average, an increase of 1 *SD* in the SES index was associated with an increase of about 0.30 *SD* units in reading achievement. A similar, yet slightly lower, relationship between reading achievement and student SES was reported in Sirin's meta-analysis⁸ for the US ($r = .27$). Assessing the heterogeneity of effect sizes showed that the relationship between reading achievement and students' SES varied substantially, $Q(df = 422) = 4917.3, p < .001; I^2 = 91.0\%$, with considerably larger variation observed between ($\tau_{Level\ 3} = 0.06$) than within countries ($\tau_{Level\ 2} = 0.03$). The 95% PI ranged from 0.17 to 0.43

(Figure 5b), which suggests that social inequality in reading achievement that is related to students' SES can be expected in most countries and PISA cycles.

Meta-analyzing the interaction between gender differences and students' SES

Our results (Table 1) showed that, on average, gender differences in reading achievement were slightly moderated by students' SES with $\gamma_{00}(\bar{\beta}_{Gender \times SES}) = -0.018$ (95% CI [-0.023, -0.013]). The interaction implies, for example, that if students' SES is 2 *SD* units above the mean, we would expect the gender gap in reading achievement to be, on average, 0.036 *SD* units (i.e., about 10%) smaller than the average gender difference. Assessing the heterogeneity of effect sizes showed that the interaction terms $\bar{\beta}_{Gender \times SES}$ varied significantly but only to a moderate degree, $Q(df = 422) = 481, p = .023; I^2 = 41.1\%$. All variation in the true effect sizes was observed between countries ($\tau_{Level\ 3} = 0.02$). The 95% PI ranged from -0.05 to 0.02, emphasizing that true effect sizes can be expected to be heterogeneous and not to have the same sign or size in all student populations (Figure 5c; see also Figure 4d for an example). Taken together, these findings provide some support for an intersectional effect¹⁴ by showing that students' gender and their SES interact in explaining achievement differences in reading achievement. However, our results also suggest that the intersectional effect varies across countries. Of note, further meta-regression analyses (see OSM.11) suggested that intersectionality effects may depend on the test mode. In particular, intersectionality effects were (on average) about -0.02 when a paper-pencil test of reading achievement was used and about zero when a computer-based assessment was used.

5.2.4 | Meta-regression

In the previous sections, we showed how to achieve one key goal of IPD meta-analyses of ELSAs: assessing the mean and the heterogeneity of the distribution of (true) effect sizes. For example, we observed substantial heterogeneity in gender differences in reading achievement within countries over time (i.e., across PISA cycles) and between countries (Table 1 and

Figures 5a and 6). A second key goal of IPD meta-analyses of ELSAs is therefore to better understand and explain this heterogeneity. To this end, we illustrate how the three-level random-effects model can be expanded into a mixed-effects meta-regression model that is typically applied to examine moderating effects.^{36,45} In particular, we used this model to examine moderator variables that had the potential to explain the heterogeneity in gender differences in reading achievement (in terms of $\bar{\beta}_{Gender}$; Model Set 1). OSM.10 and OSM.11 provide results on meta-regression models for $\bar{\beta}_{SES}$ and $\bar{\beta}_{Gender \times SES}$ (i.e., Model Sets 2 and 3).

Expanding the three-level random-effects model into a meta-regression model

Drawing on IPD from ELSAs from the US, previous meta-analytic research found no significant change in gender differences in reading achievement between 1960 and 1994⁶ or between 1988 and 2015⁷. To investigate the generalizability of these results to 92 countries, we analyzed the change in gender differences in reading achievement over time ($Time_{ct}$ was specified as a continuous variable at Level 2 and coded 0/3/6 etc. indicating the 2000/2003/2006 etc. cycles of PISA). Further, reading achievement was measured with paper-pencil tests in PISA 2000 to 2012, whereas computer-based assessments were applied in PISA 2015 and 2018. Meta-analytic research showed that the test mode (paper-pencil test vs. computer-based assessment) has no significant effect on reading achievement test performance.¹¹³ Accordingly, gender differences in reading achievement are not expected to change when the test mode changes. To test this hypothesis, we examined the extent to which gender differences were moderated by test administration mode ($Mode_{ct}$ was located at Level 2 and coded 0 = paper-pencil test if $Time_{ct} \leq 12$, 1 = computer-based assessment if $Time_{ct} > 12$). Finally, a key goal of educational policies in OECD countries is to reduce educational disparities between male and female students.^{114(p142)} We therefore examined the extent to which (a) the magnitude of gender differences and (b) the development of gender differences

over time were moderated by a country's OECD membership ($OECD_c$ was located at Level 3 and coded 0 = other countries, 1 = OECD country). Notably, the assumption that the development of gender differences may depend on OECD membership is depicted by a so-called cross-level interaction between $Time_{ct}$ (a Level 2 variable) and $OECD_c$ (a Level 3 variable).

The present moderator analyses exemplify a typical challenge that many meta-analysts have to face. Specifically, time and mode of test administration were confounded (i.e., $Mode_{ct} = 0$ if $Time_{ct} \leq 12$ and $Mode_{ct} = 1$ if $Time_{ct} > 12$). To account for the (potential) confounding of moderator variables, it is recommended that meta-regression models that include multiple moderator variables be run.^{23,45,115} Following this advice, we specified a mixed-effects meta-regression model that included $Time_{ct}$ and $Mode_{ct}$ (both of which may vary within and between countries) as moderator variables to explain the heterogeneity in observed effect sizes at Level 2.³⁵

$$\bar{\beta}_{Gender,ct} = \beta_{0c} + \beta_{1c} \cdot Time_{ct} + \beta_{2c} \cdot Mode_{ct} + u_{ct} + e_{ct} \quad (5)$$

Further, $OECD_c$ (which may vary between but not within countries) was expected to moderate the magnitude of gender differences in reading achievement. To probe this prediction, $OECD_c$ was used as a moderator variable to explain the variability in β_{0c} among true effect sizes between countries.

$$\beta_{0c} = \gamma_{00} + \gamma_{01} \cdot OECD_c + u_{0c} \quad (6)$$

Of note, Equation 6 contains a random effect u_{0c} to allow true (average) gender differences in reading achievement to vary between countries while controlling for countries' OECD membership. Further, $OECD_c$ was also expected to moderate the development of gender differences in reading achievement across time as depicted by β_{1c} .

$$\beta_{1c} = \gamma_{10} + \gamma_{11} \cdot OECD_c \quad (7)$$

Because we specified a mixed-effects meta-regression model (rather than a random-slope model), Equation 7 contains no random effects when explaining β_{1c} .³⁵ This implies that

β_{1c} is assumed to be either identical for all countries (i.e., $\gamma_{11} = 0$) or that β_{1c} can be fully explained by countries' OECD membership. Finally, we had no expectations that the relationship between $Mode_{ct}$ and the observed effect size would depend on moderator variables or that it might vary between countries. As we specified a mixed-effects model, β_{2c} was therefore assumed to be the same for all countries.

$$\beta_{2c} = \gamma_{20} \quad (8)$$

Combining Equations 5 to 8 yields a three-level mixed-effects meta-regression model.

$$\bar{\beta}_{Gender,ct} = \gamma_{00} + \gamma_{01} \cdot OECD_c + u_{0c} + (\gamma_{10} + \gamma_{11} \cdot OECD_c) \cdot Time_{ct} + \gamma_{20} \cdot Mode_{ct} + u_{ct} + e_{ct} \quad (9)$$

This meta-regression model draws on the same set of assumptions about the error terms (e_{ct}) and the residual random effects (u_{0c} and u_{ct}) as the three-level random-effects model with the variance $\tau_{Res.Level 2}^2$ depicting (residual) heterogeneity within countries and $\tau_{Res.Level 3}^2$ between countries.³⁵ Pseudo R^2 s can be computed to quantify the proportion of variance accounted for at each level by the meta-regression model: $P^2_{Level 2}$ and $P^2_{Level 3}$ depict the proportion of the total variance in true effect sizes (as estimated by the three-level random-effects model without moderator variables, see Table 1) explained by the moderator variables within and between countries.³⁶

$$P^2_{Level 2} = (\hat{\tau}_{Level 2}^2 - \hat{\tau}_{Res.Level 2}^2) / \hat{\tau}_{Level 2}^2 \quad (10)$$

$$P^2_{Level 3} = (\hat{\tau}_{Level 3}^2 - \hat{\tau}_{Res.Level 3}^2) / \hat{\tau}_{Level 3}^2 \quad (11)$$

To estimate the parameters in the meta-regression model, we used the same methods as for the three-level random-effects model (i.e., REML in combination with RVE). The interpretation of the parameters in the meta-regression is equivalent to the regression parameters in multilevel models.⁶⁹ Thus, the intercept $\gamma_{00}(\bar{\beta}_{Gender}) = 0.37$ (95% CI [0.33, 0.42]) represents the estimated average (true) gender differences in reading achievement for the year 2000 cycle as measured for a paper-pencil test in countries that were not members of the OECD. Further, $\gamma_{10} = 0.007$ indicates that, on average, gender differences in reading achievement have widened in favor of girls at 0.007 *SD* per year (95% CI [0.004, 0.010]) in

non-OECD countries. This implies, for example, that gender differences in these countries have increased (on average) by about 0.07 *SD* per decade (i.e., 0.007 *SD*/year · 10 years). Moreover, $\gamma_{20} = -0.16$ (95% CI [-0.19, -0.13]) indicates that the gap in reading achievement between male and female students narrowed, on average, by 0.16 *SD* when a computer-based assessment was used instead of a paper-pencil test. Hence, this result suggests that the test mode may affect female and male students' performance on reading achievement tests differently. Finally, γ_{01} represents the mean differences in the magnitude of gender differences in reading achievement between OECD and other countries, whereas γ_{11} depicts how changes in gender differences over time depend on a country's OECD membership. Thus, $\gamma_{01} = -0.03$ (95% CI [-0.08, 0.02]) and $\gamma_{11} = -0.001$ (95% CI [-0.003, 0.001]) indicate that gender differences in reading achievement as well as their development over time did not differ substantially (or significantly) between OECD and non-OECD countries.

Further analyses of the residual variances showed that the meta-regression model did not fully account for the heterogeneity of effect sizes between countries ($\tau_{Res.Level\ 3}^2 = 0.011$; 95% CI [0.008, 0.015]) or within countries ($\tau_{Res.Level\ 2}^2 = 0.003$; 95% CI [0.002, 0.003]). This conclusion was corroborated by the Q statistic, which indicated a significant amount of residual heterogeneity, $Q(df = 419) = 4777.1, p < .001$. Finally, $P^2_{Level\ 2} = 0.55$ indicates that *Time*, *Mode*, and *OECD* jointly explained 55% of the variance in true effects sizes within countries, whereas $P^2_{Level\ 3} = -0.09$ (truncated to 0) indicates that OECD membership explained no variance in effect sizes between countries.

Potential issues in meta-regression analyses and suggested solutions

When using the meta-regression approach with hierarchically dependent effect sizes, several issues may occur. First, all problems that are well-documented for regression analyses in single or multilevel contexts may also occur in meta-regression models. These include outliers in the effect sizes that may exert a strong influence on the results or the multicollinearity of

the moderator variables that may lead to unreliable sampling variances for the regression coefficients.^{36,116} Viechtbauer and Cheung¹¹⁷ developed diagnostic tools that can be used to examine outliers and influential effect sizes. Further, inspecting the correlations among the moderator variables and excluding some highly correlated predictors may help to mitigate the problem of multicollinearity.³⁶

Second, using a mixed-effects model to perform a meta-regression has the limitation that moderating effects cannot be specified to vary between countries. This limitation can be addressed by adding random effects to the corresponding meta-regression coefficients. For example, one could add a random effect to Equations 7 and 9 to depict the assumption that OECD membership does not fully explain between-country variation in how gender differences change over time. Doing so changes the mixed-effects model into a random-slope model.³⁵ Importantly, some scholars⁶⁹ recommend that random-slope models be used when investigating cross-level interactions (e.g., the cross-level interaction between *OECD* and *Time*) to allow for valid statistical inferences. When we introduced a random slope for *Time*, however, the corresponding variance component was estimated to be very close to zero (see OSM.9). This result suggests that the rate of change in gender differences in reading achievement did not differ between countries when controlling for a country's OECD membership. We therefore followed Raudenbush and Bryk's^{58(p28)} advice and based our conclusions on the more parsimonious mixed-effects model. Importantly, we embedded our analyses in the RVE framework, which safeguards the statistical inferences for the meta-regression coefficients against model misspecification, for example, when using a mixed-effects rather than a random-slope meta-regression model.⁹⁹

Third, when conducting meta-regression analyses, (unplanned) systematically missing data may occur for the effect sizes (e.g., when a country did not participate in a certain PISA cycle) or the moderator variables (e.g., when information about a certain gender equality factor is not available for a certain country or cycle). In our empirical examples, the number

of observed effect sizes varied between countries (see Table 1), which implies that some countries had systematically missing data on effect sizes in one or more PISA cycles.

