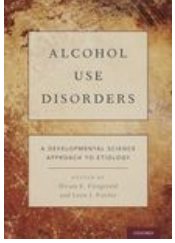

Alcohol Use Disorders: A Developmental Science Approach to Etiology

Hiram E. Fitzgerald (ed.), Leon I. Puttler (ed.)

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CHAPTER

20 Integrative Data Analysis from a Unifying Research Synthesis Perspective

Eun-Young Mun, Anne E. Ray

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Abstract

Integrative data analysis (IDA) is a promising new approach in psychological research and has been well received in the field of alcohol research. This chapter provides a larger unifying research synthesis framework for IDA. Major advantages of IDA of individual participant-level data include better and more flexible ways to examine subgroups, model complex relationships, deal with methodological and clinical heterogeneity, and examine infrequently occurring behaviors. However, between-study heterogeneity in measures, designs, and samples and systematic study-level missing data are significant barriers to IDA and, more broadly, to large-scale research synthesis. Based on the authors' experience working on the Project INTEGRATE data set, which combined individual participant-level data from 24 independent college brief alcohol intervention studies, it is also recognized that IDA investigations require a wide range of expertise and considerable resources and that some minimum standards for reporting IDA studies may be needed to improve transparency and quality of evidence.

Keywords: integrative data analysis, meta-analysis, individual participant-level data, alcohol interventions, college students

Subject: Clinical Psychology, Developmental Psychology

The purpose of this chapter is to present a broader unified framework for integrative data analysis (IDA; Curran & Hussong, 2009; Hussong, Curran, & Bauer, 2013) and to provide an overview of the strengths of IDA as well as future directions for IDA. IDA, defined as "the statistical analysis of a single data set that consists of two or more separate samples that have been pooled into one" (Curran & Hussong, 2009, p. 82), is a newly emerging set of advanced analytic techniques aimed at synthesizing large-scale evidence. IDA offers specific advantages, as well as incurs certain challenges, compared to single studies. The advantages of IDA are that it (1) provides a built-in replication mechanism across independent studies and tests between-study heterogeneity; (2) has better statistical power, greater diversity in sample, and an extended duration of observations; (3) provides a broader psychometric assessment approach to key constructs; (4) handles low base-rate behaviors better; and (5) maximizes limited resources for research (Curran & Hussong, 2009). However, these advantages are not unique to IDA. Meta-analysis using aggregate data (e.g., means, standard deviations, or effect size estimates) shares many of these advantages in common with IDA. Instead, what is unique and innovative about IDA may be best attributed to its use of individual participant-level (patient-level) data in generating large-scale evidence.

Based on our experience of conducting a large-scale IDA study of brief motivational interventions aimed at reducing alcohol use among college students (Project INTEGRATE; Mun, de la Torre, et al., 2015), this chapter intends to broaden the scope of IDA and, consequently, its utilities for future IDA investigations. Toward this goal, we place IDA in the context of other related approaches and methods that have been developed in other disciplines, highlight relatively less-known challenges of IDA, and underscore the

promise of IDA in the current research environment. Table 20.1 provides a brief summary of the promise of, common misconceptions about, and requirements for IDA.

Table 20.1 Integrative Data Analysis (IDA) from a Unifying Research Synthesis Perspective

Promise of Integrative Data Analysis
• IDA may be considered as a quantitative research synthesis approach to large-scale existing data from multiple sources. • IDA provides large-scale robust evidence. • Study- and participant-level effects, as well as their cross-level effects, can be examined systematically. • IDA offers modeling flexibility and better capacity to handle low base rate behaviors, including rare adverse events from treatment studies. • More advanced research synthesis approaches (e.g., multivariate meta-analysis) are possible with individual participant data. • IDA meets two major demands of the current research environment: (1) scientific rigor and reproducibility and (2) data sharing and collaboration.
Less-Known Aspects of Integrative Data Analysis
• IDA is not a single-entity analytic method. IDA is an inclusive term referring to a series of data handling and decision making in addition to analyzing measurement models, analytical models, and synthesis models. • IDA approaches need to be tailored to meet the specific challenges of each IDA study. • IDA requires a wide range of substantive and methodological expertise and skills and considerable resources. A team science approach is appropriate for IDA.
What to Consider When Planning Integrative Data Analysis
• Specific research questions for IDA and the study inclusion and exclusion criteria should be set clearly. • Data should be pooled only from sufficiently similar studies. • Overlap across studies in participants, measures, designs, treatment/control groups, and settings is needed to draw combined inference. • Data collection and checking processes should be carefully documented. • Study-level missing data and unexplained between-study heterogeneity are major challenges.

