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Approaches to meta-analysis: A guide for LIS researchers

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Abstract

Meta-analysis, a statistical operation used to combine results from independent studies, has been applied widely in medicine, psychology, and business among other disciplines, but has had limited application in LIS research. To introduce it in LIS research, this article offers examples from a meta-analytic study on factors affecting information needs among cancer patients to explain the literature search, criteria for inclusion of studies, data gathering, and statistics related to effect sizes in meta-analysis. Three popular approaches to meta-analysis, the details of the approach used by the author, and the interpretation of results in terms of mean effect sizes that represent strength of the observed effect of variables are also explained.

1. Introduction

Meta-analysis, which is a statistical maneuver for combining results across studies to reach conclusions, entails the mathematical synthesis of results from independent studies. When conducted, it becomes part of the larger systematic review—the processes involved in synthesizing quantitative results of independent studies related to a research problem. To clarify, meta-analysis, which is the statistical operation used to combine the results to reach an aggregate (Carr, 2002; Koretz, 2002), is not a requirement for systematic review because a researcher may choose only to provide an objective review of the quantitative results of studies related to a research problem, without any mathematical amalgamation.

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As the inclusion of meta-analysis in a systematic review allows more precise mathematical estimates of results, this article focuses on the details of meta-analysis. In addition, the author recently conducted a study using that research method (Ankem, 2004). In general, then, the reasons and advantages for any interested researcher to conduct a meta-analysis are that it (1) allows more precise results related to a research problem as these results are a mathematical aggregate of those from various studies examining the variables in question, and (2) increases power; in other words, it reduces the likelihood of a type II error, the problem of failing to reject a false null hypothesis (Koretz, 2002).

The procedure is widely used in medicine, especially in the amalgamation of outcomes of clinical trials conducted in evidence-based medicine. An organization called the Cochrane Collaboration disseminates systematic reviews, including meta-analyses, in all areas of health care. Its widely acclaimed Cochrane database is a primary source for systematic reviews on clinical trials. The use of meta-analysis is not limited to medicine, however. Other disciplines such as psychology and business have engaged in meta-analysis to examine various topics from effects of psychosocial interventions to determinants of job satisfaction.

In library and information science (LIS), meta-analysis is still a relatively unknown procedure for performing research. After conducting a preliminary meta-analysis of variables contributing to reference accuracy, Saxton (1997) discussed several methodological issues encountered. The value, however, of Saxton's study lies in its introduction of the meta-analytic procedure to the area of reference service evaluation. The parts of Saxton's (1997) meta-analysis where the study could have been extended in terms of methodology will be discussed in this article in Section 4 which presents various approaches to meta-analysis. Also, his interpretation of findings was all too brief.

The reasons for the lack of use of meta-analysis in LIS may be attributed to the difficulty in accumulating results involving variables related to the same research problem across studies and the lack of appropriately measured variables related to the same research problem across studies so that the results can be combined meaningfully.

To encourage the application of meta-analysis in LIS research, this author recently conducted a meta-analysis of factors affecting information needs among cancer patients (Ankem, 2004); examples from this study are used to explain the meta-analytic procedure in this article. This author also encountered several of the methodological issues pointed out by Saxton (1997) in his study. This author's meta-analysis, however, was not based on LIS literature. Quantitative results related to the research problem were abstracted from the literature in health-related disciplines: oncology, nursing, psychology, psychiatry, and public health. After the literature in the aforementioned disciplines was thoroughly reviewed, support for the hypotheses that several factors affect level (high versus low) of information needs among cancer patients was found.

For instance, one prominent factor was a demographic variable, age, which was found, in certain individual studies, to be related to the information needs of cancer patients. Specifically, the results abstracted from the literature showed some evidence that younger cancer patients have a higher need for information; this relationship was supported by moderate, negative correlations. However, nonsignificant correlations between age and information needs in this group of patients were also found and reported in the literature. These contradictory results regarding the relationship between age and information needs, which were abstracted, introduced ambiguity as to the true nature of the relationship between age and the information needs of cancer patients.

