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Building Up Knowledge through Meta-analysis: A Review and Reinterpretation

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Abstract:

In the last two decades, researchers have increasingly conducted meta-analyses in the information systems (IS) field. As such, we need to ensure that researchers conduct such analyses in a sound and accurate way, use appropriate and effective meta-analytic techniques, and produce reliable and valid results. Nevertheless, few papers on conducting a meta-analysis in the IS field exist. In this paper, we review and re-interpret the procedures, issues, and techniques in conducting a meta-analysis in the IS field. By doing so, we make important contributions to helping IS researchers expand their baseline knowledge of meta-analyses and, thus, more effectively design and conduct them in the future.

Keywords: Corrected Correlation, File Drawer Problem, Heterogeneity, Homogeneity, Information Systems, Inter-rater Reliability, Meta-analysis, Moderator, Weighted Average Correlation.

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1 Introduction

In general, in a meta-analysis, one quantitatively analyzes the results from empirical studies on the same or similar issues in order to make contributions beyond those that the original studies achieved (Hedges & Olkin, 1985; Schmidt & Hunter, 2014). In the last two decades, the meta-analysis has become a major form of literature review in areas such as psychology and medicine, and researchers have recognized it as the critical first step in effectively using research findings (Rahimi, Vimarlund, & Timpka, 2009; Rousseau, Manning, & Denyer, 2008). As Hunter, Schmidt, and Jackson (1982) have observed, the meta-analysis has great importance in that:

> *Scientists have known for centuries that a single study will not resolve a major issue. Indeed, a small sample study will not even resolve a minor issue. Thus, the foundation of science is the cumulation of knowledge from the results of many studies.* (p. 10)

For this same reason, researchers have increasingly used meta-analyses in the information systems (IS) field. Specifically, IS researchers have employed meta-analyses to synthesize previous studies (Lee, Kozar, & Larsen, 2003; Ma & Liu 2004; Yousafzai, Foxall, & Pallister, 2007a), detect moderators (Benbasat & Lim, 1993; King & He, 2006; Schepers & Wetzels, 2007), test theoretical hypotheses (Kohli & Devaraj 2003; Sharma & Yetton, 2003; Wu & Lederer, 2009), develop research models (Sabherwal, Jeyaraj, & Chowa, 2006; Saeed, Hwang, & Yi, 2003), and estimate variances and effect sizes (Hwang & Thorn 1999; Mohmood, Hall, & Swanberg, 2001; Wu & Du, 2012).

Given the importance and popularity of the meta-analysis in IS field, we need to ensure that researchers conduct such analyses in a sound and accurate way, use appropriate and effective meta-analytic techniques, and produce reliable and valid results. Nevertheless, few papers on conducting a meta-analysis in IS field exist. Therefore, the complicated issues involved in a meta-analysis may still confuse many IS researchers even though such an analysis constitutes a powerful tool for advancing cumulative knowledge (Schmidt, 2008).

2 Methodology

To find meta-analysis studies of interest, we searched electronic academic databases and electronic bibliographies in the areas related to information systems, such as ABI/INFORM, Business Source Premier, JSTOR, and ScienceDirect. To include studies from non-journal sources, we also searched digital libraries for proceedings of major IS conferences such as the International Conference on Information Systems (ICIS), the Americas Conference on Information Systems (AMCIS), and the Hawaii International Conference on System Sciences (HICSS). For the electronic searches, we used such key words as “meta-analysis”, “information systems”, “literature review”, “management information systems”, “technology management”, and so on. To find more studies, we also looked over bibliographies of the papers that we had already identified. With this systematic search approach, we could locate as many studies as possible. Appendix A shows the 23 major studies that we reviewed for this research.