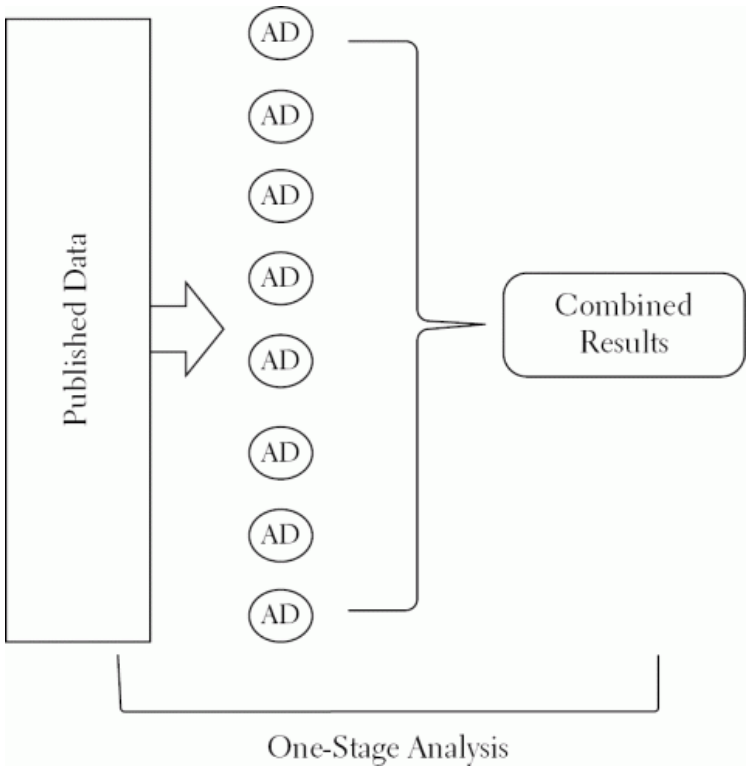
Integrative Data Analysis as One Approach to Research Synthesis

Broadly, IDA can be viewed as a special case of the large-scale research synthesis methods (or meta-analysis methods), in which individual participant data from multiple sources are analyzed together in a single, one-stage analysis. Placing IDA within a broad research synthesis framework may be helpful for several reasons. This broad perspective allows one to take advantage of a large pool of available methodological approaches to IDA, depending on the specific data characteristics, challenges, and goals of each project.

Figures 20.1–20.4 graphically show various research synthesis approaches, including IDA. Figure 20.1 shows a typical meta-analysis using aggregate data in which a single coefficient (e.g., an estimate of the standardized mean difference) is obtained per study and the obtained estimates from multiple studies are combined across studies. Figure 20.2 shows a different approach in which individual participant data are
p. 342 used to directly derive the needed estimate per study ↳ in the first stage and the resulting estimates are combined in the next stage. The two-stage approach to individual participant data illustrated in Figure 20.2 has been, by far, the most common way individual participant data have been utilized in research synthesis (Simmonds et al., 2005). Although individual participant data are reduced to aggregate data in the first stage, it is still more advantageous than the typical meta-analysis of aggregate data illustrated in Figure

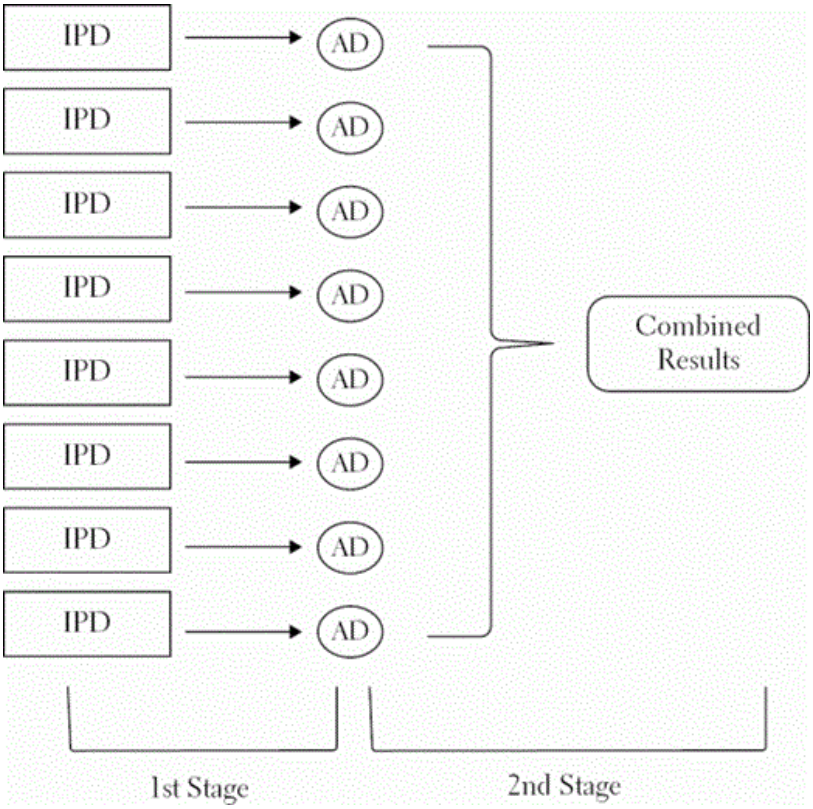
20.1 because researchers can check and correct data and also because estimates can be derived from the same model across studies. More important, this approach can accommodate necessary extensions and adaptations when the number of studies included in research synthesis increases or when more complex models are needed to adequately fit data. For example, the two-stage approach can be extended to multivariate meta-analysis for multiple related parameters (Cheung, 2015; Gasparrini, Armstrong, & Kenward, 2012; Jackson & Riley, 2014; Jackson, Riley, & White, 2011; Jiao, Mun, & Xie, 2017) and to complex synthesis combining both individual participant data and aggregate data (Donegan, Williamson, D'Alessandro, Garner, & Smith, 2013; Riley et al., 2008).

