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MODEL-DRIVEN META-ANALYSES FOR INFORMING HEALTH CARE: A DIABETES META-ANALYSIS AS AN EXEMPLAR

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Abstract

A relatively novel type of meta-analysis, a model-driven meta-analysis, involves the quantitative synthesis of descriptive, correlational data and is useful for identifying key predictors of health outcomes and informing clinical guidelines. Few such meta-analyses have been conducted and thus, large bodies of research remain unsynthesized and uninterpreted for application in health care. We describe the unique challenges of conducting a model-driven meta-analysis, focusing primarily on issues related to locating a sample of published and unpublished primary studies, extracting and verifying descriptive and correlational data, and conducting analyses. A current meta-analysis of the research on predictors of key health outcomes in diabetes is used to illustrate our main points.

Keywords

meta-analysis; type 2 diabetes; model testing

A common type of meta-analysis reported in the literature involves comparisons of medical or health treatments in order to inform future research and clinical care. Such reviews typically take the form of syntheses of randomized clinical trials (RCTs) or may on occasion include studies that employ other types of research designs, such as quasi-experiments or one-group pretest-posttest studies. A less common type of meta-analysis, particularly in the

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health sciences, involves synthesis of correlational studies and draws on postulated theories or models of how key variables relate to each other to guide the review. Such model-driven meta-analyses can be useful in identifying key predictor variables of health outcomes, as well as in discovering critical gaps in the research. Because so few model-testing meta-analyses have been conducted, large bodies of complex health-related correlational research remain unsynthesized and uninterpreted for application in clinical practice and decision-making.

Here we describe the methods for conducting a model-driven meta-analysis, using a current NIH-funded diabetes meta-analysis as an illustrative example. The primary focus of this paper is on the unique methods and challenges – in the literature search, variable coding, and data analyses — that differentiate a model-driven meta-analysis from a more traditional meta-analysis. Meta-analyses, including those involving model testing, are complex studies and very time consuming when correctly designed as comprehensive reviews of all the relevant literature, both published and unpublished. By synthesizing correlational data, researchers and clinicians can target key variables for intervention to enhance clinical outcomes. Also we can identify relationships in need of further study (Becker, 2009), and sometimes test sets of relationships never examined by primary researchers.

AN ILLUSTRATIVE EXAMPLE: PREDICTORS OF DIABETES OUTCOMES

Brief overview of the meta-analytic study

We are conducting a model-driven meta-analytic synthesis of the published and unpublished diabetes research on specific psychological, motivational, and knowledge correlates/predictors of weight loss, metabolic control, and quality of life. We treat lifestyle behaviors, such as adherence to diet and physical activity recommendations, as mediators. The model shown in Figure 1 depicts the proposed relationships among the variables of interest and has guided the literature searches, data coding, and statistical analyses. Variables included in the model are posited in the literature to affect health outcomes (Peyrot & Rubin, 2007). [Note that the unshaded boxes in Figure 1 contain variables of interest in this meta-analytic study. Variables in the three shaded boxes were examined previously in meta-analyses conducted by the first author and are not the targets of investigation in the study reported here (Brown, 1988, 1992).] A previous pilot meta-analysis (Brown & Hedges, 1994) involving a limited set of these variables showed us that a model-driven meta-analysis was feasible in this area. That is, a good number of studies using comparable measures of key constructs had examined the relationships in our model. Testable models and path coefficients from that initial study are shown in Figure 2.

The current meta-analysis will examine a more comprehensive model. Separate models will be analyzed for each of the main factors, such as Psychological Factors. First, each will be treated as a composite variable with results averaged across all studies that measure any one of its components. Then, we will examine each component (e.g., stress, anxiety, etc.). The same composite and individual analyses will be conducted for the Motivational and Behavioral Factors. Separate models will be tested for each of the outcomes of interest: body weight, metabolic control (glycosylated hemoglobin [A1C], fasting blood glucose [FBG]), and quality of life. The analytic approach we are using is iterative and the models are revised

based on the results of each analytic step. If possible, following examination of these separate models, we will create a coherent model across the factors, by synthesizing studies that cover more than one of the key important components. However, as will be discussed below, it may not be possible to examine one single over-arching model because of the patterns of missing data (and unstudied relationships) among our variables.