A quantitative synthesis of such results from independent studies, then, can be expected to provide a more precise estimate of the results than any individual study. That synthesis of the relationship between age and level of information needs among cancer patients in the author's meta-analysis produced a moderate aggregate effect size, which was negative in direction. The strength of the relationship was detected through the magnitude of the aggregate effect size.

In this way, the aggregate value provided a more accurate estimate of the effect that age has on overall information needs of cancer patients than any one independent study. Discussion of the author's meta-analytic study is interspersed throughout the article to enhance understanding of the meta-analytic procedure.

2. Process of conducting meta-analysis

A researcher starts with a comprehensive literature review. Every effort must be made to retrieve all relevant studies related to a research problem. All relevant indexing and abstracting databases are searched and complemented by other techniques (e.g., browsing bibliographies of the articles retrieved) to ensure that all relevant published studies are retrieved.

Once the literature is acquired, criteria for inclusion of studies in the meta-analysis are established. The research problem and the definition of variables involved in the hypotheses being tested must guide the development of the criteria for inclusion. Generally, some widely applied criteria for inclusion of studies in a meta-analysis are (1) examination of variables pertinent to the researcher's hypotheses in individual studies, (2) the presence of any methodological requirements, for example, those related to subjects and measurement in individual studies examining the pertinent variables, (3) use of statistics for analyzing pertinent variables in individual studies, the statistics that were predetermined by the researcher as appropriate for the synthesis, and (4) adequate presentation of results with all the necessary statistical values in individual studies to facilitate a meta-analysis. The last is important because the statistics available in independent studies become data for the meta-analysis.

In the author's meta-analysis of factors affecting information needs among cancer patients, the criteria established were the following:

- existence of a relationship between a demographic or a situational variable (related to the patient's illness situation) and the overall need for information;
- inclusion of adults as subjects;
- use of inferential statistics such as *t* test, chi-square test, analysis of variance (ANOVA), and correlations; and
- adequate presentation of required statistics representing the results.

Quality of the studies to be included is also important in a meta-analysis. Although instruments exist for scoring studies on quality (Juni, Witschi, Block, & Egger, 1999), no instrument has been standardized (Koretz, 2002). Therefore, such criteria as publication type, expertise of authorship, funding source, sampling, sample size, research design, reliability and validity of instruments administered, and statistics employed may be evaluated to determine quality of studies either by using scoring scales for the criteria developed by the researcher or solely through the judgment of the researcher, for instance, by applying the above criteria to a report as a researcher generally would in evaluating any research report. Most importantly, as Saxton (1997) points out, Hunter and colleagues suggest a sample size of, at least, 20 subjects within each study to be included in a meta-analysis.

It must be noted that no standard exists for the number of studies to be included in a meta-analysis. According to Rosenthal (1991), meta-analysis can be conducted with just two studies. The Cochrane database, in fact, includes meta-analyses that synthesize as few as two studies. Usually, one will find a higher number of studies included. When the intention in a meta-analysis is to examine either a difference in group means involving two variables or a relationship between only one independent and one dependent variable, an abundance of studies with relevant results is difficult to find. Generally speaking, one may include a minimum of 15 studies in such a meta-analysis. However, if the researcher is examining mean differences involving several variables or relationships between several independent variables and one or more dependent variables, it is feasible to conduct a sizeable synthesis where each subset representing a difference or a relationship examined includes anywhere from two to 15 studies.

The next step is the abstraction of results from independent studies. It is advised that at least two people abstract data from all the individual studies to minimize error in abstraction. Data from independent studies related to both the criteria for inclusion and the criteria for quality are recorded, and the criteria are applied to reach a sample of studies for the meta-analysis. The data abstraction is the tedious part of the procedure. All related research reports have to be sifted through for abstracting relevant findings. Not only is it necessary to examine the same variables across studies, but the variables must also be appropriately measured in comparable units, so as to combine the results meaningfully.