Figure 20.1



Traditional univariate meta-analysis using published data. AD, aggregate data.

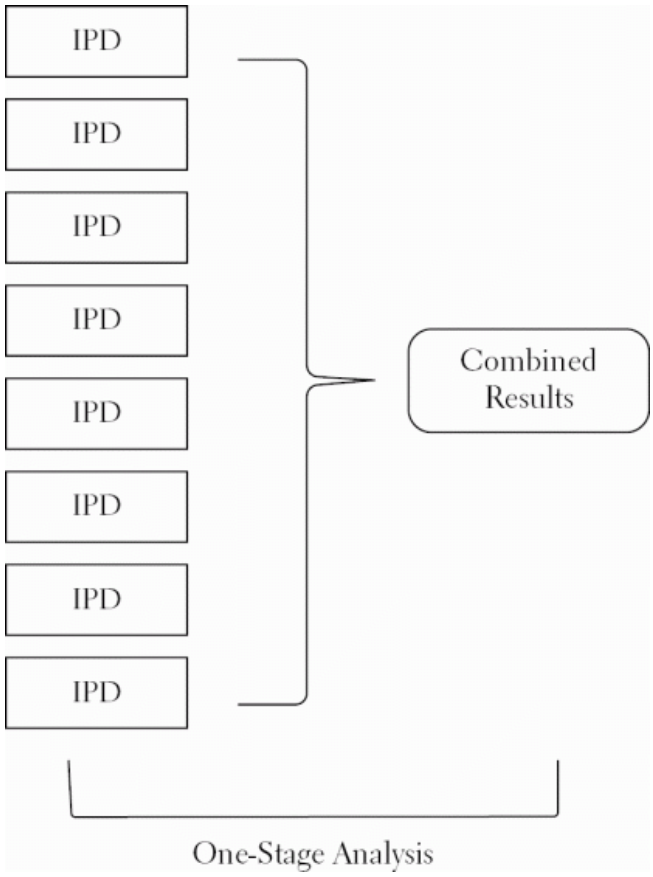
Figure 20.2



Univariate meta-analysis using aggregate data (AD) derived from individual participant data (IPD).

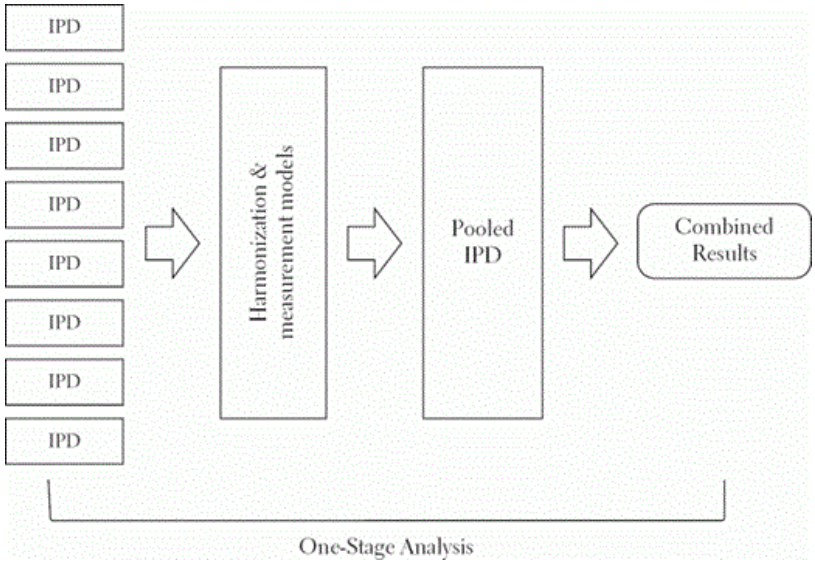
In contrast, Figures 20.3 and 20.4 both show the one-stage approach to individual participant data with one difference. The IDA approach illustrated in Figure 20.3 assumes that outcome measures hold the same
p. 343 interpretation across studies. Certain outcome ↳ measures, such as survival/death, the number of drinks per week, and the percentage of disposable income allocated to drinking, may satisfy this assumption, especially if data were originally collected from sufficiently similar samples and across similar settings. In all other cases, IDA involves prerequisite steps (Figure 20.4) to establish measurement equivalence across studies by harmonizing and linking different measures and using advanced analytical models to derive commensurate trait scores for participants from different studies (for application examples of this IDA approach, see Huh et al., 2015; Hussong et al., 2007).

Figure 20.3



Integrative data analysis using individual participant data (IPD).