Notably, the meta-regression extension of the three-level random-effects model estimates the meta-regression coefficients and their sampling variances under the assumption that the underlying missingness mechanism is MAR or MCAR.⁶⁹ This is a plausible assumption for ELSAs when data cannot be suppressed, particularly for political reasons. For example, in PISA, countries can generally only withhold certain variables (but not all their data) when the information contained in these variables would threaten the confidentiality and anonymity of individuals (e.g., students or teachers).¹⁵ However, the technical standards in PISA do not allow variables to be withheld to avoid “inconvenient” results (e.g., large gender differences in reading achievement). Further, we observed no missing data on the moderator variables. When moderator variables are missing systematically (assuming MCAR or MAR) at the cycle or country level, (multilevel) multiple imputation approaches can be applied.^{60,78} To this end, the available information on (a) effect sizes and (b) moderator variables at the cycle and country level can be used. Notably, following Pigott and Polanin²³ we do not recommend imputing systematically missing effect sizes by using moderator variables at the cycle or country level (e.g., imputing missing effect sizes for gender differences in reading achievement when a country participated in some but not all PISA cycles or for countries that never participated in PISA).

6 | GENERAL DISCUSSION

6.1 | Research opportunities with IPD meta-analyses of ELSAs

IPD meta-analyses of studies with complex survey designs offer a powerful way to study the consistency, replicability, and generalizability of socially important or theoretically interesting phenomena and trends. More specifically, we see two major research opportunities for how IPD meta-analyses of ELSAs may substantially contribute to cumulative knowledge, particularly in the behavioral and social sciences. First, one of the founding fathers of the

meta-analytic enterprise, Gene Glass, envisioned that “[m]eta-analysis needs to be replaced by archives of raw data that permit the construction of complex data landscapes that depict the relationships among independent, dependent, and mediating variables”.^{118(p230)} The present paper directly responds to Glass’ call. IPD meta-analyses of ELSAs allow researchers to draw such “landscapes” for important policy-relevant subgroups, for example, by focusing descriptive analyses on socially disadvantaged minority students or students at the lowest or highest points on the achievement distribution.⁹ Further, by using a standardized protocol to manage and analyze the data, we illustrated one key strength of IPD meta-analyses, namely, the capability to investigate how individual characteristics at the participant level may moderate the magnitude of effect sizes (which is usually not possible with AD meta-analyses, e.g., due to a lack of reported information). Questions about how outcome relationships are moderated by individuals’ characteristics are highly relevant in the behavioral and social sciences, for example, in quantitative research on intersectionality¹⁴ where one of our empirical examples was located, in the context of aptitude treatment interactions to adapt teaching to learners’ characteristics,¹¹⁹ or research on individual differences in environmental sensitivity (e.g., parenting).¹²⁰ To address such questions, the two-stage approach we presented can be expanded to meta-analyze effect sizes that are estimated with more complex models, such as generalized linear models,^{27,28} structural equation models,¹²¹ or multilevel models.⁵⁶ However, given their nonexperimental design, the results of IPD meta-analyses of ELSAs, do not allow conclusions to be drawn about causality.¹²² Nevertheless, they may help improve our understanding of causal relationships (e.g., when a postulated cause does not show the expected effect) or point to important moderating effects that can be tested in subsequent experimental studies.¹

Second, the evidence base and consequently the reach of systematic reviews on many key research topics can be substantially enriched by combining traditional AD meta-analyses with IPD meta-analyses of ELSAs.¹²³ Currently, researchers in the behavioral and social

sciences use AD meta-analyses to statistically integrate findings from systematic reviews.¹²⁴ However, the way such systematic reviews are currently conducted, it seems unrealistic to expect them to cover the complete evidence base. For example, most systematic reviews are based on publications in English and are thereby missing publications in other languages.¹²⁵ Further, the search for unpublished (grey) literature is labor-intensive and must be stopped at some point in light of limited time and financial resources.¹²⁶ Thus, it is highly plausible that there is empirical evidence that cannot be identified via standard search practices. For instance, the literature search for the systematic review of the AD meta-analysis by Barroso et al.¹²⁷ on the relationship between anxiety and achievement in mathematics identified effect sizes from 332 samples (total $N > 385,000$ individuals). Yet, the search missed 59 out of 65 samples from the PISA 2012 cycle and 2 samples from the PISA 2003 cycle, which contained data from about 465,000 students.¹²⁷ To sum up, adding evidence from IPD meta-analyses of ELSAs to AD meta-analyses will likely help to substantially improve the reliability of meta-analytic knowledge (because parameters can be estimated more precisely) and to draw more nuanced conclusions in systematic reviews in the behavioral and social sciences. For example, integrating the results obtained from IPD meta-analyses of ELSAs and AD meta-analyses creates the opportunity to probe whether the results are moderated by quality characteristics of the samples (e.g., convenience samples vs. probability samples in ELSAs).

6.2 | Where to look for further methodological guidance

To tailor the two-stage approach to the complexities of ELSAs, we focused on typical challenges that meta-analysts have to face in the parts of Stages 1 and 2 devoted to analyses. Setting this focus, our tutorial does not elaborate on the challenges that exist before and after an IPD meta-analysis of an ELSA is carried out. In particular, important further steps that need to be considered to carry out an IPD meta-analysis involve planning and preregistration,¹²⁸ computing a statistical power analysis,¹²⁹ and locating the studies from

which the IPD are to be retrieved.^{9,126} Further, we did not discuss how to set the inclusion or exclusion criteria for selecting among the identified studies,⁴ to harmonize measures across studies,^{4,40} to assess the problem of publication bias,¹³⁰ or to apply the relevant reporting standards (PRISMA-IPD).¹³¹ Moreover, further guidance on meta-analyzing a smaller number of effect sizes or countries in addition to the ones discussed here (RVE and model-based approaches)⁹⁹ can be found in Konstantopoulos³⁵ and Bender et al.¹⁰⁰

6.3 | Conclusion

The present tutorial introduced the two-stage IPD meta-analysis approach, which we tailored to the methodological challenges of studies with complex survey designs, such as ELSAs. A two-stage IPD meta-analysis can be flexibly applied to tackle (typical) meta-analytic research objectives when synthesizing empirical evidence from descriptive analyses. The guidance offered in this paper can be helpful for synthesizing research evidence from complex surveys and panel studies in the behavioral, social, economic, educational and health sciences. IPD meta-analyses of studies with complex survey designs have (a) the potential to significantly enrich the extant body of knowledge with reliable and widely generalizable evidence for socially important or theoretically interesting phenomena and trends, and (b) open up new and unique research opportunities to synthesize evidence.

HIGHLIGHTS

What is already known

- Descriptive analyses based on studies with complex survey designs, such as educational large-scale assessments (ELSAs), provide reliable findings for socially important or theoretically interesting phenomena that can be generalized to well-defined populations
- Many important phenomena can be examined by drawing on readily available individual participant data (IPD) from one study cycle or sample as well as by integrating results from multiple sets of IPD
- IPD meta-analysis is a powerful tool for integrating research evidence and for examining heterogeneity of results at the participant and study level

What is new

- IPD meta-analyses of descriptive results from studies with complex survey designs offer unique and novel research opportunities to provide strong empirical evidence of the consistency and generalizability of socially important and theoretically interesting phenomena and trends.
- Using ELSAs as an example, this tutorial introduces a two-stage approach to IPD meta-analysis that is tailored to the methodological challenges of studies with complex survey designs (e.g., sampling weights, clustered and missing IPD, dependent effect sizes), first, for conducting descriptive analyses (Stage 1), and second, for integrating the results with meta-analytic and meta-regression models (Stage 2).
- We provide thoroughly annotated R syntaxes; all datasets are available online

Potential impact for *Research Synthesis Methods* readers outside the authors' field

- The guidance offered in this tutorial is useful for synthesizing research findings from studies with complex survey designs from a variety of fields, because health, social and economic survey and panel studies share many methodological features (e.g., sampling weights, clustered and missing IPD, dependent effect sizes) with ELSAs

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Table 1

Three-Level Meta-Analytic Models to Integrate Reading Achievement's Relationships With Gender (Model Set 1) and Students' SES (Model Set 2) and Their Interaction (Model Set 3)

Meta-analytic statistics	Model Set 1 $\bar{\beta}_{Gender}$	Model Set 2 $\bar{\beta}_{SES}$	Model Set 3 $\bar{\beta}_{Gender \times SES}$
$N_{countries}$	92	92	92
k	424	422	422
$k_{country}$			
<i>Min</i>	1	1	1
<i>Mdn</i>	5	5	5
<i>Max</i>	7	7	7
γ_{00}	0.37	0.30	-.018
[95% CI]	[0.35, 0.39]	[0.29, 0.31]	[-0.023, -0.013]
95% PI	[0.13, 0.62]	[0.17, 0.43]	[-0.052, 0.017]
Q			
value	5878.4	4917.3	481.0
<i>df</i>	423	421	421
<i>p</i>	< .001	< .001	.023
τ^2	0.016	0.004	0.0003
[95% CI]	[0.012, 0.020]	[0.0033, 0.006]	[0.0002, 0.0005]
$\tau_{Level 2}^2$	0.006	0.0007	0.0000
[95% CI]	[0.005, 0.007]	[0.0005, 0.0009]	[0.0000, 0.0001]
$\tau_{Level 3}^2$	0.010	0.004	0.0003
[95% CI]	[0.007, 0.014]	[0.003, 0.005]	[0.0001, 0.0005]
τ	0.125	0.066	0.017
[95% CI]	[0.112, 0.141]	[0.058, 0.077]	[0.016, 0.023]
$\tau_{Level 2}$	0.075	0.026	0.000
[95% CI]	[0.068, 0.082]	[0.023, 0.030]	[0.000, 0.012]
$\tau_{Level 3}$	0.100	0.061	0.017
[95% CI]	[0.084, 0.120]	[0.052, 0.072]	[0.011, 0.023]
I^2	93.2%	91.0%	41.1%
$I_{Level 2}^2$	33.5%	13.9%	0.0%
$I_{Level 3}^2$	59.8%	77.1%	41.1%

Note. The table shows the meta-analytic results from integrating the standardized effect sizes that were obtained from using Model Sets 1, 2, and 3. The specification of the model sets is shown in Figure 4. $N_{countries}$ = number of countries (i.e., Level 3 units). k = total number of effect sizes. $k_{country}$ = number of effect sizes per country (i.e., Level 2 units). γ_{00} = estimated average true effect size with 95% confidence interval. $\tau^2, \tau_{Level 2}^2, \tau_{Level 3}^2$ = estimated variances of true effect sizes with 95% confidence intervals: total, within countries, between countries. $\tau, \tau_{Level 2}, \tau_{Level 3}$ = estimated standard deviations of true effect sizes with 95% confidence intervals: total, within countries, between countries. $I^2, I_{Level 2}^2, I_{Level 3}^2$ = proportion of variance due to true effect sizes to total variance: total, within countries, between countries.

Figure 1

Sample Sizes (a, b) and Participating Countries (c) in the Full PISA Sample per Cycle and in Total

Note. Across PISA cycles, IPD from $k = 433$ independent student samples were collected. IPD from $k = 424$ student samples could be used in the present analyses (depicted in this figure). Color categories in Figure 1c indicate how often a certain country/economic region participated in PISA. Countries colored in white indicate no participation.

Figure 2

Schematic Representation of IPD Meta-Analyses of ELSAs Using PISA as an Example: (a) Hierarchical Data Structure of International ELSAs and (b) One-Stage and Two-Stage Meta-Analyses Applied to These IPD

a. Data Structure of ELSAs **b. One-Stage and Two-Stage IPD Meta-Analyses with ELSAs (Using PISA 2000–2018 as an Example)**

Figure 3*Illustration of the Ecological Fallacy*

Note. Hypothetical relationships between gender differences (in terms of d) and students' SES within countries at the participant level (represented by lines) and aggregated at the country level (represented by dots). Average gender differences are substantially related to average SES ($r_{\text{between}} = .70$) in both panels. Panel a: The magnitude of gender differences is substantially positively related to students' SES within countries ($r_{\text{within}} = .50$). Panel b: The magnitude of gender differences is substantially negatively related to students' SES within countries ($r_{\text{within}} = -.50$). Adapted from Thompson and Higgins ⁴⁷.