The author's meta-analytic study involved three demographic variables (age, education, and gender) and four situational variables (time since diagnosis of cancer, stage of cancer, patient's preferred style in making treatment decisions related to illness, and type of treatment a patient underwent). The demographic and situational variables constituted independent variables for conducting the meta-analysis. The study focused on the impact of these variables on the level of information needs among cancer patients. Some variables were found to be consistently unrelated to overall need for information among cancer patients in independent studies and therefore were not included in the meta-analysis. The variables that emerged as prominent variables for studying the impact on overall information needs among cancer patients were age, education, time since diagnosis of cancer, stage of cancer, and patient preferred role in treatment decision making.

It was important to be sure that when results related to a relationship (e.g., age and information needs) were combined across studies (Graydon, Galloway, Palmer-Wickham, Harrison, & Rich-van der Bij, 1997; Harrison, Galloway, Graydon, Palmer-Wickham, & Rich-van der Bij, 1999; Harrison-Woermke & Graydon, 1993; Turk-Charles, Meyerowitz, & Gatz, 1997), these variables were measured in independent studies in a way that was consistent. For example, age was measured as both a categorical and continuous variable. The results represented as r to decipher a relationship between age and information needs were based on continuous measurement of age but could be synthesized with categorical measurements of age designed to find a mean difference in information needs between age categories. In the author's meta-analysis, only one study measured age in categories, as ≤ 55 and >55, and tested the mean difference in information needs between the categories. However, if more studies that measured age as categorical variable had existed, the categorical measurements would have had to be similar across studies. Hence, in conducting meta-analysis, accurate recording of these details related to variables requires a great deal of time and effort.

The dependent variable, information needs, in all instances was continuous. The variable was measured using different instruments—the Information Needs Questionnaire—Breast Cancer (INQ-BC), Toronto Information Needs Questionnaire—Breast Cancer (TINQ-BC), Information scale of the Krantz Health Opinion Survey, and a questionnaire developed specifically for the study. INQ-BC, the precursor to TINQ-BC, was used in one study and the latter was used in two studies (Graydon et al., 1997; Harrison et al., 1999; Harrison-Woermke & Graydon, 1993). Krantz Health Opinion Survey and other items developed specifically for the study were used in combination in one study (Turk-Charles et al., 1997). The concept that was measured across studies fit the conceptualization of information needs in the author's meta-analysis.

In addition to the issues related to definitions of variables and their measurement, a major problem in recording data is the lack of adequate statistical information, such as exact p values for both significant and nonsignificant findings, accurate sample size for each analysis performed within a study, magnitude of the test statistic, and such other relevant statistics as, for example, means and standard deviations in reporting results of a t test. While abstracting data for the author's meta-analysis, sample sizes were available in individual studies, but p values were not reported most of the time, and magnitude of the test statistic was reported infrequently. As such, p values were not recorded and an alternate approach was chosen to prove significance of the results of the meta-analysis, which is discussed in subsequent sections. Magnitude of the test statistic for some studies had to be calculated based on other statistical information provided, such as group means and standard deviations, in order to calculate t statistic.

3. Statistical maneuver in meta-analysis

Once the data related to the variables have been recorded, the analysis is conducted. The following brief introduction to the statistics and terminology in meta-analysis also outlines the three popular approaches used in conducting meta-analysis.

In meta-analysis, an effect size represents the magnitude of the relationship between two variables. There are several indicators of effect size: Glass's Δ, Cohen's d (or g), Pearson product moment correlation r, Fisher's transformation of r, Z_{Fisher}, or Hedge's unbiased estimate of d. These metrics can be converted from one metric to the other. The expression of the effect in a particular metric is less important. For instance, d gauges the difference between group means, often those from control and experimental groups, whereas r gauges the relationship between two variables (Field, 2001). Either effect size is appropriate in detecting the effect one variable has in producing a change in the other. In addition, the results of t test, F in ANOVA, chi-square, and correlation from independent studies can be converted into any of the metrics representative of effect size. Saxton (1997) limited his analysis to Pearson r values found in individual studies examining the relationship between different variables and reference accuracy. This is not a requirement. The meta-analysis could have been inclusive of other statistics mentioned above which can be converted to Pearson r. The formulas for the conversion can be found in Rosenthal (1991).