Figure 20.4

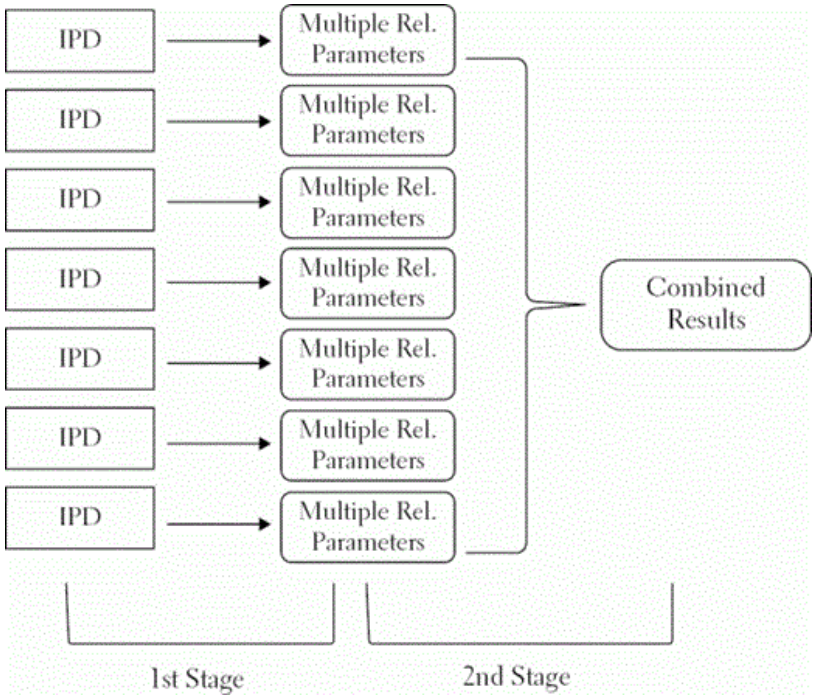


Integrative data analysis using individual participant data (IPD) with an intermediate measurement model.

The broader research synthesis framework presented in this chapter is intended for expanding the utilities of valuable individual participant data from multiple studies so that when one approach is not feasible,

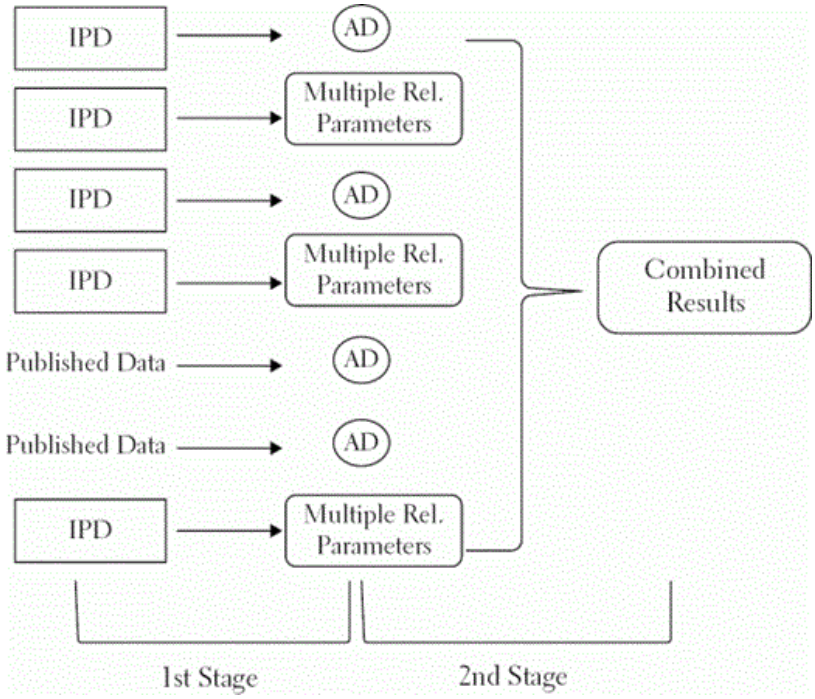
researchers can still proceed with alternative approaches, including the multivariate and mixed-evidence approaches shown in Figures 20.5 and 20.6. In this way, embarking on an IDA study does not necessarily become an "all-or-nothing" proposition. In addition, researchers can make the most out of valuable individual participant data.

Figure 20.5



Multivariate meta-analysis using individual participant data (IPD).

Figure 20.6



Mixed-evidence multivariate meta-analysis using both aggregate data (AD) and individual participant data (IPD).

Major Sources of Heterogeneity Across Different Studies

As shown graphically in Figures 20.3 and 20.4, for IDA to be feasible, there is a need to establish
p. 344 measurement equivalence across different studies ↳ as part of IDA methodologies (Curran et al., 2008). Measurement heterogeneity is an important source of between-study heterogeneity, which needs to be resolved. A number of different methodological approaches have been proposed and studied (Bauer & Hussong, 2009; Curran et al., 2008, 2014; Huo et al., 2015; McArdle, Grimm, Hamagami, Bowles, & Meredith, 2009). However, in addition to dealing with different measures across different studies, there are other challenges associated with between-study heterogeneity. Measurement heterogeneity, although important, represents only one aspect of the populations that vary across studies. In other words, for IDA studies to provide built-in replications and large-scale ↳ robust evidence (Curran & Hussong, 2009), one
p. 345 needs to consider several population boundaries to which inference is made. Cronbach (1982), for example, identified four major domains of populations to which we attempt to draw inference: unit of analysis (U; participants), treatments (T; a targeted effect), outcome measures (O), and settings (S) in which a treatment takes place. These multiple domains of populations suggest that even if outcome measures are comparable for one of the population domains across studies, there are other important sources of heterogeneity across studies that need to be carefully considered or controlled. In addition to the UTOS variations, there are design differences, such as between-study differences in the inclusion of key covariates or timing of follow-up assessments.