Literature search strategies

Locating and selecting studies for inclusion in a model-driven synthesis are more difficult and time-consuming than in traditional meta-analyses of intervention effects. The choice of a model or models for the meta-analysis is important, as the model delineates the variables to be included in the review and thus drives the literature search. A model-driven meta-analysis may be based on a particular proposed theoretical model, or can examine a model that is created by the reviewer specifically to frame the review. By choosing an initial model that is similar to others already investigated, the reviewer can be more assured of finding studies that will be suitable for the review. However, the choice need not be limited to specific existing models.

The usual rigorous literature search strategies should be used to locate relevant published and unpublished data. These include conducting online database searches, hand searching journals and reference lists of relevant articles/research reports (ancestry searching), searching diabetes registries and conference abstracts, and contacting known diabetes researchers for leads to unpublished studies. Search terms must include some or all of the names of the variables or constructs in the model, as well as information to identify the population of interest (e.g., adult patients with type 2 diabetes [T2DM]). However, it would be quite restrictive to require that every study have examined all target constructs. For example, Whiteside and Becker's (2000) synthesis of studies of child outcomes in divorcing families required that every study examine either the quality of interaction between the (divorced) parents, or the degree of father-child interaction.

For a model-driven meta-analysis, clues to the data analysis methods and results of each primary study may not be obvious in the study title or abstract. Once titles of potential reports are identified, abstracts and often the full texts need to be reviewed in detail to determine actual relevance and availability of the data. Whether to include each study in the model-driven synthesis is determined largely by the types of data analyses that were conducted. Sometimes the correlational data that are targeted for the meta-analysis are secondary to the initial aim of the primary study and may be embedded in the narrative of the research report. In other cases studies may have examined relationships of interest, but may have used more sophisticated analytic techniques such as multiple regression or structural equation modeling. Sometimes such studies do not include simple correlations in their reports. Depending on what statistics are reported it may be possible to compute measures of association for use in the synthesis. For example, when authors only report a significance level, the use of available online calculators enable meta-analysts to convert such data into a correlation/effect size. However, in other cases studies may need to be omitted because the variables of interest are bundled or the relationship is affected by covariates. For example, in this meta-analysis we were interested in relationships between

certain health beliefs (e.g., commitment, barriers, social support, benefits, expectations, etc.) and diabetes outcomes but some primary authors reported data as a “health belief composite.” In such studies all health beliefs were combined into one score, thus limiting the utility of the meta-analytic findings and confounding the conceptual meaning of the results. Research is ongoing on methods for including more complex studies into meta-analyses (Aloe & Becker, 2012). For the diabetes model-driven meta-analysis, we screened ~35,000 potentially relevant studies and 739 studies of 775 independent samples met the inclusion criteria. However, the maximum number of studies examining any one relationship in the model is 116.

Once a set of potentially relevant studies is located, typical inter-rater agreement strategies for selecting studies are employed. Each study is reviewed three times: (a) screening by two independent raters determines if the study on face value seems relevant; (b) the bibliography of each research report is reviewed to locate additional relevant studies; and (c) inclusion criteria are applied to individual primary studies. Regardless of the initial inter-rater agreement, disagreements in applying the criteria are discussed among the coders in an attempt to reach consensus; the principal investigator arbitrates any remaining disagreements (Brown et al., 2013; Brown, Upchurch, Anding, Winter, & Ramírez, 1996).