Usually, if results from studies are available in the form of differences between experimental and control groups, the researcher chooses to express an effect size in the meta-analysis as a standardized mean difference, for example, as Cohen's d. In turn, if results are available to a researcher mostly in the form of r, and it is suitable for the researcher to speak about the question at hand in terms of relationship between variables as opposed to difference between group means, the researcher would choose to express an effect size as r. In the author's meta-analytic study, many results were presented as r values, and it was logical to analyze the research problem in terms of relationship between demographics, situations, and information needs; also, the other results not presented in the form of r could all be converted into r.

In general, once the individual effect sizes for studies are calculated, these are combined to obtain an average or pooled effect size, which is a more precise indicator of strength of relationship between two variables across studies than the effect size for one study. Also, in the calculation of the pooled effect size, the individual effect sizes are weighted by sample size within each study to give more weight to the results of those studies with larger sample sizes. Upon calculation of the aggregate effect size, significance in meta-analysis is generally gauged by computing 95% confidence intervals around the average effect size. Alternatives to determining significance of the aggregate effect size by examining 95% confidence intervals built around it are discussed below within the description of the three popular approaches for conducting meta-analysis.

A concern in meta-analysis is heterogeneity of effect sizes; that is, the possibility that the samples chosen to conduct the individual studies are not part of the same population. In other words, homogeneity of effect sizes is necessary for quantitatively combining data from separate studies assuring homogeneous samples across the studies. A test termed the Q test has been developed to detect heterogeneity between effect sizes. The Q test produces the Q statistic which is based on the chi-square distribution and provides a statistical estimate of heterogeneity between effect sizes. When the result is significant, individual effect sizes are removed, one at a time, and the test is repeated until a nonsignificant result is obtained because a nonsignificant result of the Q test indicates homogeneity of sample estimates of effect sizes.

Also, there are two models in conducting meta-analysis, the fixed effects model and the random effects model. The fixed effect model adjusts for variance within a study whereas the random effects model additionally adjusts for variance between studies. In the presence of heterogeneity of effect sizes, employing a random effects model is another way to account for the heterogeneity between effect sizes. Not all meta-analytic approaches allow for both models. However, when it is possible to apply a random effects model, judgment must take precedence over even a homogeneous Q test finding. If the researcher believes that the data come from heterogeneous samples, it is advised that the random effects model be employed in conducting the analysis (Koretz, 2002). In the presence of great heterogeneity between effect sizes, data combination is not advised at all.

Another concern in meta-analysis is the existence of unpublished studies that could overturn the significant results obtained in a meta-analysis. To guard against this predicament, a fail-safe number is calculated for the meta-analysis (Rosenthal, 1991). Several formulas are provided, but one that is easier to calculate is $X = 19s - n$, where s is the number of summarized studies significant at $p < 0.05$, n is the number of summarized studies not significant at $p < 0.05$, and 19 is a standard number used as the ratio of the two numbers above, which is expected when null hypothesis is true (Rosenthal, 1991).

If the computed fail-safe number for the meta-analysis is greater than $5K + 10$ (where K is the number of studies included in the meta-analysis), it is assumed that reasonable tolerance level for the existence of unpublished studies has been reached for the meta-analysis. In other words, the fail-safe number calculated for the meta-analysis represents the minimum number of unpublished studies with nonsignificant findings required to overturn the conclusions of the meta-analysis; if $5K + 10$, which is the number of unpublished studies that actually can overturn the conclusions of the meta-analysis, is less than this fail-safe number, a tolerance level for the meta-analysis has been reached.

The fail-safe number was not a concern in the author's meta-analysis because several zero correlations existed in the results gathered across studies reducing the problem of type I error. Type I error is the problem of rejecting null hypothesis when it is true. The reasoning behind this is, that if the results synthesized in a meta-analysis include only significant results, which is the case more often in published studies, the chance of a significant outcome of the meta-analysis being untrue is heightened due to a possible existence of nonsignificant results not included in the meta-analysis from studies which tend to remain unpublished. However, if the data entered into a meta-analysis include several nonsignificant results, even if they are from published studies, it reduces the likelihood of a significant outcome of the meta-analysis being nullified by the existence of nonsignificant results in unpublished studies.