Some of the variations (e.g., assessment timing) across studies may be easily accommodated in a model. Others may be more difficult to take into account (e.g., unassessed covariates) or to justify that they merely represent random variations. For example, when individual participant data are combined from multiple studies, study-level missing data can easily result in situations in which no studies have all covariates included in the model to adequately fit data (Jiao et al., 2017). One outcome of study-level missing covariates is that those studies are by default excluded in analysis. This problem becomes more serious as the dimensions of the data analyzed (i.e., number of covariates and studies) increase. However, the need to overcome study-level missing data or other sources of between-study variation has not been thoroughly highlighted in the IDA literature, relative to the attention focused on measures across studies. These complex challenges may help explain the existing gap between the potential utilities and modeling flexibilities of individual participant data (Brown et al., 2013; Sutton & Higgins, 2008) and the actual applications (Simmonds et al., 2005). However, recent methodological advances have been made for complex synthesis methods, especially those utilizing individual participant data in statistics and biostatistics. Accordingly, we can tap into these emerging approaches for the analysis of individual participant data in research synthesis, such as combining the confidence density functions to accommodate study-level missing data under a general likelihood inference framework (Liu, Liu, & Xie, 2015).

Integrative Data Analysis Challenges and Misconceptions

The first step to IDA may be to understand the specific challenges of each IDA study and appropriately
p. 346 address them. Some may think that IDA is a ↳ well-defined analysis with established routines, such as latent curve models, so that its implementation may be similar across IDA studies. There may also be a notion that IDA is a single-entity analytic technique or is essentially a method to establish measurement equivalence. In reality, IDA involves a complex series of steps, including data handling, decision-making, and utilizing available measurement and statistical models to combine and analyze multiple data sets that were independently designed and collected. Accordingly, how IDA should be executed may be different across studies. The major considerations needed for an IDA study in which data are combined from randomized clinical trials would be different from those of a study in which data are combined from longitudinal family studies. Even within the pool of randomized clinical trials, key challenges may be different depending on the specific goals and characteristics of IDA studies. Therefore, IDA studies may require unique solutions because the nature of the specific challenges will likely be different for different studies. Consequently, there can be as many different IDA approaches as the number of IDA studies. In that sense, there are no exact recipes to follow from one IDA study to the next.

Relatedly, the level of expertise and resources required for IDA studies can be equivalent to what is required for launching a new data collection project (Hussong et al., 2013). IDA studies require a wide range of substantive, as well as methodological, expertise and skill sets to successfully implement. Thus, a team

science approach would be generally more appropriate for conducting an IDA study. Project INTEGRATE (Mun, de la Torre, et al., 2015), for example, has experts in the areas of individual-focused brief alcohol interventions for college students, alcohol-related measurement construction, alcohol etiology and prevention across the lifespan, psychometrics, biostatistics, and theoretical and mathematical statistics. Although Project INTEGRATE is the largest IDA study in alcohol research to date and, hence, the needed range of expertise may have been greater than usual, our experience suggests that a wide range of expertise is generally necessary to successfully navigate an IDA study.

IDA is sometimes referred to as secondary data analysis of existing data. In the sense that de-identified data from individual studies are combined, IDA does not involve any direct contacts with human subjects. Consequently, IDA does not pose any additional risks to human subjects. Beyond that, however, IDA digresses from secondary data analysis. The notion that IDA is "secondary data analysis" obscures the fact that IDA is a major undertaking. In an IDA study, all key aspects of studies should be examined, both individually and in connection with other studies, to be able to integrate and synthesize data across studies. This process can be quite arduous—a fact that may be lost when labeled as secondary data analysis.

In addition, there is a limit to the principle that increased heterogeneity in participant samples, measures, settings, and study designs via pooling data from multiple sources is an asset. Individual studies included in research synthesis should be "sufficiently similar" to be combined. In other words, there is an underlying assumption that studies should not be meaningfully different from one another and should have sufficient overlap. That is, important key covariates should be similarly distributed and have similar meanings across studies. This is the "similarity assumption" in network meta-analysis or meta-regression (Jansen et al., 2011). For example, if a treatment modifier (a moderator) exists, this modifier should not be confounded with the effect under investigation.

In larger IDA studies, heterogeneity in effect size estimates may be better quantified and subsequently examined. However, in small IDA studies, variability or heterogeneity in estimates may be more difficult to probe, even if they can be detected. Therefore, it is important to be aware that heterogeneous studies cannot be pooled without careful considerations and that sufficiently similar studies should be combined based on the predefined inclusion criteria. This recommendation is quite typical for meta-analysis and also applicable for IDA.

Between-Study Heterogeneity and the Underlying Assumptions of Meta-Analysis Models

As briefly discussed previously, there is a need to differentiate between-study heterogeneity that improves diversity and broadens population representation from heterogeneity that diminishes the validity of combining data from different studies (for further discussion on between-study heterogeneity, see Mun, Atkins, & Walters, 2015; Mun, Jiao, & Xie, 2016). When combining data across multiple studies, we typically use a random effects meta-analysis model. The random effects meta-analysis model assumes that there are study-specific effect sizes drawn from a superpopulation with a common true effect and between-study variability surrounding the common effect size. Therefore, the variability surrounding effect sizes can be decomposed to within-study and between-study variability. In a fixed effect meta-analysis model, in contrast, all studies are assumed to have the same true effect size and hence no between-study variability. The assumptions involved in the random effects meta-analysis model are more reasonable than those in the fixed effects meta-analysis model, although these assumptions are difficult to check in reality (Mun et al., 2016; see also Normand, 1999).