Coding procedures

A typical code sheet and codebook are developed for a model-driven meta-analysis. Our research team has used a formalized process for developing code sheets in three previous meta-analytic studies; this was described in a 2003 publication (Brown, Upchurch, & Acton). Generally, our code sheets contained four basic categories of variables: (a) methodological and substantive features; (b) study quality; (c) reliability of the measures; and (d) outcome data. Some methodological and substantive features are important variables to code in every research synthesis. Source of the study, year of publication, type of research design, and characteristics of the authors/investigators (e.g., author’s discipline) are all included to describe the literature and so that our analyses can relate these characteristics to study findings. If available, the reliabilities of the measures used in each primary study can be incorporated into secondary analyses to determine if differences in results vary by the instrument used and its stability. Alternately, corrections for attenuation due to unreliability can be applied, as is common in the validity generalization literature (e.g., Hunter & Schmidt, 2004). Research quality measures also are integrated into the study coding form (Brown, 1990, 1991; Verhagen et al., 1998; Sackett & Haynes, 1976); eventually our model will be evaluated for studies of higher quality and studies of lower quality.

For the model-testing meta-analysis, a main challenge is to develop a data extraction form that enables researchers to code correlation coefficients reflecting every possible association between variables in the model. For an extensive model, development and formatting of such a comprehensive data extraction form can be difficult and time-consuming. The form itself can be many pages long, either on paper or in terms of computer page views. We designed a PDF code sheet with individual data fields that interface with an Excel data management spreadsheet in order to facilitate data entry, particularly to enhance data accuracy (Brown et al., 2013).

In some instances, correlational data are not provided in the original research report; in such cases we have calculated correlations from other types of associational data (e.g., odds ratios) whenever possible. However, this task is not a simple matter either, because the form of the reported results may compromise our ability to obtain commensurate effect measures across studies. For example, while transformations exist for some simpler indices, if a primary study has reported path coefficients among variables of interest, they represent partial effects, not bivariate effects like Pearson's correlations, thus cannot be directly transformed to the r metric. The more strongly other variables in the model correlate with the variables we wish to study, the more such partial coefficients deviate from simple zero-order correlations (Aloe & Becker, 2012). We have tracked our calculated correlations for future analyses in which we will compare results reported as correlations by the authors of the primary studies to those calculated by us from other author-provided data.

A major challenge in this model-driven study, which involved a number of psychosocial variables, related to determining if the measures reported in primary studies fit the model we used to guide this meta-analysis. This can be difficult in any meta-analysis, especially when psychosocial variables are included as outcome measures. We employed a number of strategies to validate the decisions made regarding variable definitions and inclusion. First, we examined the literature extensively for definitions of each variable in the model and included these definitions in the study codebook that accompanied the code sheet. Second, at meetings of the research team, particularly during the initial training phase of the study, we discussed the definitions and made decisions regarding the inclusion and coding of variables. Third, we established a decision log that was available to research team members on the study website. The decision log contained decisions about variable inclusion and was modified whenever necessary to reflect the most specific guidance possible for coding variables. For example, the following described the decision we made when we found more than two measures of the same variable, such as when researchers use two measures of depression, e.g., the CES-D and the Beck:

Choice of Instrument:

1. If more than one instrument is used to measure a variable, choose the instrument that is most conceptually in alignment with the model.
2. If both instruments are conceptually equally in line with the model, choose the one with the highest reliability.

Finally, coding by two independent coders also contributed to the consistency of the decisions that were made. Disagreements were arbitrated at research team meetings.

Data analysis

Analysis overview—Correlations between each pair of variables in the model are summarized by computing an overall average correlation and conducting a test of homogeneity across studies (Hedges & Olkin, 1985). Combined matrices are created where possible, and from those we can either test individual relationships for significance, or estimate combined linear models that reflect moderators and mediating variables as shown in the models depicted in our figures. We describe each data-analysis step in detail below.

The multivariate nature of model-driven meta-analysis—Most conventional meta-analyses are univariate procedures, in the sense that only one effect size is computed per study. However, model-driven meta-analyses are inherently multivariate because of the many relationships (many different correlations) that are of interest. When several correlations (several effects) are obtained from each study, they are not independent of one another. This makes the analysis more complicated because any analysis used to combine studies must take into account the statistical dependence of the set of correlations obtained from each study. Several approaches for modeling such dependence are available (Becker, 1992b; Cheung & Chan, 2005; Prevost, Mason, Griffin, Kinmonth, Sutton, & Spiegelhalter, 2007).