Figure 4

Illustration of the Model Sets Applied to Estimate Standardized Effect Sizes (and Their Sampling Variances) Using Data from Germany (PISA 2018) as an Example: (a) Gender Differences in Reading Achievement (β_{Gender} ; Model Set 1), (b) the Relationship Between Students' SES and Reading Achievement (β_{SES} ; Model Set 2), (c) the Relationships Between Reading Achievement and Gender and SES, and the Interaction Between Gender and SES ($\beta_{\text{Gender} \times \text{SES}}$; Model Set 3), (d) Gender Differences in Reading Achievement as a Function of Students' SES (β_{Gender}^* as implied by Model Set 3)

Note. Specification of model sets and pooled results as obtained for the German PISA 2018 sample:

- (a) $z.READACH_{ict} = \beta_{0ct} + \beta_{\text{Gender},ct} \cdot \text{Gender}_{ict} = -0.11 + 0.25 \cdot \text{Gender}_{ict}$
- (b) $z.READACH_{ict} = \beta_{0ct} + \beta_{\text{SES},ct} \cdot z.HISEI_{ict} = 0.35 \cdot z.HISEI_{ict}$
- (c) $z.READACH_{ict} = \beta_{0ct} + \beta_{\text{Gender},ct} \cdot \text{Gender}_{ict} + \beta_{\text{SES},ct} \cdot z.HISEI_{ict} + \beta_{\text{Gender} \times \text{SES},ct} \cdot \text{Gender}_{ict} \cdot z.HISEI_{ict} = -0.11 + 0.24 \cdot \text{Gender}_{ict} + 0.34 \cdot z.HISEI_{ict} + 0.03 \cdot \text{Gender}_{ict} \cdot z.HISEI_{ict}$
- (d) $\beta_{\text{Gender}}^* = 0.24 + 0.03 \cdot z.HISEI_{ict}$

Indices: i = student, c = country, t = cycle. $z.READACH$ = z-standardized reading achievement score ($M = 0$, $SD = 1$ for the German sample in the year 2018 cycle). $z.HISEI$ = z-standardized SES measure ($M = 0$, $SD = 1$ for the German sample in the year 2018 cycle).

Figure 5

Distribution of Pooled Effect Sizes: (a) Gender Differences in Reading Achievement ($\bar{\beta}_{\text{Gender}}$ as Obtained From Model Set 1), (b) Relationship Between Reading Achievement and Students' SES ($\bar{\beta}_{\text{SES}}$ as Obtained From Model Set 2), and (c) Relationship Between Reading Achievement and the Interaction Between Gender and SES ($\bar{\beta}_{\text{Gender} \times \text{SES}}$ as Obtained From Model Set 3)

Note. The dots represent the observed, pooled effect sizes; the diamond the true average effect size (vertical line through the vertical points of the diamond) and the 95% CIs (horizontal points of the diamond); and the error bars the 95% PIs as obtained from three-level random-effects models.

Figure 6

Country-Specific Development of Gender Differences in Reading Achievement ($\bar{\beta}_{Gender}$) Across PISA Cycles for OECD and Other Countries

Note. Each dot represents a pooled effect size ($\bar{\beta}_{Gender,ct}$). The lines connect effect sizes as obtained for independent student samples participating in a certain cycle t within the same country c . OECD countries were defined as those countries that were members of the OECD as of the year 2000.^{114(p13)} The triangles indicate the median value of the observed effect sizes as obtained for a certain PISA cycle and the group of OECD or other countries.

Online Supplementary Materials

Meta-Analyzing Individual Participant Data From Studies With Complex Survey Designs: A Tutorial on Using the Two-Stage Approach for Data From Educational Large-Scale Assessments

Overview

OSM.1 Literature Search for Meta-Analyses of Educational Large-Scale Assessments

OSM.2 Stage 1: Example of the Computation of Weights With Stratified Multistage Random Sampling

OSM.3 Stage 1: Replication Techniques to Estimate the Sampling Variance of Effect Sizes

OSM.4 Stage 1: Descriptive Analyses With Plausible Values (PVs)

OSM.5 Stage 1: Multiple Imputations and Nested Multiple Imputations

OSM.6 Stage 1: Estimating Effect Sizes With Multiply Imputed Data From ELSAS

OSM.7 Stage 2: Two-Level Random-Effects Model

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OSM.9 Stage 2: Examining Cross-Level Interactions Between Moderators in Three-Level Random-Effects Models with Random Slopes

OSM.10 Stage 2: Three-Level Random-Effects Models to Examine Moderators of the Relationship Between Students' SES and Reading Achievement

OSM.11 Stage 2: Three-Level Random-Effects Models to Examine Moderators of the Relationship Between Reading Achievement and the Interaction Between Students' Gender and Their SES

References

OSM.1 | LITERATURE SEARCH FOR META-ANALYSES OF EDUCATIONAL LARGE-SCALE ASSESSMENTS

To determine just how common meta-analyses that use data from educational large-scale assessments (ELSAs) are, we conducted two systematic database searches. In these searches, we looked for documents that reported the application of meta-analytic methods to data from four major ELSAs: NAEP, PISA, TIMSS, and PIRLS. We chose these ELSAs because their IPD have been widely used in secondary data analyses,^{1–6} there is extensive coverage of the results of these ELSAs in the media,^{7–9} and the results of these ELSAs are intended to inform educational policies¹⁰ and are also likely to affect such policies.^{11–13} The relevance of these ELSAs was, for example, also emphasized by Kirsch and Braun^{12(p5)} who conclude that “assessments such as TIMSS, PIRLS, and PISA are arguably the largest and most widely discussed comparative international assessments”. Thus, if there are meta-analyses that explicitly rely on data from ELSAs, there is a high likelihood that at least one of these four ELSAs was used in them. Accordingly, our search should provide a good estimate of how common it is for meta-analyses to be based on data from ELSAs (among others).

To identify documents that are relevant to these major ELSAs, we searched (on March 23, 2021) two electronic databases—the Education Resources Information Center (ERIC) and PsycInfo—using a two-step strategy. In the first step, we conducted four searches to look for documents with relevance to any of the four ELSAs using the search strings: (1) “NAEP” OR “National Assessment of Educational Progress,” (2) “PISA” OR “Programme for International Student Assessment,” (3) “TIMSS” OR “Trends in International Mathematics and Science Study” OR “Third International Mathematics and Science Study,” and (4) “PIRLS” OR “Progress in International Reading Literacy Study.” We found a total of 8,371 documents for which these search strings were included in any field of the ERIC database (Table S1). In the second step, we looked for documents that applied meta-analytic models to integrate the results from these four ELSAs. To this end, we limited the search results from

ERIC by combining each set of search results with the descriptor (i.e., controlled vocabulary) “Meta Analysis.” In doing so, we ensured that a document was classified as a meta-analysis in ERIC. Specifically, we used the following four search strings: (1) descriptor: “Meta Analysis” AND (“NAEP” OR “National Assessment of Educational Progress”), (2) descriptor: “Meta Analysis” AND (“PISA” OR “Programme for International Student Assessment”), (3) descriptor: “Meta Analysis”) AND (“TIMSS” OR “Trends in International Mathematics and Science Study” OR “Third International Mathematics and Science Study”), and (4) descriptor: “Meta Analysis” AND (“PIRLS” OR “Progress in International Reading Literacy Study”). Out of the 8,371 documents found in the first step, only 34 were classified as meta-analyses.

We applied the same two-step strategy to search the PsycInfo database. We first conducted four searches to look for documents with relevance to any of the four ELSAs by using the same search strings as in the ERIC search. The PsycInfo search yielded 7,552 hits. In the next step, we restricted the search results to studies that were classified as a “meta-analysis” in PsycInfo. Only 25 out of 7,552 hits were classified as meta-analyses. To sum up, across both electronic databases, only 59 (0.4%) out of a total of 15,923 identified documents with relevance to four major educational ELSAs were classified as meta-analyses. To conclude, the results of our search suggest that data from ELSAs are rarely used in meta-analyses.

Table S1

Results of the Two-Step Literature Search in ERIC and PsycInfo: Number of Documents (a) With Relevance to a Certain ELSA (n_{ELSA}) and (b) That Were Also Classified as Meta-Analyses ($n_{ELSA \& MA}$)

ELSA	ERIC		PsycInfo		Total	
	n_{ELSA}	$n_{ELSA \& MA}$	n_{ELSA}	$n_{ELSA \& MA}$	n_{ELSA}	$n_{ELSA \& MA}$
NAEP	4,694	14	856	6	5,550	20
PISA	2,018	9	5,918	17	7,936	26
TIMSS	1,359	11	602	2	1,961	13
PIRLS	300	0	176	0	476	0
Total	8,371	34	7,552	25	15,923	59

Note. ERIC = Education Resources Information Center. NAEP = National Assessment of Educational Progress. PISA = Programme for International Student Assessment. TIMSS = Trends in International Mathematics and Science Study/Third International Mathematics and Science Study. PIRLS = Progress in International Reading Literacy Study.

OSM.2 | EXAMPLE OF THE COMPUTATION OF WEIGHTS WITH STRATIFIED MULTISTAGE RANDOM SAMPLING

In ELSAs, results from descriptive analyses are weighted to be representative of the target population. The weights in stratified multistage random sampling are computed such that they reflect the joint (i.e., multiplied) probabilities of including the primary sampling units (PSUs; e.g., schools) and those of the individuals within the PSUs (e.g., students). In two-stage sampling, the PSUs (e.g., schools) often have unequal probabilities of being selected because some may comprise a smaller or larger number of individuals (e.g., students). We illustrate this with an example (Table S2) in which a population encompasses 16 schools, and the population size is $N_{Population} = 5,600$ students. The schools are divided into two equally sized strata (1 = rural; 2 = urban schools). Suppose that $n_{sc} = 8$ schools and 10 students per school j are to be selected. Because the strata have the same size, the same number of schools as well as the same number of students will be selected per stratum. The probability p_{1j} that a certain school j is selected can be computed as $p_{1j} = (N_j \cdot n_{sc}) / N_{Population}$ with N_j denoting the number of students in school j ; the school weight is then computed as $w_{1j} = 1/p_{1j}$. For example, the probability that School 2 with $N = 200$ students is selected is $p_{12} = (200 \cdot 8) / 5600 = .2857$ (rounded to four decimals). The within-school probability that student i attending school j is selected is computed as $p_{2ji} = 10/N_j$; the within-school weight is $w_{2ji} = 1/p_{2ji}$ (e.g., in School 2 $w_{22i} = 1/(10/200) = 20$). The final student weight (also called the total weight) is then computed as $w_{ji} = 1/(p_{1j} \cdot p_{2ji}) = w_{1j} \cdot w_{2ji}$. For students in School 2, the final student weight is $w_{2i} = 1/(p_{12} \cdot p_{22i}) = 1/(.2857 \cdot .05) = 70$. The sum of the final student weights across all participating students then equals the number of population members (e.g., in Table S2: $N_{Population} = 8 \cdot 10 \cdot 70 = 5,600$).

Table S2

Sampling Weights for a Stratified Multistage Probability Sample and Weight Adjustment Factors Using Jackknife and Balanced Repeated Replication (BRR) Methods

Stratum	School	N_j	p_{1j}	w_{1j}	p_{2ji}	w_{2ji}	p_{ji}	w_{ji}	Pseudo-stratum	Jackknife				BRR				Fay BRR			
										R1	R2	R3	R4	R1	R2	R3	R4	R1	R2	R3	R4
1	1	200	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
1	2	200	.286	3.50	.050	20	.014	70	1	0	1	1	1	2	2	2	2	1.5	1.5	1.5	1.5
1	3	300	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
1	4	300	.429	2.33	.033	30	.014	70	1	2	1	1	1	0	0	0	0	0.5	0.5	0.5	0.5
1	5	400	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
1	6	400	.571	1.75	.025	40	.014	70	2	1	0	1	1	2	0	2	0	1.5	0.5	1.5	0.5
1	7	500	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
1	8	500	.714	1.40	.020	50	.014	70	2	1	2	1	1	0	2	0	2	0.5	1.5	0.5	1.5
2	9	200	.286	3.50	.050	20	.014	70	3	1	1	2	1	2	2	0	0	1.5	1.5	0.5	0.5
2	10	200	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
2	11	300	.429	2.33	.033	30	.014	70	3	1	1	0	1	0	0	2	2	0.5	0.5	1.5	1.5
2	12	300	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
2	13	400	.571	1.75	.025	40	.014	70	4	1	1	1	2	2	0	0	2	1.5	0.5	0.5	1.5
2	14	400	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
2	15	500	.714	1.40	.020	50	.014	70	4	1	1	1	0	0	2	2	0	0.5	1.5	1.5	0.5
2	16	500	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--

Note. Out of 16 schools, eight schools (four per stratum) were randomly selected with the selection probability for each school j (p_{1j}) being proportional to school size N_j . Dashes indicate that a school was not selected in the sample. Within each school, 10 students were randomly selected. w_{1j} = school weight. p_{2ji} = within-school probability of student i being selected. w_{2ji} = within-school weight. p_{ji} = final student probability. w_{ji} = final weight. Fay BRR uses $k_{Fay} = 0.5$ as the deflating factor for the weights. Probabilities are rounded to three decimal places.