4. Three approaches to meta-analysis

The three popular approaches to meta-analysis are Hedges and Olkin (1985), Rosenthal and Rubin (1978), and Hunter and Schmidt (1990). Each procedure can be conducted using either Statistical Analysis System (SAS) or Statistical Package for the Social Sciences (SPSS) software. Both programs, however, require syntax for running the various analyses. In addition, special software programs for conducting meta-analysis have been developed.

4.1. Hedges and Olkin approach

In this relatively new approach to meta-analysis, d values, which represent effect sizes for independent studies, are calculated. As mentioned earlier, d represents the magnitude of difference between two group means. Also, different inferential statistics can be converted to d. Homogeneity is examined using the Q test. The d values from individual studies, weighted by sample size, are combined. The aggregate d represents the average effect in terms of difference between group means across studies, the significance of which is determined using 95% confidence intervals built around the mean effect size. According to Cohen (1988), d = 0.2, 0.5, and 0.8 are considered small, medium, and large effects, respectively. Hedges and colleagues present both fixed and random effects models (Hedges & Olkin, 1985; Hedges & Vevea, 1998). The main reference for this approach is Hedges and Olkin (1985).

4.2. Rosenthal and Rubin approach

In the Rosenthal and Rubin (1978) approach, study outcomes are converted into Z_{Fisher}, r-to-Z transformation. Rosenthal (1991) provides the formulas for converting various inferential statistics to r, first. Hedges and Olkin (1985) also have an approach for use of correlations in meta-analysis, in addition to their approach discussed above. The combined approach is often referred to as the Rosenthal and Rubin/Hedges and Olkin approach for correlation coefficients, and this approach was employed by this author in her meta-analytic study which will be discussed in detail in subsequent sections. The Rosenthal and Rubin and Hedges and Olkin approaches for correlations in meta-analysis are similar except for a few differences (Field, 2001).

In both approaches, first the effect sizes are transformed to Z_{Fisher} and back to r. The individual effect sizes are weighted by sample size and pooled Z_{Fisher}, and pooled r are calculated. In addition, the p values of obtaining the effect size from individual studies are converted to individual Z scores, and the pooled Z_{Fisher} is converted to a combined Z score. Hedges and Olkin (1985) recommend that the probability of obtaining the combined Z score be examined to determine significance of mean effect size Z_{Fisher} (Field, 2001). Unlike Hedges and Olkin, Rosenthal and Rubin (1978) suggest that the probability of obtaining the mean effect size Z_{Fisher} be arrived at by combining the probabilities of the correlation coefficients for individual studies (Field, 2001). Another difference between the Rosenthal and Rubin and the Hedges and Olkin approaches for meta-analysis is that the former only provides the fixed effect model whereas the latter provides a random effects model as well (Field, 2001). Homogeneity of effect sizes for both approaches can be gauged through the Q test. The references for this approach are Rosenthal and Rubin (1978), Rosenthal (1991), Hedges and Olkin (1985), and Hedges and Vevea (1998).

Alternatively, the mean effect size can be examined as the pooled Pearson r (mean effect size r calculated after the individual Z_{Fisher} values are converted back to individual r values) which allows for the observation of the effect's strength directly in terms of relationship between two variables. According to Cohen (1988), mean effect size r = 0.1, 0.3, and 0.5 can be considered small, medium, and large effects, respectively. Significance of this mean effect size r can be determined using 95% confidence intervals built around the mean effect size. Details of determining significance of mean effect size r are discussed in Section 5 which presents interpretation of results in meta-analysis.

4.3. Hunter and colleagues approach

The least used meta-analytic approach is the Hunter and Schmidt (1990) approach, which adjusts for sources of errors (sampling error and reliability of measurement of variables) reported in individual studies before combining effect sizes to arrive at the mean effect size of correlation coefficients (Johnson, Mullen, & Salas, 1995). Significance, again, is determined by calculating combined Z score and examining the probability of obtaining the combined Z score (Field, 2001). However, the calculation of the combined Z score is based on mean effect size r, not the mean Z_{Fisher}, r-to-Z transformation (Field, 2001). Weighting of individual effect sizes to obtain the mean effect size r is also different in this approach.