Second, the structure of the multivariate data in a model-driven meta-analysis is almost always incomplete. It is likely that no one study will provide a complete set of data for all variables of interest, so “pieces” of data are extracted from various studies to create the data set for the path models. In our synthesis we targeted 30 variables subsumed under the six main components of our model. A complete 30×30 correlation matrix includes 435 unique relationships. However, the maximum number of correlations reported by any one study in our data set was 52, and most studies (509 or 66%) had five or fewer r values.

Missing data may result from incomplete reporting of data by authors of the primary studies, thus limiting the usefulness of those studies for the meta-analysis. For example, an author may report a correlation between two variables in the model that we propose to test, but the authors may not report the sample size. Also, authors commonly report correlations of sets of predictors with an outcome, but not with each other. For example, our data include 182 correlations of either stress or depression with A1C levels, but only 48 correlations of stress with depression. More problematically, researchers sometimes report only significant correlations, leading to publication bias. In these cases, we contact the study authors to obtain the needed data. We have used this approach in previous meta-analyses. The key to successfully obtaining a response from authors is to be as specific as possible about the request so as to minimize the effort required by the author to address the request.

Correlations may also be “missing” because a given author has simply not studied one or more of the target variables in a model. For example, even though readiness for change is one of the motivational factors listed in our model, few articles had examined it. We found only four correlations of this variable with psychological factors, and only 13 with ensuing behavioral factors such as diet and medication adherence. Other less-studied variables in our model include the health-belief components of commitment and job impact, as well as the tendency to keep appointments with health care providers. While less-studied variables create difficulties in data analysis, omitted variables are less likely to lead to bias in a specific direction than are censored results. In addition, although missing correlations are not desirable, they provide information about where our knowledge is weak, thus suggesting areas for further study.

When one begins a model-driven synthesis with a particular model in mind, it is possible that a particular relationship has not been examined in any of the collected studies. In such cases some models simply cannot be estimated. For example, none of our studies has

reported a correlation between anxiety and a composite health beliefs measure. Thus, we cannot include a path between these two variables in our analyses. To make the most of our data we will construct several simpler models without all possible components or paths of interest.

Combining and analyzing correlational effects—The general statistical theory required for combining correlations across studies to estimate a common correlation matrix under both fixed- and random-effects models is known (Becker, 1992b). Several statistical analysis programs, such as SAS, SPSS, and R, use programming languages that incorporate complex matrix operations, such as the ones needed for multivariate random-effects meta-analyses. Also, packages for structural equation modeling, such as Mplus and LISREL, allow for this complex modeling process. We use these programs to: (a) implement fixed-effects estimation of the common correlation matrix from several studies, (b) test for heterogeneity of these same correlation matrices, (c) estimate the between-studies covariance components matrix, and (d) estimate random-effects estimates of the common correlation matrix. These results can then be used to obtain either fixed- or random-effects estimates of the path coefficients of the predictive model, their associated standard errors, and significance tests. Modifications to the computing algorithms described by Becker and Schram (1994) permit estimation when some studies do not provide estimates of every correlation of interest, so that analyses can be performed even when some studies provide incomplete data.

Correlation matrix estimation and homogeneity testing—One of the first steps in model-testing data analysis is to use the correlation matrix fragments extracted from each study to estimate a pooled correlation matrix among variables in the predictive model. Homogeneity testing procedures (Becker, 1992b; Becker & Schram, 1994) can determine whether the correlation matrix fragments from different studies are consistent enough to warrant the assumption that all of the studies are estimating the same underlying correlation matrix. If the data are found to be entirely homogeneous across studies, the correlation matrices will be combined using fixed-effects methods (Hedges & Vevea, 1998) and the path coefficients of the model (and their standard errors and associated significance tests) can be computed by fixed-effects methods. Virtually all modern approaches to meta-analysis involve inverse-variance weighting (Cooper, Hedges, & Valentine, 2009). The specific weights used depend on what model is adopted for the study outcomes. Under fixed-effects models the weights account only for sampling variation.