Contribution:

In this paper, we review and re-interpret the procedures, issues, and techniques in conducting a meta-analysis and, thus, make several primary contributions to the IS field. First, by synthesizing recent works in the literature, we propose four major procedures for conducting a meta-analysis. As such, we view the meta-analysis as a complete empirical study itself that focuses on extracting, analyzing, and testing quantitative data to build up knowledge. Therefore, this paper helps to position the meta-analysis and develop meta-analysis procedures. In addition, to tackle the complexity in meta-analyses, we specifically address issues such as outlying studies and the file drawer problem. By doing so, we contribute to the practice of meta-analysis and suggest that, although meta-analyses are not perfect and subject to many issues, researchers can overcome and control them. We also identify and describe important meta-analysis techniques such as the heterogeneity test and corrected standard deviation. By presenting these techniques, we contribute to the methodology of IS research and indicate that meta-analysis represents a methodically rigorous research tool if one conducts it properly. Finally, we also introduce software tools for efficiently synthesizing and analyzing the data in each meta-analysis step. In summary, this paper makes important contributions to helping IS researchers expand their baseline knowledge of meta-analyses and, consequently, more effectively design and conduct them.

2.1 Fundamental Theories Involved in These 23 Studies

Most of these major studies involve some fundamental theories that they use to explain technology acceptance and usage, such as the technology acceptance model (TAM), the system success model (SSM), and the unified theory of acceptance and use of technology (UTAUT). Rooted in the theory of reasoned action (TRA) (Ajzen & Fishbein, 1980) and the theory of planned behavior (TPB) (Ajzen 1985), TAM asserts that the intention to use or actual use of an information system is a function of perceived ease of use and perceived usefulness (Davis, Bagozzi, & Warshaw, 1989). Based on comprehensive reviewing the literature, DeLone and McLean (1992) developed the SSM that posits that six factors determine an information system’s success: system quality, information quality, use, user satisfaction, individual impact, and organizational impact. With a unified view of system-use behavior, UTAUT suggests that four key constructs primarily influence user intention and system usage: 1) performance expectancy, 2) effort expectancy, 3) social influence, and 4) facilitating conditions (Venkatesh, Morris, Davis, & Davis, 2003).

These meta-analysis studies discuss one non-IT acceptance theory, the organizational control theory (OCT), which includes all organizational actions taken to ensure adherence to organizational strategies, objectives, and plans (Sundaramurthy & Lewis, 2003). Thus, one can view organizational control as a process of planning, measurement, evaluation, and feedback, and one can usually accomplish it through structural mechanisms such as rules, policies, and hierarchy (Henry, Narayanaswamy, & Purvis, 2015). Using meta-analyses, researchers have found that organizational control impacts system development performance even though the strength of the impact varies across different types of control and different measures of performance (Henry et al., 2015).

2.2 An Overview of Meta-analysis Process

Emphasizing the fundamental value of meta-analyses to scientific enterprise, Cooper and Hedges (1994) provided a five-step process for conducting them: 1) formulating the problem, which involves clearly defining the research problem and specifying and discussing the variables that the meta-analysis will examine; 2) collecting data, which involves collecting all published and even unpublished studies available in the literature; 3) evaluating the data, which involves evaluating the usefulness of the identified studies and collecting all relevant data from them; 4) analyzing and interpreting data, which involves using appropriate statistical procedures to analyze and assign meaning to the data; and 5) presenting the results, which involves discussing the results and their implications and making recommendations for future research.

Using a comprehensive model to investigate IS success, Sabherwal et al. (2006) employed Hunter and Schmidt’s (1990) methods and presented three steps in a meta-analysis: 1) identifying the individual studies to include in the analysis, b) coding the individual studies, and 3) accumulating the findings that the individual studies report. Here, coding the individual studies involves developing a coding sheet that records the data extracted from these eligible studies. Therefore, these three steps match the second to fourth steps in the process that Cooper and Hedges (1994) proposed. Other IS researchers have also reported the same three steps in conducting meta-analyses (Mahmood et al., 2001; Sharma & Yetton, 2003).

Given that nearly all empirical studies need to conduct the first and last steps in Cooper and Hedges’ (1994) process, it makes sense not to include these two steps into a process specifically designed for meta-analyses. As such, we draw on previous research and propose a process that includes procedures that pertain only to a meta-analysis. As Table 1 shows, this process comprises four major procedures: 1) collect studies, 2) code the data, 3) synthesize the data, and 4) analyze the data. In Sections 2.3 to 2.6, we discuss the procedures and associated issues and techniques in detail.