Sources of error related to sampling and reliability of measurement of variables are rarely reported in studies. Hence, the Hunter and Schmidt approach, which is explained as the random effects model, is infrequently applied in meta-analysis (Field, 2001). A homogeneity test statistic represented as chi-square can be applied to detect heterogeneity of effect sizes (Field, 2001). The references for this approach are Hunter, Schmidt, and Jackson (1982) and Hunter and Schmidt (1990).

The author, in her meta-analysis of factors affecting information needs of cancer patients, used the Rosenthal and Rubin/Hedges and Olkin approach for correlation coefficients. Separate analyses were conducted for each relationship under examination:

- age and overall need for information;
- education and overall need for information;
- time since diagnosis and overall need for information;
- stage of disease and overall need for information; and
- patient preferred role in treatment decision-making and overall need for information.

All inferential statistics were converted to r, and the Rosenthal and Rubin/Hedges and Olkin approach was used to calculate mean effect size r for each of the five subset relationships. Only the relationship between age and information needs will be discussed in detail to provide examples in this article.

Upon calculating individual effect size values, in her meta-analysis, the author used sample syntax for the Rosenthal and Rubin/Hedges and Olkin approach available at the Raynald's SPSS Tools Web site to perform further analyses (Levesque, 2003). The abovementioned Web site provides SPSS syntax for other meta-analysis approaches as well.

The test for checking homogeneity of effect sizes, performed to eliminate any outliers, was also included in the syntax. If the test results showed that the effect sizes – for example, the six r values gathered across studies representing the relationship between age and information needs – were heterogeneous, the individual effect sizes were removed one at a time and the homogeneity test was repeated until the results showed that the remaining effect sizes were homogeneous.

As noted earlier, the combined Rosenthal and Rubin/Hedges and Olkin approach for r is inclusive of a random-effects model that is absent from the original Rosenthal and Rubin approach. In the author's meta-analysis, to be conservative, results that were derived from the random effects model were used to find the magnitude of each mean effect size r representing each aggregate relationship examined between an independent and dependent variable.

To recap, in the Rosenthal and Rubin/Hedges and Olkin approach, a mean Z_{Fisher} is computed based on the data entered in the form of r values. In addition, a mean effect size r may also be computed (after all transformed effect size Z_{Fisher} values are converted back to r values); this mean effect size r is close in value to mean Z_{Fisher} because the computation in both is based on Fisher's r-to-Z transformation. To prove significance of the mean effect size Z_{Fisher}, Rosenthal and Rubin suggest combining p values of individual effect sizes while Hedges and Olkin suggest calculating a Z score based on the mean effect size Z_{Fisher}.

The author, in her meta-analytic study, alternatively chose to use 95% confidence intervals built around the pooled effect size r to determine significance of the mean effect size r. These 95% confidence intervals were also produced as part of the SPSS output. A Forest plot that was included in the output provided a graphical display of 95% confidence intervals for the individual effect size r values and the mean effect size r (Fig. 1).

5. Interpretation of results in meta-analysis

Only the interpretation of aggregate d, aggregate Z_{Fisher}, and aggregate r are discussed here because these metrics are most widely used in meta-analysis. As already mentioned, in the author's meta-analytic study, the strength of the aggregate effect size was gauged primarily through the mean effect size r. A mean effect size r of -0.26, produced as part of the SPSS output, was found which represented a moderate, negative relationship between age and overall information needs among cancer patients.

Then, confidence intervals also produced as part of the SPSS output were used to determine significance of the mean effect size r found. The Forest plot in Fig. 1 graphically displays the subset meta-analysis for this one relationship, that between age and information needs, from the author's meta-analytic study. In the Forest plot, x-axis represents correlation coefficients and y-axis, labeled study, represents studies – both the four independent studies and the one aggregate study – involved in the meta-analysis. Confidence intervals, labeled as aggregate in Fig. 1, display those for the pooled or mean effect size r. The other confidence intervals display those for each r included in the combination. Therefore, r values entered as data for conducting the meta-analysis must all be within their respective confidence intervals. The confidence intervals are numerically labeled in the order in which data in the form of correlations were entered into the syntax file.