OSM.3 | STAGE 1: REPLICATION TECHNIQUES TO ESTIMATE THE SAMPLING VARIANCE OF EFFECT SIZES

ELSAs typically apply multistage sampling procedures to select study participants. Multistage sampling processes induce dependencies among the selected individuals and lead to clustered data.^{14–16} These dependencies (e.g., students nested within schools) need to be taken into account because they increase the size of the sampling variances of the effect sizes.¹⁶

Replication techniques have been developed to estimate sampling variances when analyzing clustered data. Two replication techniques are commonly applied in ELSAs for which so-called replicate weights are provided in public use files that can be used to estimate the sampling variance of effect sizes¹⁷: The Jackknife (JK) method, which is used (with different modifications, e.g., JK2) to estimate sampling variances in TIMSS, PIRLS, and NAEP, and the Balanced Repeated Replication (BRR) method, which is applied in a modified form (i.e., Fay BRR) in PISA.^{14,18} In the following, we briefly describe how the sampling variances of effect sizes are calculated with these replication techniques in ELSAs.

OSM.3.1 | The Jackknife method

In the Jackknife method, PSUs are systematically paired with similar PSUs. To this end, a stratification scheme is used in which PSUs are ordered both by explicit strata (and, if applied, implicit stratification variables) and by size. In ELSAs, a specific type of Jackknife (JK2) is typically used in which (in most cases) two PSUs are grouped into so-called pseudostrata.^{14,19,20} Pseudostrata are also called variance strata or Jackknife zones. In Table S2, schools were sorted by size within each explicit stratum, yielding two pseudostrata per stratum and a total of four pseudostrata. In doing so, for example, Schools 2 and 4 as well as Schools 6 and 8 in Stratum 1 form pseudostrata because they are similar in size. To obtain a certain replicate h (e.g., R1), one PSU within a certain pseudostratum (e.g., School 2 in R1)

will be randomly selected; the IPD from all individuals within this PSU will be “deleted.”* To this end, the weight of this PSU (i.e., w_{1j}) will be multiplied by zero, which implies that all individuals in that PSU have an adjusted final replicate weight of zero. The weights (i.e., w_{1j}) of the remaining PSUs within this pseudostratum will be adjusted by multiplying the original weights of the PSUs by 2 as a weight “inflation” factor. For example, in R1, the weight of School 4 will be multiplied by 2 to obtain the adjusted replicate weight. The schools (and students) in the other pseudostrata keep their weights (i.e., the original weight w_{1j} of each PSU is multiplied by 1). The total number of replicate samples H equals the number of pseudostrata. In our example, there are $H = 4$ replicates R1 to R4, which were obtained by applying the procedure as described above. The next step of the Jackknife method is to use the final weights to estimate a certain effect size T . Then, the adjusted replicate weights are used to obtain an effect size estimate T_h for each replicate sample^{14,20,22}: For example, T_h is estimated four times by using the replicates R1, R2, R3, and R4. The sampling variance $v(T)_{JK2}$ of effect size T can then be computed as^{20(p289)}

$$v(T)_{JK2} = \sum_{h=1}^H (T_h - T)^2. \quad (S1)$$

OSM.3.2 | Balanced Repeated Replication (BRR)

Sampling variances of effect sizes are calculated in a similar way in the BRR and JK2 method.^{14,20,22} However, whereas JK2 only “deletes” one out of two PSUs within a single pseudostratum, the BRR method deletes one PSU within each pseudostratum to obtain a certain replicate (see Table S2). The PSUs to be deleted are selected randomly, and their weights are multiplied by zero (e.g., in R1, the weights of Schools 4, 8, and 11 are multiplied by zero; see Table S2), which yields adjusted replicate weights of zero for each individual in these PSUs. The remaining PSUs are kept for the analyses. Their replicate weights are

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* Beginning with TIMSS 2015 and PIRLS 2016, a slightly modified version of the JK2 procedure is applied in which two replicates are created for each pseudostratum by using the first school of the pseudostratum in the first replicate and the second school for the second replicate. The sampling variance is computed according to Equation S1 across all replicates and then divided by two.^{19,21}

obtained by inflating the original weights by a factor of two. Notably, to substantially decrease the required number of replicates, a so-called balanced set of replicates is created with Hadamard matrices. These matrices are used to randomly select PSUs within pseudostrata for each replicate. They help to obtain orthogonal sets of replicates, meaning that the selection of PSUs in one replicate does not predict the selection of PSUs in any other replicate. Using Hadamard matrices also implies that the number of replicates is always a multiple of four that is greater or equal to the number of pseudostrata. In our example, we have four pseudostrata and therefore $H = 4$ replicates. If there were five pseudostrata, there would be eight replicates and so forth. As for the Jackknife method, the next step of the BRR method is to use the final weights to estimate T . Then, the adjusted replicate weights are used to obtain an effect size estimate T_h for each replicate sample.^{14,20,22} The sampling variance $v(T)_{BRR}$ of effect size T can then be computed as^{20(p290)}

$$v(T)_{BRR} = \frac{1}{H} \sum_{h=1}^H (T_h - T)^2. \quad (S2)$$

However, the elimination of one half of the original sample within each replicate in the BRR method may cause problems when estimating the sampling variance of effect sizes for rare subpopulations or for rare events.^{14,20,22} To overcome this problem, Fay²³ developed a variant of the BRR, Fay BRR, where all PSUs are kept in each replicate but with different weights. Rather than assigning a weight of zero to one of the PSUs (that would be “deleted”), their weights are deflated by multiplying them by a factor of k_{Fay} with $0 < k_{Fay} < 1$. The weights of the other PSUs are then inflated by multiplying them by the factor $2 - k_{Fay}$. For example, in PISA, k_{Fay} is set to $k_{Fay} = .50$ for the PSUs that are to be deflated (see Table S2). The procedure for computing the sampling variance is the same as for JK2 or standard BRR, and the formula for the sampling variance is adjusted for k_{Fay} ^{20(p291)}

$$v(T)_{BRR.Fay} = \frac{1}{H \cdot k_{Fay}^2} \sum_{h=1}^H (T_h - T)^2. \quad (S3)$$

OSM.4 | STAGE 1: DESCRIPTIVE ANALYSES WITH PLAUSIBLE VALUES

In ELSAs, vital individual characteristics (e.g., reading or mathematics achievement) are assessed with so-called plausible values (PVs). PVs reflect the idea that the skills and knowledge that underlie achievement measures are latent variables that cannot be observed directly but need to be estimated.^{14,24} To reflect the uncertainty underlying the estimation of a certain individual characteristic, a range of possible achievement values, the PVs, are estimated for each participant rather than a single point estimate. Correctly accounting for PVs in descriptive analyses requires the estimation of effect sizes T_n ($n = 1, \dots, N$; by using the final weights) and their sampling variance $v(T_n)$ for each PV (e.g., by using JK2 or Fay BRR). Further, the uncertainty associated with PVs being an imperfect measure of a latent variable adds some variability to the results. Specifically, in addition to the sampling variance for each PV, there is a (between-imputation) variance of effect sizes T_n around the mean effect size $\bar{T}_N$ such that $\bar{T}_N$ is obtained as the average T_n across N PVs. The total sampling variability $v(\bar{T}_N)$ for the average effect size $\bar{T}_N$ is then computed as the sum of the average sampling variances and the between-imputation variance^{14(p100)}

$$v(\bar{T}_N) = \frac{\sum_{n=1}^N v(T_n)}{N} + \left(1 + \frac{1}{N}\right) \frac{\sum_{n=1}^N (T_n - \bar{T}_N)^2}{N-1}. \quad (\text{S4})$$

For example, PISA 2018 provided 10 PVs and 80 replicate weights to estimate the sampling variance with Fay BRR. To obtain $v(\bar{T}_N)$ requires, first, that the researcher estimates T_n by using the final student weight, and second, that the researcher repeats these analyses 80 times for each replicate for a single PV to estimate $v(T_n)$. To obtain $\bar{T}_N$ and its sampling variance $v(\bar{T}_N)$ therefore requires these analyses to be redone $N = 10$ times for each PV. This comes to a total of $10 \cdot 81 = 810$ analyses.

OSM.5 | STAGE 1: MULTIPLE IMPUTATIONS AND NESTED MULTIPLE IMPUTATIONS

In this section, we describe how data from ELSAs can be imputed using multiple imputation and nested multiple imputation techniques.

OSM.5.1 | Multiple imputations

The substantive-model-compatible sequential modeling (SMC-SM) approach, as any other multiple imputation approach, involves three steps for handling missing data.²⁵ First, the missing values in the original data are imputed M times to obtain M complete data sets. In the second step, researchers apply their target model to estimate the M target effect size(s) T_m ($m = 1, \dots, M$; by using the final weights) and their sampling variance $v(T_m)$ (e.g., by using JK2 or Fay BRR) from each of the M imputed data sets (e.g., by using some kind of regression model; see Figure 4 in the main paper). In the third step, the M effect size estimates obtained in the previous step need to be pooled. As for PVs, the uncertainty that results from imputing unknown missing values adds variability to the results. Specifically, in addition to the sampling variance $v(T_m)$ as observed in each imputed data set, there is a (between-imputation) variance of effect sizes T_m around the average effect size $\bar{T}_M$ with $\bar{T}_M$ being obtained as the average T_m across M multiply imputed data sets. The total sampling variability $v(\bar{T}_M)$ for the average effect size $\bar{T}_M$ is then computed as the sum of the average sampling variances and the between-imputation variance²⁶

$$v(\bar{T}_M) = \frac{\sum_{m=1}^M v(T_m)}{M} + \left(1 + \frac{1}{M}\right) \frac{\sum_{m=1}^M (T_m - \bar{T}_M)^2}{M-1} \quad (\text{S5})$$

OSM.5.2 | Nested multiple imputations

Key outcome variables in ELSAs are individuals' achievement and skills, which are often represented as a set of N PVs rather than a single variable. When using PVs, multiple imputation approaches, such as the SMC-SM approach, can be extended as a nested multiple imputation approach.^{27,28} To this end, for each of the N PVs, a set of M imputed data sets are

obtained by using the SMC-SM approach. Doing so yields $N \cdot M$ complete data sets as well as $N \cdot M$ effect size estimates T_{nm} and $N \cdot M$ sampling variances $v(T_{nm})$. To obtain the target average effect size $\bar{T}$ requires a user to compute the average across all $N \cdot M$ effect size estimates T_{nm} . Further, to obtain the sampling variance $v(\bar{T})$ of the average effect size $\bar{T}$ requires a user to compute the average effect size $\bar{T}_n$ for each PV by taking the average across the effect sizes T_{nm} as obtained for the M imputed data sets for a certain PV n . The total sampling variability $v(\bar{T})$ (see Equation S9) for the average effect size $\bar{T}$ is then computed as²⁷

$$v(\bar{T}) = \bar{v}(T_{nm}) + \frac{1}{M} \left(1 + \frac{1}{N}\right) MS_b + \left(1 - \frac{1}{M}\right) MS_w. \quad (S6)$$

In Equation S6, $\bar{v}(T_{nm})$ represents the average sampling variance,

$$\bar{v}(T_{nm}) = \frac{\sum_{n=1}^N \sum_{m=1}^M v(T_{nm})}{N \cdot M}, \quad (S7)$$

MS_b represents the mean square MS_b of $\bar{T}_n$ around $\bar{T}$

$$MS_b = \left(\frac{M}{N-1}\right) \sum_{n=1}^N (\bar{T}_n - \bar{T})^2, \quad (S7)$$

and MS_w represents the mean square of T_{nm} around $\bar{T}_n$

$$MS_w = \left(\frac{1}{N(M-1)}\right) \sum_{n=1}^N \sum_{m=1}^M (T_{nm} - \bar{T}_n)^2. \quad (S9)$$

For example, PISA 2018 provided $N = 10$ PVs and 80 replicate weights to estimate the sampling variance with Fay BRR. In our examples, we imputed $M = 10$ complete data sets for each PV. To obtain the target average effect size $\bar{T}$, we had to compute the average across $N \cdot M = 10 \cdot 10 = 100$ effect size estimates T_{nm} where T_{nm} could be estimated by using the final student weight for each of the $N \cdot M$ complete data sets. Further, to obtain the sampling variance $v(T_{nm})$ for a certain effect size estimate T_{nm} , we had to repeat the analyses 80 times (using the 80 replicate weights) for a certain complete data set. To obtain $\bar{T}$ and its sampling variance $v(\bar{T})$ for a certain student sample, we therefore needed $100 + 100 \cdot 80 = 8,100$ analyses.