In the more likely event that correlation matrices are *not* found to be homogeneous across studies, an overall estimate of the average correlation can be obtained using random-effects methods. Under random-effects assumptions, effect-size estimates from different studies can differ because of sampling error of the estimates about the true effect parameter in the study, or because of between-study variation in the parameter itself. In random-effects analyses, between-studies variation in correlations that cannot be explained by study features is treated as random and estimated, then added to the uncertainty of the meta-analytic findings.

The statistical procedures for random-effects modeling in model-driven meta-analysis are somewhat more complex than in conventional meta-analyses (Becker, 2009). Conventional

(univariate) random-effects analysis estimates the amount of between-studies variation in one set of effect parameters (the between-studies variance component for say, one correlation or relationship). However, a model-based meta-analysis examines many relationships and effect parameters and ideally would estimate not only sampling variances, but also within-study covariances. The same applies to between-studies variation: multivariate random-effects analysis must estimate not only the variation of each correlation parameter across studies, but also the covariation of each pair of parameters (the between-study covariance components). These variance and covariance components are then used in the multivariate random-effects procedure for combining correlations across studies. This analysis produces a combined correlation matrix and a variance-covariance matrix expressing the uncertainty of the correlation matrix. These results in turn allow us to estimate path coefficients for the predictive model and their standard errors, which are used in significance tests (Becker & Schram, 1994).

Standard procedures for studying heterogeneity can help determine whether the observed heterogeneity is a consequence of systematic differences between identifiable types or subsets of studies, or is the result of one or a few outliers. Such procedures include regression or analysis of variance analogues in meta-analysis to identify the relation between a priori study characteristics and correlations between specific variables, or the use of residuals to identify outliers (Hedges & Olkin, 1985). Alternately multi-group structural equation modeling (SEM) analyses can be applied along with their associated tests of fit (Cheung & Chan, 2005).

If relatively simple and substantively meaningful patterns of study characteristics appear to explain heterogeneity across studies, then the predictive model is examined conditionally upon various patterns of study characteristics, if the data permit. Similarly, if outliers appear to be responsible for heterogeneity, analyses both with and without outliers can help to determine if those effects have a substantively important impact on results of the meta-analysis. If correlations exhibit statistically reliable heterogeneity across studies, but some of the heterogeneity is unrelated to coded study characteristics, the data are analyzed via a random-effects modeling procedure (Hedges, 1994), also sometimes called mixed-effects modeling.

We typically analyze the data based on characteristics of the study (e.g., research design, publication status) and sample (e.g., age, gender, race/ethnicity) to determine whether the pattern of relationships varies across groups. Using race/ethnicity as an example, we code the minority group, or the percentage of the sample that represents each racial/ethnic group, for each primary study. Correlations among relevant variables measured only on individuals in each racial/ethnic subgroup can be combined to estimate a common correlation matrix for each of the subgroups and its between-studies variance and covariance components. These data are used to estimate path coefficients and their standard errors for each group-specific model.

For example, one model might be estimated using data from only Hispanic/Latino subjects and another model is estimated using only data of African-American subjects. To illustrate, let b_H represent a particular path coefficient (e.g., the coefficient relating weight loss to

metabolic control while controlling for adherence) and let SE_H represent its standard error for Hispanic/Latino subjects. Similarly, let b_A and SE_A be the corresponding coefficient and standard error for African-American subjects. Then, to test whether the corresponding path coefficients differ for the different racial/ethnic groups, we can compute a test statistic z , which has a standard normal distribution when the two path coefficients are the same. If the absolute value of z exceeds 1.96, two path coefficients are significantly different at the $p=.05$ level of significance. Comparisons among other subgroups (e.g., male/female) are carried out in the same way. More complex tests for equality of several path coefficients at once can also be done (Becker & Schram, 1994).

Partial, indirect and mediating effects—Another feature that distinguishes model-driven meta-analyses is that partial effects are estimated. That is, when one estimates coefficients for any paths where multiple other predictors contribute to an outcome, the effects are no longer bivariate. By so doing, the meta-analyst can examine the impact of controlling for several variables at once, and also can evaluate indirect effects and mediator effects when a larger model is considered.