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Increased heterogeneity by pooling data from multiple studies improves population representation only if it can reasonably be assumed that all the study-specific effects included in analysis are related and stem from the same underlying superpopulation. If this assumption is reasonable, within-study and between-study variability can be quantified and accordingly attributed to observed and unobserved factors at the participant and study level. However, if this assumption is unreasonable, combining data from heterogeneous studies would be like mixing apples, berries, and melons when attempting to make an apple pie. Using the same analogy, apple pies can be made using different apple varieties but using more or less the same recipe (i.e., generalizable and robust). In reality, however, the underlying assumption is difficult to verify. Therefore, any research synthesis project should have clear research goals and prespecified inclusion criteria. Following screening, one needs to select eligible studies that can be broadly representative. The

population representativeness issue has been raised before (Curran & Hussong, 2009, p. 88), and we have faced these questions when publishing studies from Project INTEGRATE (Mun, de la Torre, et al., 2015). Because of the limited availability of individual participant data in the psychological literature, IDA studies tend to have convenience samples. With more individual participant data expected to become accessible and searchable in the future, there is a greater need to justify the inclusion criteria and sampling of eligible studies for IDA and to characterize how the pooled sample can be viewed in relation to broader populations.

In terms of achieving population representation as well as examining potential subgroups, note that a larger IDA study is needed. It is difficult to derive a rule of thumb about the number of studies. Nonetheless, 5 or fewer studies may be considered too small (Borenstein, Hedges, Higgins, & Rothstein, 2009, p. 163). Some investigators have indicated that at least 10 or 20 studies may be needed (Hussong et al., 2013, p. 68). Also note that the level of difficulty increases considerably as the number of studies to be combined increases, especially for a one-stage simultaneous analysis of individual participant data. However, if individual studies are conducted in a highly standardized manner, it may be possible to combine data from just a few studies to determine how strong the effect of interest is in its magnitude and how consistent it is across studies.

Tackling Other Sources of Between-Study Heterogeneity

Similar to other well-known analyses, such as analysis of covariance or regression analysis, it is important to identify the sources of variability in data and reduce their influence when conducting IDA with individual participant data. One of the sources in intervention and prevention research may stem from different intervention groups sharing the same brand names across studies or, alternatively, from similar intervention groups holding different labels. Namely, intervention groups may not be equivalent across different studies despite similar labels.

For example, Project INTEGRATE (Mun, de la Torre, et al., 2015) obtained all intervention materials from individual studies (for descriptions of coding, see Ray et al., 2014). There were a total of 67 groups across 24 studies. These groups were created by crossing sample characteristics (e.g., volunteer vs. mandated within studies) with intervention conditions (e.g., feedback intervention vs. control). There were a total of 12 control groups across studies. We examined a total of seven intervention coding variables that had some variability across studies for principal component analysis (PCA). These variables were as follows:

1. The total number of content areas covered
2. The level of personalization of the content
3. Whether the intervention was delivered in person
4. Whether a personalized feedback profile was given

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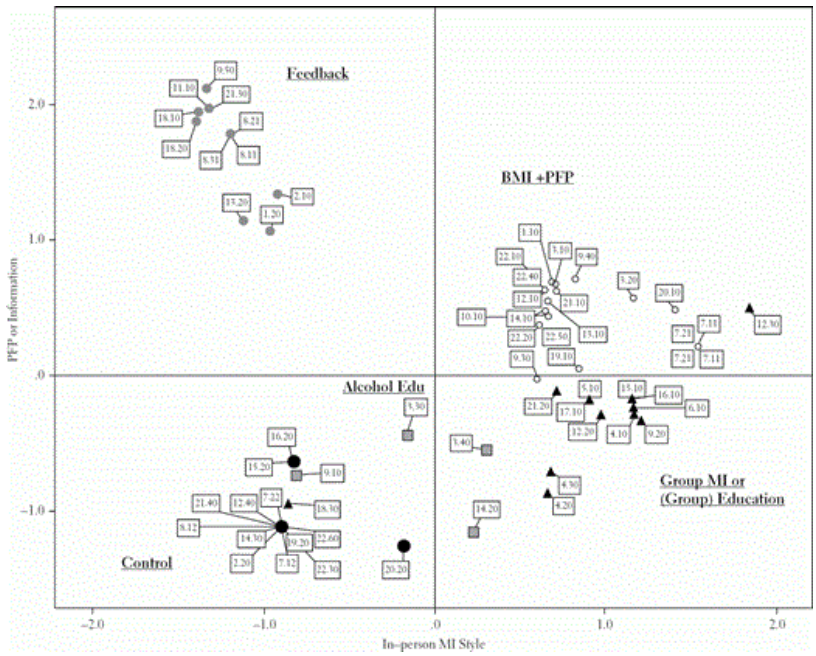
5. ↳ Whether motivational interviewing was incorporated
6. The number of intervention sessions
7. The duration of the total sessions in minutes

These variables were chosen because they represented important substantive distinctions but also because their values showed variability across studies. For example, whether interventions included content about alcohol use would not be a good variable to consider (and impossible to include in any analysis) because no variability existed among interventions.