OSM.6 | STAGE 1: ESTIMATING EFFECT SIZES WITH MULTIPLY IMPUTED DATA FROM ELSAS

In this section, we explain how different standardized effect sizes in IPD meta-analyses of ELSAs can be estimated with multiply imputed data. Using exemplary ELSA data from PISA 2000–2018, we first explain the rules we used to select the countries and economic regions for which the effect sizes were calculated. Then, we show what types of missing data can occur in data from an ELSA. Subsequently, we demonstrate which missing values can be imputed with the SMC-SM approach²⁵ and nested multiple imputation techniques²⁸ presented in Chapter OSM.5. Finally, we illustrate how the nested multiply imputed data can be used to calculate effect sizes and their sampling variances (Stage 1 of the two-stage approach for IPD meta-analyses). In our empirical examples, we apply different sets of linear regression models to the IPD as obtained for each student i in a certain country c who participated in a certain PISA cycle t to do this.

OSM.6.1 | Rules for the selection of countries and economic regions for effect size estimation: The example of PISA 2000–2018

For PISA 2000–2018, the public use files contain IPD from 433 student samples (Table S3).

In some PISA cycles, both a country and one or more economic regions of that country participated in the assessment (e.g., in PISA 2015, Spain as well as all Autonomous Communities of Spain were assessed). To avoid the “double” participation of countries and to prevent specific economic regions within countries from biasing the overall effect size estimation, we established clear rules for when to include countries and economic regions before analyzing the data. For our empirical example, we applied the following rules:

- (1) If only one or more economic regions (and never the entire country) participated in PISA, the economic regions were included and analyzed (separately).*

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* This applied to the following regions: B-S-J-G (China; PISA 2015), B-S-J-Z (China; PISA 2018), Shanghai (China; PISA 2009, 2012), Miranda (Venezuela; PISA 2009), Chinese Taipei (PISA 2006, 2009, 2012, 2015, 2018), Himachal Pradesh (India; PISA 2009), Tamil Nadu (India; PISA 2009).

- (2) If one or more economic regions and the corresponding country participated at the same time, only the country was included and analyzed.*
- (3) If one or more economic regions and the country participated, but at different times, both were included and analyzed.†

Applying these rules reduced the number of student samples included in the analyses from 433 to 426 (see Table S3).

OSM.6.2 | Different types of missing data: The example of PISA 2000–2018

The selected IPD from 426 independent student samples encompassed systematically and sporadically missing data. For the variables used in our applications (see Table S3), we observed systematically missing values for reading achievement in PISA 2006 in the US (due to severe printing errors)^{29(p281)} and for reading (and mathematics) achievement in PISA 2018 in Vietnam (because the international comparability of the applied achievement measures could not be assured)^{30(p21)}. Further, we observed systematically missing values for two student samples on the *HISEI* index, which we applied as a measure of students' SES. More specifically, *HISEI* data were not provided for Albania (a) in 2012 because of evidence of systematic errors and violations of technical standards,^{31(p283)} and (b) in 2015 because the student questionnaire data could not be properly matched with the achievement data.^{32(p269)} Taken together, due to systematically missing data on reading achievement, we used the IPD from 424 student samples to estimate gender differences in reading achievement. Further, we used data from 422 student samples to estimate the effect sizes for the relationship between reading achievement and students' SES and for the relationship between gender differences in reading achievement and students' SES.

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* This applied to the following regions, which were consequently excluded: Spain (Regions, ESP; PISA 2015), Moscow Region (RUS; PISA 2018), Perm Region (RUS; PISA 2012), Tatarstan (RUS; PISA 2018), Massachusetts (USA; PISA 2015), Puerto Rico (USA; PISA 2015), North Carolina (USA; PISA 2015).

† This applied to the following regions: Ciudad Autónoma de Buenos Aires (Argentina; PISA 2015), Baku (Azerbaijan; PISA 2018).

Table S3

Number of Student Samples Available in Public Use Files With Systematically Missing Values on Target Variables and With Valid Data to Estimate Effect Sizes per PISA Cycle

Number of student samples...	PISA cycle							Total
	2000	2003	2006	2009	2012	2015	2018	
...available in public use files	43	41	57	74	65	73	80	433
...considered ^a	43	41	57	74	64	69	78	426
...with systematically missing values								
Reading achievement	0	0	1	0	0	0	1	2
Mathematics achievement	—	0	0	0	0	0	1	1
HISEI index	0	0	0	0	1	1	0	2
Gender	0	0	0	0	0	0	0	0
...with valid data for effect size estimation								
Model Set 1: Gender differences in reading achievement	43	41	56	74	64	69	77	424
Model Set 2: Relationship between reading achievement and students' SES	43	41	56	74	63	68	77	422
Model Set 3: Relationship between reading achievement and the interaction between gender and students' SES	43	41	56	74	63	68	77	422

Note. A dash indicates that mathematics achievement was not used as an auxiliary variable for multiple imputation in this cycle.

^a Considered after applying the rules for the selection of countries and economic regions for effect-size estimation.

In addition to systematically missing values, the public use files from PISA 2000–2018 also contain planned systematically and sporadically missing data on the variables used in our applications (Table S4). In particular, we used mathematics achievement as an auxiliary variable in PISA 2003–2018 to enhance the plausibility of the MAR assumption. In PISA, a planned missing design (booklet design) is applied by which each student is randomly assigned to a test booklet that comprises a selected item subset taken from a pool of several hundred test items.¹⁸ In contrast to all subsequent PISA cycles, in PISA 2000, PVs for mathematics achievement were only estimated for the random subsample of 5/9 of the total student sample who worked on booklets that contained mathematics items. Thus, in PISA

2000, we observed planned missing values that could be considered to be MCAR for about 4/9 of the students in each sample. Moreover, we observed some sporadically missing data on the gender variable, with a maximum sample-specific percentage of students with missing data on gender of 3%. Third, there were some sporadically missing data on the *HISEI* index. The maximum sample-specific percentage of students with missing data on this index was 62%. Taken together, across all PISA cycles, the maximum sample-specific percentage of students with one or more sporadically missing values on the target variables that we used in the analyses was 62%.

There is no clear-cut rule for the required number of imputations in general or for nested multiple imputation in particular. Van Buren (2018, Chapter 2.8) reviewed the results from several simulation studies that assessed the performance of multiple imputation procedures and concluded that between 20 and 100 complete data sets are sufficient for obtaining unbiased parameter estimates with reliable standard errors and confidence intervals and that even 5 to 20 complete data sets may be sufficient when missingness is moderate. Further, one general rule of thumb that was developed for multiple imputation procedures is that the number of imputed data sets should be at least as large as the maximum percentage of individuals within a sample with one or more (sporadically) missing values.^{33(p388)} Drawing on these recommendations, we set $M = 10$ imputations for each PV, resulting in $N \cdot M = 5 \text{ PVs} \cdot 10 = 50$ imputed data sets for PISA 2000–2012, and $10 \text{ PVs} \cdot 10 = 100$ imputed data sets for PISA 2015–2018. In doing so, the total number of imputed data sets (a) was in the recommended range between 20 and 100 complete data sets and (b) clearly exceeded the maximum percentage of individuals within a sample with one or more (sporadically) missing values.*

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* The sole exception to this was Japan in PISA 2000, where the sample-specific percentage of students with at least one (sporadically) missing value was 62% (Table S4). Thus, in this case, the number of imputed data sets (i.e., 50) was somewhat below this rule of thumb with $M = 10$ for each of five PVs.

Table S4

Sample-Specific Percentages of Students With Planned Systematically or Sporadically Missing Values per PISA Cycle

	PISA cycles						
	2000	2003	2006	2009	2012	2015	2018
Number of student samples with valid data	43	41	56	74	64	69	77
Reading achievement							
<i>Min</i>	0	0	0	0	0	0	0
<i>Mdn</i>	0	0	0	0	0	0	0
<i>Max</i>	0	0	0	0	0	0	0
Mathematics achievement							
<i>Min</i>	—	0	0	0	0	0	0
<i>Mdn</i>	—	0	0	0	0	0	0
<i>Max</i>	—	0	0	0	0	0	0
<i>HISEI</i> index							
<i>Min</i>	2	1	1	1	0	2	0
<i>Mdn</i>	5	4	4	5	5	9	7
<i>Max</i>	62	16	41	33	23	24	19
Gender							
<i>Min</i>	0	0	0	0	0	0	0
<i>Mdn</i>	1	0	0	0	0	0	0
<i>Max</i>	2	3	0	0	0	0	0
Sample-specific percentage of students with at least one (sporadically) missing value							
<i>Min</i>	2	1	1	1	0	2	2
<i>Mdn</i>	5	4	4	5	5	9	7
<i>Max</i>	62	16	41	33	23	24	19

Note. A dash indicates that mathematics achievement was not used as an auxiliary variable for multiple imputation in this cycle.

To impute sporadically missing data in PISA cycles 2000–2018, we specified an imputation model using the SMC-SM approach.²⁵ The imputation model was applied to impute missing values for students in those 422 student samples for which data on reading (and mathematics) achievement, gender, and the *HISEI* index were available. Of note, we deliberately decided not to impute missing values for gender because the mechanism underlying the missing values on gender may be MNAR, reflecting that students' gender identity was not represented well by the binary response format used in the PISA student questionnaire.

Using the SMC-SM approach, we decomposed the joint distribution of the analysis model variables (Sequence 1) and the conditional model variables for *HISEI* (Sequence 2) as shown in Table S5. For each conditional model, we specified a multilevel regression model for normally distributed outcomes (see Table S5). To set up the sequence of the conditional models, we followed the recommendations given in Lüdtke et al.²⁵ Specifically, we ordered the sequence of each conditional model by the percentage of missing data of the variables to be imputed, starting with the variables that showed the lowest percentage of missing observations. Mathematics achievement was used as an auxiliary variable for multiple imputations in PISA cycles 2003–2018. In PISA 2000, the percentage of systematically missing values on the mathematics achievement variable was too high for it to serve as an auxiliary variable (> 40% across countries). Moreover, we added school-specific random effects for the intercept in each conditional model to take the clustered structure of the data into account (with students being nested within schools). These imputation models are compatible with all regression model sets that we used to estimate the target effect sizes.

Importantly, we harmonized the variances of the variables included in the imputation model by z-standardized reading achievement, mathematics achievement, and the *HISEI* index before imputation, a technique that helps improve the convergence of the imputation procedure. Imputation diagnostics indicated that a burn-in phase of 5,000 iterations and 13,500 iterations thereafter was sufficient for the imputation algorithm to converge.* Once the imputed data were available, we back-transformed the variables in each imputed data set into their raw metrics.

Following the recommendations in Debray et al.,^{34(pp509-510)} we imputed missing data separately for each student sample. To this end, we used the R package “mdmb” (version 1.5.8)³⁵ to create $M = 10$ complete data sets for each PV using the raw data provided in the

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* For Japan in PISA 2000, a burn-in phase of 5,000 iterations and 100,000 iterations thereafter was needed for the imputation algorithm to converge.

public use files for a certain student sample. As noted above, doing so yielded 5 PVs · 10 imputations = 50 (PISA 2000-2012) or 10 PVs · 10 imputations = 100 (PISA 2015-2018) multiply imputed data sets for each student sample.

Table S5*Specification of the Imputation Model for the SMC-SM Approach*

Sequence	Target variable	Outcome distribution	Regression model	Conditional model
<i>Applied to IPD from PISA 2000 cycle</i>				
1	Reading achievement	Normal	Multilevel regression	$READACH \mid Gender + HISEI + Gender \times HISEI + (1 \mid SCHOOLID)$
2	<i>HISEI</i> index	Normal	Multilevel regression	$HISEI \mid Gender + (1 \mid SCHOOLID)$
<i>Applied to IPD from PISA 2003 to 2018 cycles</i>				
1	Reading achievement	Normal	Multilevel regression	$READACH \mid Gender + MATHACH^a + HISEI + Gender \times HISEI + (1 \mid SCHOOLID)$
2	<i>HISEI</i> index	Normal	Multilevel regression	$HISEI \mid Gender + MATHACH^a + (1 \mid SCHOOLID)$

Note. *READACH* = reading achievement. *MATHACH* = mathematics achievement. Each conditional model contained school-specific random effects for the intercept (as represented by “(1 | *SCHOOLID*)”) to take the clustered structure of the data into account (with students nested within schools).