Table 1. Meta-analysis Procedures, Issues, and Techniques

Procedures	Issues and techniques	Software tools
Collect studies: conduct a literature search in journals, books, conference proceedings, and unpublished dissertations to identify and collect relevant studies.	File drawer problem. Independence of each study.	Maybe not necessary
Code the data: extract useful data from the studies and, if necessary, code study characteristics (e.g., technology (utilitarian vs. hedonic), environment (voluntary vs. mandatory), and participants (employees vs. students)).	Inter-rater reliability and agreement. Convert test statistics into correlations.	**PLS-Graph** or **SmartPLS** for composite reliability. **SPSS** for intraclass correlation, Pearson's correlation, Cohen's kappa, and Cronbach's alpha (i.e., internal consistency reliability). **Excel** for Pearson's correlation.
Synthesize the data: summarize the data and calculate the descriptive statistics (e.g., mean, standard deviation, maximum, minimum, etc.).	Outlying studies. Publication bias test. Corrected correlation. Weighted average correlation. Corrected standard deviation. Heterogeneity or homogeneity test.	**Excel** or **SPSS** for mean, standard deviation, and scatter plots. **Excel** for fail-safe N, corrected correlation, weighted average correlation, corrected standard deviation, and heterogeneity or homogeneity test.
Analyze the data: apply appropriate statistical analysis methods to identify moderators, estimate variances explained in dependent variables, and/or test theoretical hypotheses and research models.	Identify moderators. Estimate explained variances. Test research models.	**SPSS** for ordinary least squares regression and weighted least squares regression. **Excel** for explained variances. **LISREL** for structural equation modeling (SEM).

2.3 Study-collection Procedure

To identify as many studies as possible, IS researchers need to comprehensively search the literature, which includes searching academic databases, digital libraries, and the bibliographies of papers one has already identified. In the IS field, researchers commonly use the following academic databases: ABI/INFORM, Business Source Premier, JSTOR, ScienceDirect, Social Science Citation Index, ProQuest Dissertation and Thesis, and WorldCat Dissertation and Thesis. These databases serve as the main source for journal papers and unpublished dissertations and theses. One usually searches digital libraries to identify papers from the major IS conferences such as the AMCIS, HICSS, and ICIS. In addition, one should search the bibliographies of papers one has already identified to locate additional studies. With such a comprehensive search strategy, IS researchers can reduce source bias, maximize the number of studies they include, and, thus, improve the quality of their meta-analyses.

The electronic searches in academic databases and digital libraries involve using keywords relevant to the research topic. A keyword can be general such as information systems or specific such as knowledge management systems, but, in either case, should be of great importance to the meta-analysts. IS researchers should also develop criteria for including studies. Although inclusion criteria vary across meta-analyses, common ones include: 1) the original studies reveal sample size and 2) they report at least one correlation of interest.

2.3.1 File Drawer Problem

The file drawer problem—journals' tendency to more frequently publish studies with positive results than those with negative or inconclusive outcomes—can potentially threaten the results from meta-analyses (Rosenthal, 1979). Indeed, researchers widely believe that journals tend to publish studies with significant, hypothesis-supporting results and, thus, can suffer from file drawer problems (Geyskens, Steenkamp, & Kumar, 2006; Ma & Liu, 2004; Phillips, 1998). To alleviate this problem, IS researchers need to include individual studies from non-journal sources such as books, conference proceedings, and non-published dissertations (Sharma & Yetton, 2003).

2.3.2 Independence

A meta-analysis relies on independent studies (Bamberger, Kluger, & Suchard, 1999; Ma & Liu, 2004). To ensure that they use such studies, IS researchers need to detect duplicate studies by carefully comparing their authorship, description, and statistical data. To do so, one usually begins by investigating common authorship. Next, one should compare as many details as possible of how these shared authorship studies describe themselves (Wood, 2008). Such details involve the study context, research participants, target IT system, method, data-collection period, and so forth. Next, one needs to compare the reported data such as sample size, demographics of the participants, and values of the correlations between variables.

Past research suggests that, if two or more papers use the same data set, one needs to treat them as duplicate and use only one (Geyskens et al., 2006). Moreover, when a study presents multiple data sets based on the same sample, one should also treat them as duplicate and use their simple average values for the meta-analysis (Heneman, 1986). Nevertheless, when a study presents multiple data sets based on different samples, one should treat each data set as an independent study since doing so does not violate the criterion for independence (Hunter et al., 1982).