For instance, in our pilot meta-analysis models shown in Figure 2, correlation coefficients computed across studies ranged from $r = .086$ to $r = .350$. Patient compliance appears as a potential mediator of the effects of knowledge, health belief composite variable, and four selected individual health beliefs, e.g., support, expectancies, commitment, and barriers, on outcomes. The results in Figure 2 must be interpreted cautiously because this was a pilot study that included a limited number of published studies located through a preliminary literature search; thus the need to conduct the more comprehensive and systematic study described here. In our newer expanded model, knowledge itself is viewed as a mediator, along with compliance (called adherence in Figure 1). We can add and remove different variable to assess their impact on key path coefficients, and also can test for the fit of competing models, as in traditional structural equation modeling (Kaplan, 2000). Becker (2009) provides a more detailed discussion of these features of model-driven meta-analysis.

DISCUSSION

In this model-driven meta-analysis, we hope to identify those factors that predict the best diabetes outcomes. Our belief is that "...meta-analysis results (...properly derived) have a certain robustness that makes them especially attractive as a basis for policy, practice guidelines, and the like" (Lipsey & Wilson, 2001, p. 167). Measurement reliability and validity issues are addressed by coding variable measures and their reported reliability indices; these will be incorporated into the analysis and result in recommendations that are based on the most reliable and valid measures currently available. Researchers can also use this information in designing future studies and making measurement decisions, since our synthesis includes an in-depth analysis of the reliability and validity of the instruments used to measure the important variables shown in the model (Figure 1). Below we include some of the major challenges that we encountered and give their implications for the reporting of future correlational research.

Challenges

Sampling and publication bias—One of the most challenging issues in conducting any meta-analysis is to determine a priori whether the literature is sufficient to warrant application of meta-analysis procedures. This task is even more onerous in a model-driven meta-analysis due to the difficulties inherent in locating published and unpublished research data, and in finding relatively complete correlation matrices. While literature search strategies associated with this meta-analysis are extensive, the potential for missing relevant data is always a concern, as is publication bias. Publication bias relates to the fact that statistically significant research findings are more likely to be published than are non-significant results. Published data that are most easily accessed may reflect this bias and result in meta-analytic results that are stronger than results from unpublished sources (Lipsey & Wilson, 2001). Thus, the published research may not be representative of the entire body of literature on a given topic (Hunter & Schmidt, 2004; Rosenthal, 1990). A funnel plot (a scatterplot with the effect size on the X-axis and sample size or standard error on the Y-axis) and Egger's test (Egger, Smith, Schneider, & Minder, 1997) can help us to assess the extent of publication bias. In a model-based analysis, we may create funnel plots for each pair of variables, or they may be made for only the most critical or well-studied relationships. In future primary studies, authors should include complete correlation matrices among variables when possible. Further, authors should provide clear sample sizes for each measure as sample sizes may vary from measure to measure. Such attention to sample sizes and complete reporting can foster the use of such studies in subsequent meta-analyses.

Determining the direction of effects—Second only to the challenge of locating relevant correlational data is the issue of determining the sign (positive or negative) so that each correlation correctly indicates the direction of the relationship. Determining the direction of each variable's association is a part of conducting all meta-analyses, but is perhaps even more challenging when conducting model-testing meta-analyses. Discerning the direction of effects becomes difficult when authors of the original studies do not pay adequate attention to the signs of the correlations; suspicions may be raised when inconsistencies are seen between the directions of correlations in the research report and the author's narrative description of the relationship. Also, researchers measure variables in numerous ways and directions, sometimes with instruments developed by the investigator for that particular study. For example, adherence to physical activity recommendations can be measured as the number of days per week that an individual engages in brisk walking for more than 30 minutes; here the range of scores would be zero to seven with higher scores indicating greater adherence. Thus, a positive correlation between adherence to physical activity and A1C would reflect an overall undesirable outcome. That is, more adherence to physical activity is associated with higher levels of A1C; lower A1C is the desirable target.