^aAuxiliary variable.

OSM.6.3 | Model Set 1: Standardized mean differences in reading achievement between female and male students

To estimate standardized mean differences in reading achievement between female and male students, we used a z -standardized reading achievement score ($z.READACH$) as the dependent variable. To compute $z.READACH$, we used the multiply imputed data sets as obtained from the application of the SMC-SM approach. Using these data (which contain each variable in its raw metric) and applying the final weights, we first estimated the population mean and standard deviation of reading achievement for each multiply imputed data set for each student sample from a certain country c and PISA cycle t . In each multiply imputed data set (as obtained for each student sample), we then computed $z.READACH$ by subtracting the estimated population mean from students' reading achievement score and dividing this difference by the estimated population standard deviation.³⁶ Finally, we specified $z.READACH$ as the outcome variable in a linear regression model.

$$z.READACH_{ict} = \beta_{0ct} + \beta_{Gender,ct} \cdot Gender_{ict} \quad (S10)$$

In this model, the subscript i denotes individual students and the intercept β_{0ct} captures the mean z -standardized reading achievement score of male students. The standardized mean difference between male and female students (equivalent to d) is captured by the standardized regression coefficient $\beta_{Gender,ct}$ (see Figure 4a for an illustration).

We applied the model depicted in Equation S10 using the final weights to each multiply imputed data sets that we obtained for each of the 424 student samples (see Table S3). The sampling variances of the regression coefficients were estimated with 80 replicates using Fay BRR (with $k_{Fay} = 0.5$) for each multiply imputed data set as obtained for each student sample. For example, to estimate gender differences in reading achievement, the regression model shown in Equation S10 was applied to each of the 100 imputed data sets as obtained for the student samples from 77 countries participating in the PISA 2018 cycle (see Table S4). Hence, a total of $77 \cdot (100 + 100 \cdot 80) = 623,700$ analyses were required for PISA

2018 to obtain estimates of $\bar{\beta}_{Gender, c2018}$ and their sampling variances $v(\bar{\beta}_{Gender, c2018})$. To pool the results as obtained for each country, we used the nested multiple imputation procedure as implemented in the `pool_mni()` function from the R package “miceadds”.³⁷ Taken together, using these procedures, we obtained a total of 424 standardized mean differences ($\bar{\beta}_{Gender, ct}$) and their sampling variances that we meta-analyzed in Stage 2 of the IPD meta-analysis.

OSM.6.4 | Model Set 2: Bivariate correlation between reading achievement and students' SES

To estimate the correlation between students' SES and their reading achievement, we applied bivariate linear regression models in which both the outcome and the predictor were *z*-standardized. Specifically, we drew on the multiply imputed data sets as obtained for each sample and applied the same procedure that we used to obtain *z.READACH* to *z*-standardize the HISEI index (*z.HISEI*). We then used *z.READACH* as the outcome and *z.HISEI* as the predictor variable in a bivariate linear regression model (see Figure 4b for an illustration).

$$z.READACH_{ict} = \beta_{0ct} + \beta_{SES, ct} \cdot z.HISEI_{ict} \quad (S11)$$

Z-standardizing the outcome and the predictor variable implies that (a) the intercept β_{0ct} is zero (in each country and PISA cycle) and (b) the standardized regression coefficient $\beta_{SES, ct}$ is identical in value and interpretation to the corresponding correlation coefficient r between the HISEI index and reading achievement.³⁶ Using the model shown in Equation S11 and the same procedures as outlined above, we estimated a total of 422 (pooled) effect sizes in terms of $\bar{\beta}_{SES, ct}$ and their sampling variances that we meta-analyzed in Stage 2 of the IPD meta-analysis.

OSM.6.5 | Model set 3: Interaction between gender differences in reading achievement and students' SES

A particular strength of IPD meta-analysis is that it can be used to examine the extent to which the magnitude of an effect size depends on moderator variables at the participant level. In particular, we drew on the multiply imputed data sets as obtained for each student sample to estimate standardized effect sizes that reflect the extent to which gender differences in reading achievement were moderated by students' SES (see Figures 4c and 4d for illustrations). To this end, we combined the regression models in Equations S10 and S11 and added a multiplicative term between the *z*-standardized HISEI index $z.HISEI$ and gender.

$$z.READACH_{ict} = \beta_{0ct} + \beta_{Gender,ct} \cdot Gender_{ict} + \beta_{SES,ct} \cdot z.HISEI_{ict} + \beta_{Gender \times SES,ct} \cdot Gender_{ict} \cdot z.HISEI_{ict} \quad (S12)$$

In this model, the intercept β_{0ct} captures the mean reading achievement score as observed for male students with an HISEI index that is equal to the country average (i.e., $z.HISEI_{i,ct} = 0$). When we rearrange Equation S12, it becomes evident that $\beta_{Gender \times SES}$ depicts the extent to which the standardized mean difference between male and female students' reading achievement depends on students' SES.

$$z.READACH_{ict} = \beta_{0ct} + (\beta_{Gender,ct} + \beta_{Gender \times SES,ct} \cdot z.HISEI_{ict}) \cdot Gender_{i,ct} + \beta_{SES,ct} \cdot z.HISEI_{ict} \quad (S13)$$

The model parameters and their sampling variances as depicted in Equation S13 were estimated for each multiply imputed data set as obtained for each student sample using the same procedures as described above. In doing so, we obtained a total of 422 (pooled average) effect sizes in terms of $\bar{\beta}_{Gender \times SES,ct}$ and their sampling variances that we meta-analyzed in Stage 2 of the IPD meta-analysis.

OSM.7 | STAGE 2: TWO-LEVEL RANDOM-EFFECTS MODEL

When it is reasonable to assume that the effect sizes as observed in an ELSA are independent, two-level random-effects models can be applied. Here, we illustrate the application of the two-level random-effects model to meta-analyze gender differences in reading achievement in terms of $\bar{\beta}_{Gender,c,2018}$ as observed in independent student samples from 77 countries participating in the PISA 2018 cycle (see Figure S1).

The two-level random-effects model involves two stages of sampling.³⁸ The first stage of the sampling process assumes that the effect sizes $\bar{T}_{c,2018}$ (i.e., $\bar{\beta}_{Gender,c,2018}$) that were observed for each country c in PISA 2018 estimate a true effect size $\vartheta_{c,2018}$ for each country c with some estimation error $e_{c,2018}$.

$$\bar{T}_{c,2018} = \vartheta_{c,2018} + e_{c,2018} \quad (\text{S14})$$

The sampling errors $e_{c,2018}$ are assumed to follow a normal distribution with mean zero and the variance being equal to the country-specific sampling variance $v(\bar{T}_{c,2018})$ of the observed effect size $\bar{T}_{c,2018}$. Further, the sampling errors of different countries are assumed to be uncorrelated (i.e., there are no dependencies among the sampling errors). The second stage in the sampling process assumes that the true effect sizes $\vartheta_{c,2018}$ are sampled from a distribution of true effect sizes characterized by a mean true effect β_0 and the variance of the true effects τ^2 . The second stage of the sampling process implies that each true effect size may also contain some random effect $u_{c,2018}$, which represents the deviation of the true country-specific effect size $\vartheta_{c,2018}$ from β_0 .

$$\vartheta_{c,2018} = \beta_0 + u_{c,2018} \quad (\text{S15})$$

The random effects $u_{c,2018}$ are assumed to follow a normal distribution with mean zero and variance τ^2 . Further, the random effects of different countries are assumed to be uncorrelated with each other and uncorrelated with the sampling errors. When Equations S14 and S15 are combined, the observed effect size can be written as

$$\bar{T}_{c,2018} = \beta_0 + u_{c,2018} + e_{c,2018}. \quad (S16)$$

In the two-level random-effects model, there are two sources of variation that affect the distribution of observed effect sizes: the variance of the sampling errors $e_{c,2018}$ and the variance of the true effect sizes around the average true effect size τ^2 . Importantly, each observed effect size $\bar{T}_{c,2018}$ is assigned a weight $W_{c,2018}$ when estimating the mean and variance of the true effect sizes. In random-effects models, an inverse variance scheme is applied to represent the idea that effect sizes with smaller sampling variance (reflecting more precise effect size estimates) should have a larger influence on the estimated meta-analytic parameters.³⁸ Specifically, for each observed effect size, the weights in a two-level random-effects model are computed as

$$W_{c,2018} = 1/(\hat{\tau}^2 + v(\bar{T}_{c,2018})). \quad (S17)$$

As shown in Equation S17, the computation of weights requires an estimate $\hat{\tau}^2$ of the variance of the true effects. Following Viechtbauer³⁹ and Veroniki et al.,⁴⁰ we applied the restricted maximum likelihood estimator (REML) to estimate $\hat{\tau}^2$ and its 95% CI by using the profile likelihood method. Once an estimate of τ^2 is available, it is possible to compute the weights and to estimate the mean true effect size β_0 .^{38(pp101-102)} To estimate the 95% CI of β_0 , we followed Veroniki et al.⁴¹ and used the Hartung-Knapp/Sidik-Jonkman approach. Model convergence can be assessed with a profile likelihood plot for τ^2 (see OSM.8).⁴²

Using the two-level random-effects model, the average (true) magnitude of gender differences was estimated with $\beta_0(\bar{\beta}_{Gender}) = 0.32$ standard deviation units in favor of female students (95% CI [0.30, 0.35]). This advantage of 15-year-old female students in reading is similar in size to the advantage reported for female eighth-grade students in the US.⁶ The variance of true effect sizes was estimated with $\tau^2 = 0.011$ (95% CI [0.008, 0.016]) and the standard deviation with $\tau = 0.10$ (95% CI [0.09, 0.13]). The profile likelihood plot for τ^2 indicated proper convergence of the REML estimation procedure (see Figure S2). Our further

assessment of the heterogeneity of effect sizes showed that gender differences in reading achievement varied substantially ($Q(df = 76) = 1249.4, p < .0001; I^2 = 92.9\%$). According to the benchmark ranges proposed by Hyde⁴³ to evaluate effect sizes for gender differences (negligible: $0.00 < |d| \leq 0.10$, small: $0.10 < |d| \leq 0.35$, moderate: $0.35 < |d| \leq 0.65$, large: $0.65 < |d| \leq 1.00$, and very large: $|d| > 1.00$), the average gender difference in reading achievement can be considered small in size. The 95% prediction interval (95% PI [0.11, 0.53]), which is symmetrical around the average true effect size, indicates that about half of the gender differences will likely be small, and the other half will probably be moderate in size (see also Figure S1).

Figure S1

Distribution of Gender Differences in Reading Achievement in Terms of $\bar{\beta}_{Gender}$ as Obtained From Model Set 1 in PISA 2018

Note. The dots represent the observed (pooled) effect sizes; the diamond the true average effect size (vertical line through the vertical points of the diamond) and the 95% CIs (horizontal points of the diamond); and the error bars the 95% PIs as obtained from two-level random-effects models.

Figure S2

Profile Likelihood Plot for the Variance Estimate of True Effects (τ^2) as Obtained From the Two-Level Random-Effects Model to Meta-Analyze Gender Differences in Reading Achievement ($\bar{\beta}_{\text{Gender}}$ as Obtained From Model Set 1 for PISA 2018)

OSM.8 | STAGE 2: PROFILE LIKELIHOOD PLOTS TO CHECK THE CONVERGENCE OF THREE-LEVEL RANDOM-EFFECTS MODELS

To ensure that random-effects models, such as the two-level or three-level random-effects models, converge properly, the convergence of the REML estimation procedure can be assessed by profiling the restricted log-likelihood of the estimated variances and correlations of the true effect sizes, for example, τ^2 for a two-level random-effects model, or $\tau_{Level\ 2}^2$ and $\tau_{Level\ 3}^2$ for a three-level random-effects model.⁴² The restricted log-likelihood of the estimated variances of true effect sizes represents the differences between the model-implied and observed data. Applied to the three-level random-effects model, profiling the restricted log-likelihood implies, for example, fixing the variance of $\tau_{Level\ 2}^2$ at different values (e.g., the dots in Figure S3). Using these values, the restricted log-likelihood is then estimated for the remaining parameters in the three-level random-effects model (i.e., γ_{00} and $\tau_{Level\ 3}^2$). Proper convergence is indicated when the profile plot peaks at the $\tau_{Level\ 2}^2$ value that was estimated in the original model.