2.4 Data-coding Procedure

To obtain the data for a meta-analysis, researchers need to extract necessary numerical information from each primary study. Undoubtedly, the index of effect sizes represents the most needed numerical information (Hunter et al., 1982). The r and d indexes represent the two main ones that statisticians propose (Hunter & Schmidt, 1990; Schmidt & Hunter, 2014). The r index measures the strength of the relationship between the independent variable and the dependent variable, whereas the d index measures the magnitude of the difference between the levels of the independent variable with respect to the dependent variable (Leech, Barrett, & Morgan, 2007). In IS, as in other business fields, researchers primarily use the r index. The most well-known r index, the Pearson's correlation coefficient, varies between -1 and +1 with 0 representing no effect and -1 or +1 the maximum effect (Pearson, 1895). So, in this step, meta-analysis researchers need to extract all r values from each individual study and prepare them so they can synthesize and/or analyze them afterwards.

One also needs sample size and internal consistency reliability information. One can use sample size, an important study statistic, as a weight to calculate weighted average correlations and to analyze the statistical power of a meta-analysis (Hedges & Olkin, 1985). Internal consistency reliability refers to the consistency of the items in a measurement scale; it reflects the degree to which items correlate with each other (Hunter et al., 1982). It also indicates the amount of error in measuring variables. As such, one needs it to correct originally reported correlations (Hunter & Schmidt, 1990; Schmidt & Hunter, 2014). Based on mean inter-item correlation, Cronbach's alpha is the most popular statistic testing internal consistency reliability. One can find its definition and formula in Cronbach (1956). Composite reliability, which Werts, Linn, and Joreskog (1974) proposed, constitutes the other widely used internal consistency statistic. Many believe that composite reliability can more appropriately estimate the internal consistency of latent variables in partial least squares (PLS) path models (Chin, Marcolin, & Newsted, 2003).

Meta-analysts also need to extract necessary textual information from each primary study. Past research suggests that such textual information may involve authors, title, year, source, and setting. A source specifies the type of publication (i.e., journal paper, book, dissertation, or conference paper). Setting refers to the context in which a study's authors conducted empirical research. It usually explains when and where one conducted a study, the participants, how one recruited them, and how one collected the data. In the IS field, when describing a study's setting, researchers may also describe the target information system, where and why the study used it, the information system's users, and so on. In order to obtain useful data, IS researchers sometimes need to use a pre-developed scale to rate some aspects of a study's description. For example, Sharma and Yetton (2003) have estimated task interdependence by using a six-item scale to rate the description of IS innovation; Wu and Lederer (2009) have measured voluntariness by using a four-item scale to rate the description of system-use environment. Note that one should create descriptions by taking all portions of text verbatim from each primary study and not make any changes unless to link extracts coming from different parts of the study.

2.4.1 Inter-rater Reliability and Agreement

Inter-rater reliability measures the consistency of ratings across different raters. Raters can have high inter-rater reliability if their ratings are very close and in the same relative order. In other words, one does not have to assign exactly the same ratings to each of the objects for inter-rater reliability to be high (Tinsley & Weiss, 2000). Just like internal consistency reliability, one calculates inter-rater reliability as correlations between the ratings that different raters assign. In conducting a meta-analysis on environment-based voluntariness, Wu and Lederer (2009) determined inter-rater reliability using Shrout and Fleiss's (1979) intraclass correlation for all the raters and Pearson's correlation for any two of the raters (i.e., if three different raters exist, one can calculate three Pearson's correlations).

Inter-rater agreement differs from inter-rater reliability. Inter-rater agreement measures the degree to which different raters assign exactly the same ratings to each object (Tinsley & Weiss, 2000). As such, inter-rater agreement is very sensitive to the difference in ratings, and a high inter-rater agreement signifies that different raters have assigned precisely the same ratings to many of the objects. A deceptively simple measure of inter-rater agreement is the proportion or percentage of agreements, whereas a more complex one is Cohen's kappa (Cohen, 1960), which adjusts the observed proportional agreement to consider the amount of agreement that one would expect by chance.