Alternatively, an investigator may decide to measure physical activity as the number of days per week that an individual missed the prescribed walking regimen. So, a higher rating would indicate lower adherence to physical activity recommendations. In this instance, a positive correlation between adherence to physical activity recommendations and A1C would be interpreted as an overall expected outcome; lower adherence is associated with

higher A1C. Considerable time and effort is required during a model-driven meta-analysis to review and confirm the agreed-upon direction of effect of each correlation, sometimes by contacting directly the authors of the primary study, prior to pooling effects across studies. In some cases the signs of correlations will need to be changed so that a study's results are comparable with those of other studies. Thus, it is imperative that investigators of primary studies report clear directions of correlational results. One helpful strategy is for authors to include a legend with each table of results indicating the direction of each of the measured variables. For example, "higher scores on the exercise instrument mean less physical activity."

Other potentially important variables not included in the model—The model that informs our model-driven meta-analysis was derived from the diabetes research literature and includes many commonly used variables (Akimoto et al., 2004; Cardarelli, Vernon, Baumler, Tortolero, & Low, 2007; K. L. Fisher, 2006; L. Fisher & Glasgow, 2007; Peyrot & Rubin, 2007; Sultan & Heurtier-Hartemann, 2001). During our in-depth literature search, some additional key variables were located, such as coping, appointment keeping, and diabetes symptoms. The research team decided early in the meta-analysis process which variables would be coded for inclusion in the analyses. However, decisions about other variables may need to be made as the project progresses. For example, considering the health belief variables, we included in the model only perceived barriers and social support because those tend to be the most frequently studied components of the health belief model. If a sufficient sample of studies provides codeable data on other health belief components, e.g., commitment or expectations, we will include these additional variables in the analyses. Although there is no specific guideline for a "sufficient sample of studies," we generally set the minimum number at five and suggest that readers interpret with caution any findings that are based on fewer studies. Also as mentioned above, by keeping track of these variables that appear less frequently, we may identify promising areas for future inquiry. We balance the inclusion of further variables with the statistical issues that would result from including too many variables. Future primary researchers need to consider the issue of how variables tend to be measured in the literature and avoid using established instruments in a manner that is not consistent with the existing literature. If every study uses a totally unique instrument, meta-analysts may be precluded from making comparisons of findings across multiple studies. However, some degree of variation is valuable, and can lead to stronger conclusions of generalizability of a relationship, if similar findings arise regardless of the particular instrument used.

The model-driven meta-analytic study described here examines a series of predictive models of health outcomes in individuals diagnosed with T2DM, using data synthesized from previously reported studies. We are using established causal modeling procedures to combine correlations across studies, test for heterogeneity of the correlation matrices, estimate the between-studies covariances and random-effects of the common correlation matrix, and estimate either the fixed- or random-effects of path coefficients of the predictive model, along with the associated standard errors and significance tests. While conducting model-driven meta-analyses is challenging, particularly in terms of locating relevant primary studies, extracting data from these studies, and conducting appropriate data analyses,

properly done complex meta-analyses can inform both clinical guidelines and future research.

Alternatives to model-driven meta-analysis are several—First, one could conduct a prospective observational study including some of the variables in the model and use path analysis to predict diabetes outcomes. However, because of time demands on participants and cost considerations, most researchers would not be able to examine in a single study all of the variables that could be reviewed in a meta-analysis. Secondly, an investigator could locate all available studies with the variables shown in any proposed model and “synthesize the existing results for each of the predictor-outcome relationships found in the literature. The synthesis would be ‘empirically guided’ because the relationships to be examined would arise from the collected literature” (Becker, 1992a, p. 215). However, for this study we chose the third option, which is to guide the synthesis with the use of a theoretical model derived from the literature and based on key well-defined health outcomes associated with T2DM. We believe this systematic approach yields more meaningful results, compared to the other options discussed above. However, relevant models are not always available to guide meta-analytic studies. Such model-testing studies as the one reported here in the diabetes field are enabled because standard diabetes health outcomes have been identified and models have been developed. Also, meta-analyses may be useful for developing models in scientific areas where models do not currently exist.

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Figure 1.

Figure 2.

Testable Models from Pilot Meta-analysis*

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