PCA results indicated that two principal components explained 83% of the total variance. We utilized a varimax rotation method for better interpretation. Based on the PCA result, we discussed the nature of one group (18.30 in Figure 20.7) that was originally labeled "Education" but was subsequently relabeled as a control. In addition, group 9.10 was originally labeled as "Alcohol Edu," which is generally regarded as an education condition. However, there are many different versions of this intervention because it has been updated over time. Upon further discussion, we obtained the closest version available to the one given to participants at the time of intervention and recoded its content. The number of content areas covered was subsequently changed from 7 to 13. The reanalysis result was largely the same (not shown); the position of

the Alcohol Edu on the y-axis moved up but remained below zero. Overall, the results showed that there were different degrees of similarity among interventions sharing the same name. For example, the group Education appears to be more heterogeneous than other intervention groups. In contrast, brief alcohol interventions utilizing an in-person motivational interviewing style combined with normative feedback
p. 349 were quite similar to one another. The purpose of reviewing this analysis is to show that intervention ↳ characteristics and modalities can be dismantled and numerically coded. Any irregularities can then be brought to attention for necessary follow-up actions. Furthermore, one can assess the extent of heterogeneity within similar interventions and across different types of interventions.

Figure 20.7



Intervention groups examined (and subsequently re-evaluated). MI, motivational interviewing. BMI, Brief motivational intervention. PFP, Personalized feedback profile.

Promise of Individual Participant Data in Quantitative Research Synthesis

Despite the noted complexities of pooling and analyzing individual participant data in research synthesis, it remains an important lure that we can better examine subgroups using individual participant data (Borenstein & Higgins, 2013). The lack of consistency of the overall (combined) estimate across studies, which suggests the presence of subgroups, is just as important as the estimate itself in research synthesis. In the context of interventions, these subgroups can indicate that intervention/treatment effect modifiers or moderators exist, which widely encompass different types of interventions, delivery settings, participant characteristics (high-risk vs. low-risk drinkers), and post-intervention responses (immediate response, sustained benefits, sleeper effects, etc.). Although some of these potential modifiers (e.g., study-level variables such as intervention modality) can be examined in an analysis using study-level aggregate data, it is much more advantageous to analyze individual participant data when the effect in question may vary across individual-level variables. In addition, inference from individual participant data analysis is less susceptible to ecological bias compared to that from the analysis of aggregate data. Ecological bias or fallacy refers to incorrectly drawing inference about a phenomenon at the lower level from the analysis with the higher level data structure (e.g., inference about within-person change made from between-individual data).

Furthermore, the analysis of individual participant data allows better modeling flexibility. Whereas the analysis of aggregate data has a well-established set of analytic techniques, for analytical models, there are no limits as to how individual participant data can be analyzed. In addition to testing whether an overall effect exists and whether the effect differs across studies in subsequent subgroup analysis, discovery-oriented investigations are possible because individual participant data from multiple sources represent a larger and more diverse sample than those from single studies. This modeling flexibility encompasses the capacity to use more advanced techniques to address questions previously unanswered or to address new

questions, better tackle or reduce methodological and clinical heterogeneity across studies, and benefit from greater power when examining subgroups.

In line with modeling flexibility, another important benefit of obtaining individual participant data is that more advanced research synthesis approaches are possible. For example, multivariate meta-analysis is feasible with individual participant data. Multivariate meta-analysis (Jackson et al., 2011) is a method that combines related data, such as multiple related outcomes (also called multiple endpoints; e.g., any survival and disease-specific survival, and heavy drinking and alcohol-related consequences) and multiple related interventions (e.g., multiple competing interventions in a trial). This approach borrows strength from within-study correlations, which reduces standard errors of overall effect estimates (increased precision) and mean-square error (between-study variance; for a simulation study, see Riley, 2009), thus resulting in more desirable estimates. It is possible to conduct multivariate meta-analysis using aggregate data, as long as the correlations between related conditions are known. However, they are typically unreported in published studies and are subsequently more difficult to obtain. In contrast, with individual participant data, any necessary information can be derived directly from the data in the first stage and then combined in the second stage for multivariate meta-analysis.

The modeling flexibility of individual participant data also applies when included studies in IDA provide limited overlap in measures, participants, observed time periods, and any other design aspects, which renders IDA not feasible. The principle of chaining or linking across studies is based on the availability of sufficient overlap across sufficiently similar studies. Whether sufficient overlap exists across studies can be difficult to ascertain prior to embarking on an IDA study because necessary information is not always available based on published studies alone. When individual studies cannot reasonably be linked, however, one can still check and correct data and derive equivalent estimates from each study and also combine the resulting estimates across studies for their overall magnitude and consistency.