2.4.2 Convert Test Statistics into Correlations

Some studies may not report correlations (r) of interest but other test statistics that one can convert into correlations, such as shared variance (r^2), which one can convert into a correlation by square rooting it, and covariance (cov(x, y)), which one can obtain the corresponding correlation for via the formula:

$$r = \frac{\mathrm{cov}(x, y)}{\sigma_x \sigma_y}, \qquad (1)$$

where σ is the standard deviation.

The F-value, the ratio of the regression mean square to the error mean square, represents another such statistic. If a study has only one independent variable, one can obtain the correlation value (r) from an F-value with the formula:

$$r = \sqrt{\frac{F}{F + n - 2}}, \qquad (2)$$

where n is the number of observations.

Finally, the t-value of regression coefficient represents yet another statistic. If the regression test contains only one independent value, one can obtain the correlation value (r) from a t-value with the formula:

$$r = \sqrt{\frac{t^2}{t^2 + n - 2}}, \qquad (3)$$

where n is the number of observations. The standardized regression coefficient β value can also be such a test statistic. If the regression test contains only one independent variable, then one can use β equals to correlation (r) as correlation.

2.5 Synthesize the Data

Second, one needs to synthesize the data that one has collected from the primary studies. In particular, in this process, one combines the data and calculates descriptive statistics such as mean, median, maximum, minimum, standard deviation, and number of observations for each of the different correlations. This procedure involves calculating meta-sample size and total sample size. While meta-sample size refers to the number of individual studies that a meta-analysis includes, total sample size refers to the total number of subjects who participated in one of these studies. Researchers argue that total sample size may be more important because it is the key to the accuracy of the estimate of mean correlation (Schmidt & Hunter, 2014; Hwang, 1996). Past IS meta-analyses suggest that synthesizing data also involves other calculations such as corrected correlation and weighted average and other investigations such as outlying studies, publication bias, and heterogeneity issue.

2.5.1 Outlying Studies

Outlying studies refer to those studies whose data deviates so much from that of other studies that a meta-analysis includes (Hawkins, 1980). Because outlying studies may generate abnormal analysis results, one must handle them appropriately when synthesizing and analyzing data (Sterne, Egger, & Moher, 2008). To detect outlying studies, researchers may employ the three standard deviation technique. This commonly used technique flags a study as a potential outlier if its data lies outside of the interval: (Mean – 3*SD, Mean + 3*SD), where mean refers to the average of the data set collected from the primary studies and SD to the standard deviation of the data set (Pukelsheim, 1994). The justification of this technique relies on the assumption that a normally distributed data set should have nearly 99.7 percent of its observations within three standard deviations of the mean (Kazmier, 2003).

According to Argo and Main (2004), if one uses sample size as a weight, a study with a large outlying sample size may dominate a meta-analysis and generate deviant results. Therefore, researchers need to carefully deal with primary studies that report disproportionately large sample sizes. Some IS researchers choose to exclude such outlying studies from further analysis, such as He (2013). However, in order to compare the results and discover whether they significantly differ, other IS researchers have followed Hunter and Schmidt (1990) and analyzed the data with and without the outlying studies (Wu & Lu, 2013).

2.5.2 Publication Bias Test

Publication bias essentially refers to the file drawer problem. Although one can alleviate potential bias by including studies from non-journal sources, meta-analysts may still need to employ fail-safe *N* and funnel plots to determine its significance. Proposed by Rosenthal (1979), fail-safe *N* is the number of additional non-significant studies needed to reduce the effect size to a pre-specified non-significant level. Because $p \leq 0.05$ is the standard level of statistical significance, many researchers use $p > 0.05$ as the pre-specified non-significant level. Focusing on statistical significance rather than on effect size, Rosenthal's method of calculating fail-safe *N* often generates a very large *N*-value, which suggests that one needs a great number of additional studies to raise the p-value to above 0.05. Because a great number of additional studies do not likely exist, the fail-safe *N* test supports the conclusion that publication bias does not exist and that a study's findings did not likely occur by chance. However, this conclusion may be weak in that the combined study results can be highly statistically significant even with a small or very small mean effect size (Hunter & Schmidt, 1990).