In the following, we apply profile likelihood plots to check the convergence of the three-level random-effects models that we used in our empirical examples: meta-analyzing gender differences in reading achievement (Figure S3), meta-analyzing the relationship between students' SES and reading achievement (Figure S4), and meta-analyzing the relationship between reading achievement and the interaction between gender and students' SES (Figure S5) using data from PISA 2000–2018. To conclude, the profile log-likelihood plots indicated that there were no convergence problems for the variance estimates $\tau_{Level\ 2}^2$ and $\tau_{Level\ 3}^2$ in the applied three-level random-effects models.

Figure S3

Profile Likelihood Plots for the Variance Estimates of True Effects ($\tau_{\text{Level } 2}^2$ and $\tau_{\text{Level } 3}^2$) as Obtained From the Three-Level Random-Effects Model to Meta-Analyze Gender Differences in Reading Achievement ($\bar{\beta}_{\text{Gender}}$ as Obtained From Model Set 1)

Figure S4

Profile Likelihood Plots for the Variance Estimates of True Effects ($\tau_{\text{Level } 2}^2$ and $\tau_{\text{Level } 3}^2$) as Obtained From the Three-Level Random-Effects Model to Meta-Analyze the Relationship Between Students' SES and Reading Achievement ($\bar{\beta}_{\text{SES}}$ as Obtained From Model Set 2)

Figure S5

Profile Likelihood Plots for the Variance Estimates of True Effects ($\tau_{\text{Level } 2}^2$ and $\tau_{\text{Level } 3}^2$) as Obtained From the Three-Level Random-Effects Model to Meta-Analyze the Relationship Between Reading Achievement and the Interaction Between Gender and Students' SES ($\bar{\beta}_{\text{Gender} \times \text{SES}}$ as Obtained From Model Set 3)

OSM.9 | STAGE 2: EXAMINING CROSS-LEVEL INTERACTIONS BETWEEN MODERATORS IN THREE-LEVEL RANDOM-EFFECTS MODELS WITH RANDOM SLOPES

When examining interactions between moderators in IPD meta-analyses of ELSAs, it is possible that moderating effects within countries are related to one or more moderator variables located at the country level. This is referred to as a cross-level interaction. Cross-level interactions can be examined with random-slope models, which are extensions of mixed-effects models.¹⁶ In the following, we illustrate how cross-level interactions between moderators in IPD meta-analyses of ELSAs can be examined.

As an example of a cross-level interaction, we investigate whether OECD membership (varying between countries) affects changes in gender differences in reading over time (varying within countries). To this end, we expand the three-level mixed-effects model (Equations 5 to 9 in the main paper) by adding a random slope for *Time*. Doing so implies that the development of (i.e., the change in) gender differences in reading achievement may vary between countries (over and above the effect of *OECD*). Equations S20 and S22 therefore now contain a random effect u_{1c} , which depicts the possibility that country-specific slopes may differ from the average rate of change as predicted by their OECD membership. The residual terms u_{1c} are assumed to follow a normal distribution with mean zero and variance τ_{u1}^2 . The residual terms u_{1c} are assumed to be uncorrelated with u_{ct} and e_{ct} . However, the residual terms u_{0c} and u_{1c} may be correlated with τ_{01} to allow for the possibility that the intercept and slope of the gender differences in reading achievement are systematically related.

$$\bar{\beta}_{Gender,ct} = \beta_{0c} + \beta_{1c} \cdot Time_{ct} + \beta_{2c} \cdot Mode_{ct} + u_{ct} + e_{ct} \quad (S18)$$

$$\beta_{0c} = \gamma_{00} + \gamma_{01} \cdot OECD_c + u_{0c} \quad (S19)$$

$$\beta_{1c} = \gamma_{10} + \gamma_{11} \cdot OECD_c + u_{1c} \quad (S20)$$

$$\beta_{2c} = \gamma_{20} \quad (\text{S21})$$

Combining Equations S18 to S21 yields

$$\bar{\beta}_{Gender,ct} = \gamma_{00} + \gamma_{01} \cdot OECD_c + u_{0c} + (\gamma_{10} + \gamma_{11} \cdot OECD_c + u_{1c}) \cdot Time_{ct} + \gamma_{20} \cdot Mode_{ct} + u_{ct} + e_{ct} \quad (\text{S22})$$

Equation 22 represents the random-slope model that depicts the cross-level interaction between *OECD* and *Time*. Further, this model also contains an interaction between the random coefficient u_{1c} and *Time* (i.e., $u_{1c} \cdot Time_{ct}$), which allows for the possibility that the variance of the observed effect sizes may depend on *Time*.¹⁶ Some scholars argue that this interaction term is needed to allow for valid statistical inferences about the cross-level interaction.^{16(p104)} Notably, applying the random-slope model as a working model in the RVE framework may lead to smaller sampling variances in the meta-analytic parameters than using a mixed-effects meta-regression model. That is, the precision of estimation may improve. However, the RVE framework also allows for valid statistical inferences even when using the mixed-effects model (without the random slope) as the working model because RVE safeguards these inferences against the misspecification of the working model.⁴⁴

To estimate the random-slope model in Equation S22, we used the REML estimation procedure as implemented in the R package “metafor”.⁴² Standard errors for the meta-regression coefficients were adjusted by using RVE as implemented in the “clubSandwich” package.⁴⁵ Model convergence was assessed with profile likelihood plots.⁴² Notably, the variance term of the slope of *Time* was estimated to be very small ($\tau_{u1}^2 = 0.0003$; Table S6), which implied that the correlation τ_{01} could not be reliably estimated (see Figure S6b). We therefore followed Raudenbush and Bryk’s^{46(p28)} recommendation and constrained the variance of the slope of *Time* to zero, yielding the mixed-effects meta-regression model as described in the main text. The profile likelihood plots obtained for the mixed-effects meta-regression model indicated the proper convergence of the REML estimation procedure (see Figure S6a).

Table S6

Three-Level Meta-Regression Models to Examine How Gender Differences in Reading Achievement (in Terms of $\bar{\beta}_{Gender}$) (a) Change Over Time and (b) Are Moderated by the Mode of Test Administration or (c) Are Moderated by the Socioeconomic Context: Results Obtained for the Mixed-Effects Model (Equation 9 in the Main Paper) Versus the Random-Slope Model (Equation S22 in the Online Supplement)

Meta-analytic statistics	Mixed-effects model [95% CI]	Random-slope model [95% CI]
Regression coefficients		
Intercept: γ_{00}	0.37 [0.33, 0.42]	0.37 [0.33, 0.42]
Time: γ_{10}	0.007 [0.004, 0.010]	0.007 [0.004, 0.010]
Mode: γ_{20}	-0.16 [-0.19, -0.13]	-0.16 [-0.19, -0.13]
OECD: γ_{01}	-0.03 [-0.08, 0.02]	-0.03 [-0.08, 0.02]
OECD x Time: γ_{11}	-0.001 [-0.003, 0.001]	-0.001 [-0.003, 0.001]
(Residual) variance components		
Residuals u_{ci} : $\tau_{Res.Level\ 2}^2$	0.0025	0.0025
Intercept u_{0c} : $\tau_{Res.Level\ 3}^2$	0.0109	0.0117
Slope u_{1c} : τ_{u1}^2	--	0.0003
Correlation		
Intercept with slope: τ_{01}	--	-1 ^a
Q		
value	4878	4777
df	423	419
p	< .001	< .001

Note. Dashes indicate that a certain meta-analytic parameter was not estimated in the mixed-effects meta-regression model.

^a The correlation between the intercept and slope could not be estimated reliably.

Figure S6

Profile Likelihood Plots as Obtained for the Random Effects That Were Specified (a) in the Mixed-Effects Meta-Regression Model and (b) in the Random-Slope Meta-Regression Model to Examine Moderating Effects on the Relationship Between Reading Achievement and Students' Gender (in Terms of $\bar{\beta}_{Gender}$)

a. Mixed-effects meta-regression model

b. Random-slope meta-regression model

OSM.10 | STAGE 2: THREE-LEVEL RANDOM-EFFECTS MODELS TO EXAMINE MODERATORS OF THE RELATIONSHIP BETWEEN STUDENTS' SES AND READING ACHIEVEMENT

In this section, we present the results obtained from three-level meta-regression models that examine moderator variables that can explain the heterogeneity in the relationship between students' SES and their reading achievement (in terms of $\bar{\beta}_{SES}$ as estimated in Model Set 2).

As potential moderators of students' reading achievement, we assessed chronological time,⁴⁷ the mode of assessment for reading achievement,⁴⁸ and a country's OECD membership.

Figure S7 illustrates the variation in the observed effect sizes as a function of these variables.

Previous meta-analytic research by Sirin^{47(p437)} suggested that the relationship between achievement and students' SES in the US became somewhat weaker between 1918 and 1975 (with an average correlation of $r = .34$) and between 1990 and 2000 (with an average correlation of $r = .30$). To investigate the generalizability of these results, we analyzed the change in the relationship of students' SES and their reading achievement over time (*Time* was coded as a continuous variable such that 0/3/6 etc. indicated the 2000/2003/2006 etc. cycles of PISA).

The mode for assessing reading achievement in PISA changed between the 2012 and the 2015 cycle. Between 2000 and 2012, reading achievement was assessed with paper-pencil tests, whereas computer-based assessments were applied in the PISA 2015 and 2018 cycles. The meta-analysis by Scherer and Siddiq⁴⁸ showed that students with higher SES demonstrated stronger ICT literacy skills (average correlation $r = .21$). Thus, the relationship between students' SES and reading achievement may have become stronger when using a computer-based assessment. Other meta-analytic research showed, however, that test mode (paper-pencil test vs. computer-based assessment) had no significant effect on performance on reading achievement tests.⁴⁹ Accordingly, the magnitude of the relationship between students' SES and their reading achievement could be expected not to change when the test mode

changes. To test these hypotheses, we examined the extent to which the magnitude of the correlation between students' SES and their reading achievement was moderated by the mode of test administration (*Mode* with 0 = paper-pencil test if *Time* ≤ 12, 1 = computer-based assessment if *Time* > 12).

Finally, an important goal of educational policies in OECD countries is to reduce the number of educational disparities that can be attributed to students' SES.^{50(p164)} We therefore examined the extent to which the magnitude of the correlation between students' SES and their reading achievement as well as the development of this relationship were moderated by a country's OECD membership (*OECD*; 0 = other countries, 1 = OECD country). To account for their (potential) confounding, we specified a meta-regression model that included the three moderator variables and the interaction between *Time* and *OECD*. Because the moderating effect of *OECD* and *Time* represents a cross-level interaction, we followed Snijders and Bosker¹⁶ and applied a random-slope model (i.e., with the regression coefficient for *Time* varying between countries)

$$\bar{\beta}_{SES,ct} = \gamma_{00} + \gamma_{01} \cdot OECD_c + u_{0c} + (\gamma_{10} + \gamma_{11} \cdot OECD_c + u_{1c}) \cdot Time_{ct} + \gamma_{20} \cdot Mode_{ct} + u_{ct} + e_{ct} \quad (S23)$$

Using the same estimation procedures as for the three-level random-effects model (i.e., REML in combination with RVE), the variance term of the slope for *Time* was estimated to be about zero with a value of $\tau_{u1}^2 = 0.0000$ (Table S7). We therefore followed Raudenbush and Bryk's^{46(p28)} recommendation and removed u_{1c} from Equation S23 yielding the mixed-effects model

$$\bar{\beta}_{SES,ct} = \gamma_{00} + \gamma_{01} \cdot OECD_c + u_{0c} + (\gamma_{10} + \gamma_{11} \cdot OECD_c) \cdot Time_{ct} + \gamma_{20} \cdot Mode_{ct} + u_{ct} + e_{ct} \quad (S24)$$

The profile likelihood plots suggest proper convergence of the REML estimation procedure for the mixed-effects model (see Figure S8). The intercept in the mixed-effects model was estimated with $\gamma_{00}(\bar{\beta}_{SES}) = 0.29$ (95% CI [0.27, 0.32]), which represents the average correlation between students' SES and reading achievement for PISA 2000 as measured for a paper-pencil test in countries that were not members of the OECD (Table S7).