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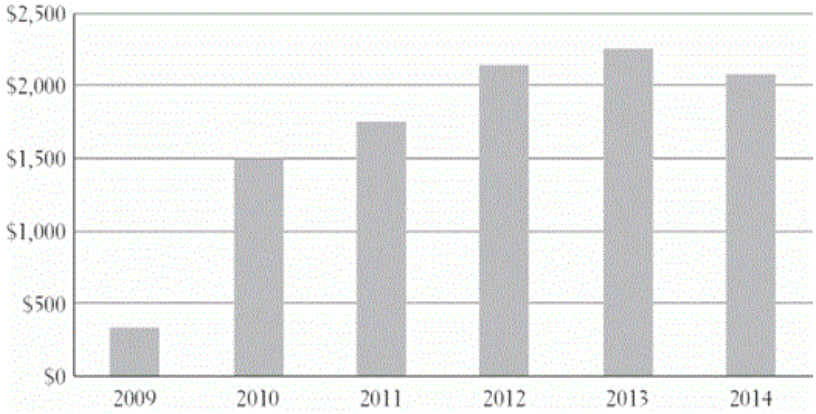
In addition, rare adverse effects or infrequent behaviors can be better examined by using individual participant data. Infrequent low base-rate behaviors tend to be unreported in individual studies. Thus, when collecting individual participant data from individual studies, individual participant data provide unique opportunities to reasonably approach these understudied behaviors. Even when no available statistical procedures are available, a rarely observed behavior or no such behavior from a sample of 10,000 carries a different meaning than that from a sample of 500. Even for relatively more frequent behaviors, when the extent or severity of these behaviors provides additional substantive implications, a large-scale data set would provide an opportunity to test the robustness of the results from existing studies in the literature.

Conclusions and Future Directions

The current discussion on IDA is timely because the number of funded IDA studies from the National Institute on Alcohol Abuse and Alcoholism (NIAAA), the National Institute on Drug Abuse (NIDA), and the National Institute of Mental Health (NIMH) has steadily increased each year for the past 5 years (Figure 20.8) (National Institutes of Health, 2015), but IDA as a method is relatively novel in the psychology literature. The understanding that individual participant data can be utilized in several ways can save one from labor-intensive, unsuccessful efforts to analyze individual participant data in a one-stage analysis by taking alternative routes when they are called for. The current chapter highlights various approaches to individual participant data in the context of a more unified research synthesis framework. Depending on the purpose of research and features of individual participant data at hand, the most appropriate approaches can be selected to provide large-scale evidence for more robust inference. IDA is quite challenging but has the potential to facilitate new discoveries, strengthen large-scale inference, and shore up current research practice.

Figure 20.8



Total funding for IDA studies. Cumulatively, a total of 42 projects were funded by NIAAA, NIDA, and NIMH for fiscal years 2009 through 2014. Y-axis dollars are in thousands. Search keywords = "integrative data analysis" or "a multi-sample analysis."

Despite the noted challenges in this chapter, IDA is very promising given the current research environment. First, the current research environment increasingly emphasizes data sharing and collaboration for faster access to clinical findings. For example, the 21st Century Cures Act enacted into law in 2016 is intended to speed up access to clinical data and promote data sharing. Similarly, the Precision Medicine Initiative announced by President Obama during the 2015 State of the Union Address has been shaped by the availability of large-scale data and computing innovation to enable individualized treatment strategies (Collins & Varmus, 2015). A better understanding of what works for whom, under what circumstances, and how is a necessary condition for developing individualized treatment strategies, which can be fulfilled by large-scale IDA investigations. Second, the scientific community has increasingly been concerned about improving reproducibility or replicability (Collins & Tabak, 2014). IDA or research synthesis approaches are aimed at meeting both of these demands.

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Given the promise of IDA, it seems critical to develop some reporting guidelines to ensure the growth of IDA as a method in the field. There is a new guideline for a systematic review and meta-analysis of individual participant data (Stewart et al., 2015) based on the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA; Moher et al., 2009) of randomized controlled trials. This guideline can be extended or adapted for other types of IDA investigations. Similarly, there is a need to discuss what should be reported in IDA studies to improve transparency of such studies and to evaluate the quality of evidence resulting from IDA studies. Given the flexibility of this approach and potentially far-reaching applications, it may not be easy to establish specific standards. Nonetheless, this is necessary so that the field can develop consensus about how IDA investigations may be best reported.

Based on the discussion in this chapter, we may start by including the keywords *IDA (meta-analysis)* and *individual participant data* in the title or abstract of studies that utilize IDA for better identification and discoverability. This can be followed by a description about research goals, inclusion criteria, search and selection of eligible studies, and the representation of the combined sample in relation to broader populations. In addition, the measurement approach and missing data should be explained in sufficient detail. Also, it is recommended to include a description of how individual participant data from studies were combined, namely how between-study differences were examined and incorporated in analytical models. Finally, any challenges or issues should be clearly discussed. With continued discussions about how IDA may be best utilized to answer new questions and improve our research practice, methodological innovation is likely to follow to meet new challenges in the field.

IDA is a promising new research direction that will be called upon more frequently in the existing research environment (Hussong et al., 2013). The integration of IDA methodologies into the broader research synthesis framework may spur a wide range of new IDA investigations in the addiction field, as well as new methodological advances needed for addiction research. To maximally benefit from this approach, it is important that investigators who seek to conduct an IDA study understand that it is not a one-size-fits-all methodology. Accordingly, decisions regarding how to apply IDA to a given research question should take into account the considerations outlined in this chapter.

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