To address this issue, Hunter and Schmidt (1990) have placed more focus on effect size (i.e., *r*-value) and derived a different formula to calculate fail-safe *N*:

$$N = k(\overline{r_k} / \overline{r_c} - 1), \quad (4)$$

where k is the number of studies included in a meta-analysis, $\overline{r_k}$ is the mean of the correlations, and $\overline{r_c}$ is the predefined value that one can determine with the formula:

$$t = \overline{r_c} / \sqrt{(1 - \overline{r_c}^{2}) / (n-2)}, \quad (5)$$

where t = 1.96 when $p \leq 0.05$ and n is the average sample size. Hunter and Schmidt (1990) also suggest that publication bias may not be a problem if the fail-safe *N* exceeds 90.

As a visual tool, a funnel plot is simply a scatter plot with effect size on the horizontal axis and the sample size on the vertical axis (Cooper & Hedges, 1994). In the absence of bias, a funnel plot normally shows a symmetric inverted funnel shape with effect sizes from small studies scattering widely at the bottom of the graph and the spread narrowing toward the top of the plot for studies with larger sample size (Butler, Perryman, & Ranft, 2012). Because publication bias may not be the only reason for problematic funnel plots, one should take caution in interpreting plot results and view funnel plots in conjunction with other publication bias tests such as the fail-safe *N* (Sabherwal et al., 2006).

2.5.3 Corrected Correlation

According to Hunter and Schmidt (1990), study design artifacts can affect the size of correlation coefficient; thus, one must correct them whenever possible. Measurement error represents one such artifact; that is, the error of measuring variables. Statisticians believe that measurement error in variables can cause their correlation to be lower than it would be if one perfectly measured them. As we note above, the internal consistency reliability of a variable indicates measurement error. Because reliability can be obtained, it is thus possible to correct the observed correlation for measurement error. Specifically, it is corrected through dividing reported correlation by the square root of the product of the reliabilities of the two variables (Hunter & Schmidt, 1990).

2.5.4 Weighted Average Correlation

Naturally, different primary studies have a different sample size. Therefore, the best estimate of mean *r*-value is not the simple average across studies but a weighted average in which each correlation is weighted by the sample size in that study (Hunter & Schmidt, 1990). One can calculate the weighted average correlation using the formula:

$$\bar{r} = \frac{\sum(N_i r_i)}{\sum N_i}, \quad (6)$$

where $\bar{r}$ is the weighted average correlation, r_i is the correlation in study *i*, and N_i is the sample size in study *i*. Some IS researchers in their meta-analyses such as Sabherwal et al. (2006) and He (2013) have adopted this weighted average formula. Note also that these two studies have corrected correlations for measurement error and, thus, calculated corrected weighted average.

2.5.5 Corrected Standard Deviation

Sampling error represents another important artifact that meta-analysts need to correct. Sampling error refers to the error incurred when using samples of a population to estimate statistical characteristics of that population. Statisticians believe that sampling error can cause a standard deviation of a correlation to be higher than it would be if one obtained the data from the whole population (Hunter & Schmidt, 1990). Therefore, meta-analysts need to correct a standard deviation for sampling error by taking the following steps:

1) Employ the corrected correlation (i.e., corrected for measurement error) and the formula presented above to calculate $\bar{r}$, the weighted average corrected correlation.
2) Calculate σ_r^2, the variance across studies, using the formula: $\sigma_r^2 = \frac{\sum[N_i(r_i - \bar{r})^2]}{\sum N_i}$
3) Calculate σ_r^2, the variance across studies, using the formula:
4) Calculate $\bar{N}$, the average sample size across studies using the formula: $\bar{N} = T / K$, where T is the total sample size across studies and K is the number of studies included in the meta-analysis.
5) Calculate σ_e^2, sampling error variance, using the formula: $\sigma_e^2 = (1 - \bar{r}^2)^2 / (\bar{N} - 1)$.
6) Calculate σ_p^2, the corrected variance across studies or the estimate of population variance, using the formula: $\sigma_p^2 = \sigma_r^2 - \sigma_e^2$.
7) Calculate σ_p, the corrected standard deviation or the estimate of population standard deviation, using the formula: $\sigma_p = \sqrt{\sigma_p^2}$.