Further, γ_{10} represents the rate of linear change in the correlation between SES and reading achievement. Specifically, $\gamma_{10} = 0.001$ (95% CI [-0.001, 0.003]) indicates that the correlation between SES and reading achievement remained largely the same in non-OECD countries. Further, $\gamma_{20} = -0.02$ in combination with the 95% CI [-0.04, -0.01] indicates that—contrary to our expectations—the magnitude of the correlation between SES and reading achievement decreased when a computer-based assessment was used to measure reading achievement rather than a paper-pencil test. Finally, $\gamma_{01} = 0.016$ (95% CI [-0.020, 0.052]) indicates that the (true) relationship between students' SES and their reading achievement in PISA 2000 in OECD countries was similar in size to that found in other countries. The development of this relationship also did not differ significantly between these groups ($\gamma_{11} = 0.000$; 95% CI [-0.002, 0.002]). Thus, the relationship between SES and reading achievement as observed for OECD countries followed about the same trend as that for non-OECD countries.

The variance estimates $\tau_{Res.Level\ 3}^2 = 0.0036$ (95% CI [0.0027, 0.0051]) and $\tau_{Res.Level\ 2}^2 = 0.0006$ (95% CI [0.0005, 0.0009]) represent the amount of residual heterogeneity in true effect sizes between countries (i.e., the variance of u_{0c}) and within countries (i.e., the variance of u_{ct}), respectively. As indicated by the 95% CIs, a significant amount of heterogeneity in true effect sizes remained within as well as between countries when controlling for the moderator variables in the meta-regression model. This conclusion was further corroborated by the Q statistic indicating a statistically significant amount of residual heterogeneity. To quantify the amount of variation in true effect sizes that was explained by the meta-regression model, we computed $P^2_{Level\ 2}$ and $P^2_{Level\ 3}$. $P^2_{Level\ 2} = 0.05$ shows that *Time*, *Mode*, and *OECD* jointly explained 5% of the variance in true effects sizes that was located within countries. $P^2_{Level\ 3} = 0.02$ shows that *OECD* explained almost none of the variance in true effect sizes that was observed between countries.

Table S7

Three-Level Meta-Regression Models to Examine How The Relationship Between Students' SES and Their Reading Achievement (in terms of $\bar{\beta}_{SES}$) (a) Changes Over Time and (b) Is Moderated by the Mode of Test Administration or (c) Is Moderated by the Socioeconomic Context: Results Obtained for the Mixed-Effects Model (Equation S24) Versus the Random-Slope Model (Equation S23)

Meta-analytic statistics	Mixed-effects model [95% CI]	Random-slope model [95% CI]
Regression coefficients		
Intercept: γ_{00}	0.29 [0.27, 0.32]	0.29 [0.27, 0.31]
Time: γ_{10}	0.001 [-0.001, 0.003]	0.001 [-0.001, 0.003]
Mode: γ_{20}	-0.02 [-0.04, -0.01]	-0.03 [-0.04, -0.02]
OECD: γ_{01}	0.016 [-0.020, 0.052]	0.019 [-0.017, 0.055]
OECD x Time: γ_{11}	0.000 [-0.002, 0.002]	0.000 [-0.002, 0.002]
(Residual) variance components		
Residuals u_{ci} : $\tau_{Res.Level\ 2}^2$	0.0006	0.0004
Intercept u_{0c} : $\tau_{Res.Level\ 3}^2$	0.0036	0.0047
Slope u_{1c} : τ_{u1}^2	--	0.0000
Correlation		
Intercept with slope: τ_{01}	--	-0.47
Q		
value	4762.5	4762.5
df	417	417
p	< .001	< .001

Note. Dashes indicate that a certain meta-analytic parameter was not estimated in the mixed-effects meta-regression model.

Figure S7

Country-Specific Development of the Relationship Between Students' SES and Their Reading Achievement ($\bar{\beta}_{SES}$) Across PISA Cycles for OECD and Other Countries

Note. Each dot represents a (pooled) effect size. The lines connect effect sizes as obtained for independent student samples participating in a certain PISA cycle within the same country c . OECD countries were defined as those countries that were members of the OECD as of the year 2000.^{50(p13)} The triangles indicate the median value of the observed effect sizes as obtained for a certain PISA cycle and the group of OECD or other countries.

Figure S8

Profile Likelihood Plots as Obtained for the Random Effects That Were Specified (a) in the Mixed-Effects Meta-Regression Model and (b) in the Random-Slope Meta-Regression Model to Examine Moderating Effects on the Relationship Between Reading Achievement and Students' SES (in Terms of $\bar{\beta}_{SES}$)

a. Mixed-Effects Meta-Regression Model

b. Random-Slope Meta-Regression Model

OSM.11 | STAGE 2: THREE-LEVEL RANDOM-EFFECTS MODELS FOR EXAMINING MODERATORS OF THE RELATIONSHIP BETWEEN READING ACHIEVEMENT AND THE INTERACTION BETWEEN STUDENTS' GENDER AND THEIR SES

This section presents the results obtained from three-level meta-regression models to examine moderator variables that may explain the heterogeneity in the relationship between students' reading achievement and the interaction between students' SES and their gender (in terms of $\bar{\beta}_{Gender \times SES}$ as estimated in Model Set 3). We examined the same moderator variables as for $\bar{\beta}_{Gender}$ and $\bar{\beta}_{SES}$. Figure S9 illustrates the variation in the observed effect sizes as a function of these variables.

Of note, there are no meta-analyses that have examined the intersection between reading achievement, gender, and SES (at the participant level). Hence, the analysis of how the interaction between gender and SES may change across time was exploratory in nature. However, there is some meta-analytic evidence that test mode (paper-pencil test vs. computer-based assessment) has no significant effect on performance on reading achievement tests.⁴⁹ Thus, it could be expected that the magnitude of the interaction between gender and students' SES does not change when the test mode changes. Finally, an important goal of educational policies in OECD countries is to reduce educational disparities between male and female students as well as between students from socioeconomically advantaged and disadvantaged backgrounds.^{50(pp142 and 164)} We therefore examined the extent to which the magnitude of the interaction between students' SES and gender differences in reading achievement as well as the development of this interaction over time were moderated by a country's OECD membership (*OECD*; 0 = other countries, 1 = OECD country). To account for their (potential) confounding, we specified a meta-regression model that included the three moderator variables and the interaction between *Time* and *OECD*. Because the moderating effect of

OECD and *Time* represents a cross-level interaction, we specified a random-slope model (i.e., with the regression coefficient for *Time* varying between countries)

$$\bar{\beta}_{Gender \times SES,ct} = \gamma_{00} + \gamma_{01} \cdot OECD_c + u_{0c} + (\gamma_{10} + \gamma_{11} \cdot OECD_c + u_{1c}) \cdot Time_{ct} + \gamma_{20} \cdot Mode_{ct} + u_{ct} + e_{ct} \quad (S25)$$

Using the same estimation procedures as for the three-level random-effects model (i.e., REML in combination with RVE), the variance term of the slope of *Time* was estimated to be about zero with a value of $\tau_{u1}^2 = 0.0000$, which implied that the correlation τ_{01} could not be reliably estimated (see Figure S10b). We therefore followed Raudenbush and Bryk's^{46(p28)} recommendation and removed u_{1c} from Equation S25, yielding the mixed-effects model

$$\bar{\beta}_{Gender \times SES,ct} = \gamma_{00} + \gamma_{01} \cdot OECD_c + u_{0c} + (\gamma_{10} + \gamma_{11} \cdot OECD_c) \cdot Time_{ct} + \gamma_{20} \cdot Mode_{ct} + u_{ct} + e_{ct} \quad (S26)$$

As shown in Table S8, the regression coefficients and the corresponding 95% CIs as obtained for the mixed-effects model and the random-slope model were very similar, showing that substantive conclusions were robust against the different model specifications. The intercept in the mixed-effects model was estimated with $\gamma_{00}(\bar{\beta}_{Gender \times SES}) = -0.022$ (95% CI [-0.035, -0.008]), which suggests that students' SES and gender differences did interact in explaining reading achievement for PISA 2000 as measured for a paper-pencil test in countries that were not members of the OECD. In these countries at that point in time, the gender gap in reading achievement (in favor of female students) narrowed when students' SES increased. Further, $\hat{\gamma}_{10}$ represents the rate of linear change in the size of this interaction. Specifically, $\gamma_{10} = -0.0002$ (95% CI [-0.0017, 0.0012]) indicates that the interaction term remained unchanged in non-OECD countries (while controlling for the other moderator variables). Further, $\gamma_{20} = 0.023$ in combination with the 95% CI [0.011, 0.035] indicates that the magnitude of the interaction term increased when a computer-based assessment was used to measure reading achievement rather than a paper-pencil test. This implies that intersectionality effects are on average about zero when using a computer-based assessment (because the mode effect is added to the baseline observed in PISA 2000). Finally, $\gamma_{01} = 0.004$ (95% CI [-0.012, 0.020]) and $\gamma_{11} = -0.0008$ (95% CI [-0.0020, 0.0005]) indicate

that OECD countries show a similar intercept and development in the interaction term as other countries. Thus, OECD countries were not more or less likely to be successful than other countries in reducing educational disparities related to the interaction between students' gender and their SES.

The Q statistic indicated a statistically significant amount of residual heterogeneity. The estimates of the residual variances for the true effect sizes suggested that some residual heterogeneity in true effect sizes remained between countries (i.e., the variance of $u_{0,c}$), whereas the residual variance within countries (i.e., the variance of u_{ct}) was almost zero (see Table S8). To quantify the amount of variation in true effect sizes that was explained by the meta-regression model, we computed $P^2_{Level\ 2}$ and $P^2_{Level\ 3}$. $P^2_{Level\ 2} = 0.67$ shows that *Time*, *Mode*, and *OECD* jointly explained 67% of the variance in true effects sizes that was located within countries. $P^2_{Level\ 3} = -0.01$ (truncated to 0) shows that *OECD* explained no variance in true effect sizes between countries.

Table S8

Three-Level Meta-Regression Models to Examine How the Relationship Between Reading Achievement and the Interaction Between Gender and Students' SES (in Terms of $\bar{\beta}_{Gender \times SES}$) (a) Changes Over Time and (b) Is Moderated by the Test Administration Mode or (c) Is Moderated by the Socioeconomic Context: Results Obtained for the Mixed-Effects Model (Equation S26) Versus the Random-Slope Model (Equation S25)

Meta-analytic statistics	Mixed-effects model [95% CI]	Random-slope model [95% CI]
Regression coefficients		
Intercept: γ_{00}	-0.022 [-0.035, -0.008]	-0.022 [0.036, -0.008]
Time: γ_{10}	-0.0002 [-0.0017, 0.0012]	-0.0002 [-0.0017, 0.0012]
Mode: γ_{20}	0.023 [0.011, 0.035]	0.024 [0.012, 0.036]
OECD: γ_{01}	0.004 [-0.012, 0.020]	0.001 [-0.011, 0.020]
OECD x Time: γ_{11}	-0.0008 [-0.0020, 0.0005]	-0.0008 [-0.0021, 0.0004]
(Residual) variance components		
Residuals u_{ci} : $\tau_{Res.Level\ 2}^2$	0.0000	0.0000
Intercept u_{0c} : $\tau_{Res.Level\ 3}^2$	0.0003	0.0001
Slope u_{1c} : τ_{u1}^2	--	0.0000
Correlation		
Intercept with slope: τ_{01}	--	1.000 ^a
Q		
value	448.6	448.6
df	417	417
p	0.1378	0.1378

Note. Dashes indicate that a certain meta-analytic parameter was not estimated in the mixed-effects meta-regression model.

^a The correlation between the intercept and slope could not be estimated reliably.

Figure S9

Country-Specific Development in How Reading Achievement Depends on the Interaction Between Gender and Students' SES ($\bar{\beta}_{\text{Gender} \times \text{SES}}$) Across PISA Cycles for OECD and Other Countries

Note. Each dot represents a (pooled) effect size. The lines connect effect sizes as obtained for independent student samples participating in a certain cycle within the same country c . OECD countries were defined as those countries that were members of the OECD as of the year 2000.^{50(p13)} The triangles indicate the median value of the observed effect sizes as obtained for a certain PISA cycle and the group of OECD or other countries.

Figure S10

Profile Likelihood Plots as Obtained for the Random Effects That Were Specified (a) in the Mixed-Effects Meta-Regression Model and (b) in the Random-Slope Meta-Regression Model to Examine Moderating Effects on the Relationship Between Reading Achievement and the Interaction Between Gender and Students' SES (in Terms of $\bar{\beta}_{\text{Gender} \times \text{SES}}$)

a. Mixed-Effects Meta-Regression Model

b. Random-Slope Meta-Regression Model

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