Further examination of the confidence intervals displayed for the aggregate relationship between age and information needs of cancer patients in Fig. 1 shows that zero was not within 95% confidence intervals (−0.37, −0.15). This allows one to reject the null hypothesis of a zero correlation and infer the significance of the mean effect size r (−0.26) representing the pooled relationship between age and overall information needs among cancer patients. Then, in summary, a moderate mean effect size r = −0.26, negative in direction, representing the magnitude of the aggregate impact that age has on information needs of cancer patients was observed, and it was found to be significant.

Alternatively, mean effect size d could have been calculated. Definitions of mean effect size d = 0.2, 0.5, and 0.8 as small, medium, and large effects, respectively (Cohen,

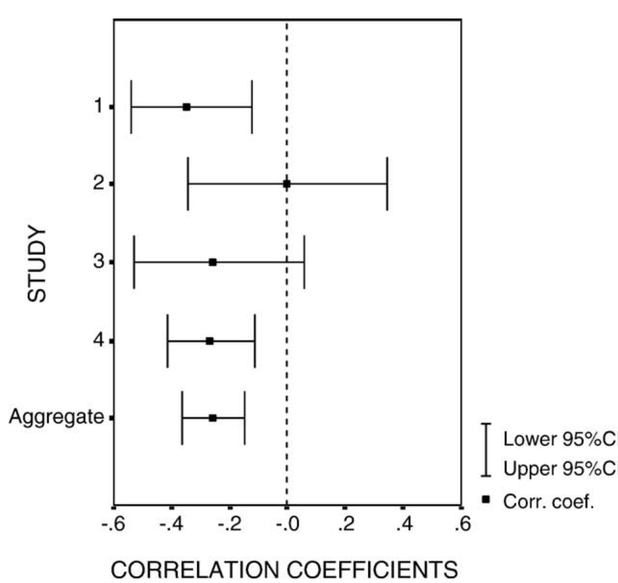

Fig. 1. Forest plot of effect sizes representing relationship between age and overall information need among cancer patients. (Note: Aggregate shows confidence intervals for the mean effect size r. Numbers 1–4 show confidence intervals for the individual effect sizes observed in the four studies entered in the meta-analysis.)

1988), are used to interpret the magnitude of the aggregate difference between group means. Significance of aggregate d value may also be determined using 95% confidence intervals. Examining the mean effect size in the standardized form Z_{Fisher} is somewhat different. As described earlier, based on Z_{Fisher} values for independent studies and Z scores calculated for individual studies, aggregate Z_{Fisher} and a combined Z score are computed, the significance of which is determined by examining the probability level, p, of obtaining the combined Z score. Hedges and Olkin (1985) recommend this approach. Rosenthal and Rubin (1978), of course, recommend combining the probabilities of obtaining the individual effect sizes (correlation coefficients) to prove significance of the aggregate Z_{Fisher}.

6. Conclusion

Meta-analysis is a powerful research method which is capable of improving the precision of results found in independent studies. The relationship found in the author's study between age and information needs, for instance, validates existing findings of select reports. In addition, the meta-analytic finding provides support for the conclusion that the result must guide information provision in all relevant contexts, whether in hospitals or in information centers, where one must take the patient's personal characteristics, such as age, into consideration. As younger people need more information to cope and older patients may be overwhelmed with too much information, information provision must be designed accordingly.

The meta-analytic method has several possible applications in LIS. However, for increased applicability in LIS, independent studies must be conducted where variables are adequately defined and measured and are examined as part of a larger body of a research problem. To facilitate cumulating findings across studies in a research area, it is important for authors to report definitions of variables examined, details regarding the measurement of variables, p values for both significant and nonsignificant results, accurate sample sizes for separate analyses performed within a study, magnitude of test statistics observed, and other statistical information relevant to test statistics observed.

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