2.5.6 Heterogeneity or Homogeneity Test

Heterogeneity or homogeneity in a meta-analysis refers to differences or similarities in study results between the primary studies. Based on this definition, researchers propose that one needs to use a between-study heterogeneity as an aid in deciding whether observed effect sizes are more variable than one would expect from sampling error alone (Hedges, 1982; Rosenthal & Rubin, 1982). A heterogeneity test involves the *Q* statistic in which the distribution is similar to chi-square with *k-1* degrees of freedom where *k* is the number of studies included in the meta-analysis (Hedges & Olkin, 1985). More specifically, Hedges and Olkin (1985) and Cooper and Hedges (1994) recommend three steps to conduct a heterogeneity test:

1) Normalize correlations using Fisher's *z* transformation: $z = 0.5 \times \ln((1+r)/(1-r))$
2) Calculate weighted average z: $\bar{z} = \sum n_i z_i / \sum n_i$, where n_i is the sample size in study *i*, and
3) Compute the Q statistic: $Q = \sum (n_i - 3)(z_i - \bar{z})^2$.

A statistically significant *Q* suggests that sampling error does not explain all the observed variance in the effect sizes and, thus, warrants a search for moderators (Hunter & Schmidt, 1990). Hence, researchers argue that heterogeneity of primary studies does not represent a burden but, rather, an opportunity. Past IS research suggests that meta-analysis rarely include homogenous studies. For example, in their meta-analyses, King and He (2006), Schepers and Wetzels (2007), and Yousafzai, Foxall, and Pallister (2007b) all found significant Qs for the effect sizes in the models for technology acceptance.

2.6 Data-analysis Procedure

2.6.1 Identify Moderators

A moderating effect occurs when the direct relationship between two variables depends on the value of a third variable, the moderator (Aguinis & Stone-Romero, 1997). In the IS field, many researchers conduct meta-analyses to identify moderators that they may classify into two types: categorical or continuous. Quite a few theories and research models in IS and related fields posit the impact of moderating effects of categorical variables (Sun & Zhang, 2006). A review of the literature shows that many studies have discussed and even empirically investigated categorical moderators such as gender, research participants (employees vs. students), system-use context (mandatory vs. voluntary), nature of task (routine vs. non-routine), and type of technology (utilitarian vs. hedonic). In tests for such moderating effects, one assigns each primary study a numerical value based on the moderator and then groups them accordingly. One can then compare the mean group effect sizes can computing a t-statistic or a between-group heterogeneity statistic Q_B.

A t-test allows a comparison between two groups and employs the formula:

$$t = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}}, \quad (7)$$

where $\overline{X}_1$ and $\overline{X}_2$ are the mean effect sizes in the two groups, S_1 and S_2 are the standard deviations of the effect sizes in the two groups, and n_1 and n_2 are the number of primary studies included in each of the two groups. Similar to the between-study heterogeneity test that we discuss above, a between-group heterogeneity test also uses Fisher's z transformation, and one can apply it to two or more groups. One computes the statistic via the formula:

$$Q_B = \sum W_i (\overline{Z}_i - \overline{Z}_o)^2, \quad (8)$$

where Wi is the sum of the weights in the ith group, $\overline{Z}_i$ is the mean effect size in the ith group, and $\overline{Z}_o$ is the overall mean effect size of all the primary studies. A statistically significant t or Q_B suggests a difference between the groups and, thus, supports the presence of the moderator.

One can also use an ordinary (or linear) least squares regression analysis to investigate the moderating effects of several categorical variables together (Cotton & Tuttle, 1986; Huffmeier, Freund, Zerres, Backhaus, & Hertel, 2014). More specifically, one will perform this type of regression analysis with the correlation between the first two variables as the dependent variable and the categorical variables (moderators) as independent variables. Therefore, we can illustrate such a regression model as follows:

$$\text{Correlation}_{\text{between 1st \& 2nd variables}} = b_0 + b_1\text{Moderator1} + \ldots + \text{bnModeratorN} + \text{error}.$$

Sharma and Yetton's (2003) and Wu and Lederer's (2009) papers represent two typical meta-analysis studies that focus on identifying continuous moderators. Focusing on institutional context, Sharma and Yetton (2003) proposed a contingent model in which task interdependence moderates the effect of management support on IS implementation success. They measured the continuous moderator—task interdependence—with six items on a five-point Likert scale anchored from disagree to agree. Drawing on the literature on technology acceptance model (TAM), Wu and Lederer (2009) suggested that environment-based voluntariness moderates the relationships among the four primary TAM constructs. To measure the continuous moderator—voluntariness, they employed four items and also rated them on a five-point Likert scale anchored from disagree to agree.

Following the methodology that Hedges and Olkin (1985) outline, these two studies employed a weighted least squares regression (WLSR) procedure to test the moderating effects for a continuous variable. Unlike linear/nonlinear least squares regression, WLSR incorporates extra nonnegative constants—the weights—into the model-fitting criteria. By assigning a weight to each observation, researchers can give each data point its proper amount of impact on the final parameter estimates. Typically, a WLSR procedure tests the slope in a regression model with the sample size of each primary study as its weight, the moderator (i.e., the third variable) as the independent variable, and the correlation between the first two variables as the dependent variable. As such, we can illustrate a WLSR model as follows:

$$\text{Correlation}_{\text{between 1st \& 2nd variables}} = b_0 + b_1\text{Moderator} + \text{error}.$$

2.6.2 Estimate Explained Variances

Among other reasons, researchers conduct a meta-analysis to estimate variances explained in dependent variables. If only one independent variable predicts a dependent variable, one can obtain the explained variance by squaring their correlation (Hunter and Schmidt 1990). Moreover, if a dependent variable has two predictor variables, one can calculate its explained variance with the formula:

$$R^2_{Y.12} = \frac{r^2_{Y1} + r^2_{Y2} - 2 \times r_{Y1} \times r_{Y2} \times r_{12}}{1 - r^2_{12}}, \quad (9)$$

where r is the correlation, 1 and 2 are the independent predictors, and Y is the dependent variable.

2.6.3 Test Research Models

Researchers can also conduct a meta-analysis to test a research model. To do so, they first synthesize the correlations and compute a pooled correlation matrix for the constructs in the model and then use structural equation modeling (SEM) tool to analyze the matrix. SEM has become an important statistical tool in the social and behavioral sciences. Researchers often employ it to test proposed relationships between constructs in a research model. The combination of meta-analytic techniques with SEM provides a unique method for building up knowledge in a field (Viswesvaran & Ones, 1995). One can see examples where researchers have combined these two methods in the business, education, and social sciences fields (Furlow & Beretvas, 2005).

Sabherwal et al.'s (2006) paper represents such an example in the IS field. These authors tested an IS success model using LISREL and a correlation matrix based on 612 findings from 121 studies published between 1980 and 2004. LISREL requires a single sample size for the entire correlation matrix, whereas different correlations in the matrix may be based on different sample sizes. To resolve this issue, researchers can use either minimum sample size (Tett & Meyer, 1993) or harmonic mean sample size

(Viswesvaran & Ones, 1995). Also note that, because corrected correlations should be free of measurement errors, the reliabilities of their corresponding variables equal one and the error variances equal zero (Hunter & Schmidt, 1990).

3 Discussion

Among the 23 major studies that we reviewed for this research (see Appendix A), 19 synthesized and/or analyzed data, whereas the other three did not. By analyzing and synthesizing these major meta-analysis studies, we discovered three insightful findings. First, among the 19 studies that synthesize and/or analyze data, nine synthesized data by only analyzing the values of correlations, which indicates that measuring effect size (i.e., correlation coefficient) likely constitutes the most basic purpose for conducting meta-analysis research and the most widely used technique for synthesizing the data in such research.

Second, only four of these 19 studies examined variances explained in dependent variables, which shows that relatively fewer researchers have used the explained variance technique to analyze meta-analysis data. One probable reason for why may be that fewer researchers know about the technique of estimating explained variances compared to that of measuring effect size, and, thus, many meta-analysis researchers may not know they could use a technique to measure the variances that more than one independent variable explains.

Third, only five of these 19 studies developed and tested some research hypotheses to identify moderators or to validate a theoretical model[1], which suggests that hypothesis-testing meta-analysis studies are rare and, thus, require more research attention. This finding may also suggest that one cannot easily conduct such meta-analysis studies because they require well-established theories to identify moderators or develop models and because the literature does not readily contain appropriate individual studies. However, if one can successfully conduct a hypothesis-testing meta-analysis study, its findings often provide insightful and enlightening findings, and the paper will usually appear in top journals. For example, among these five hypothesis-testing meta-analysis studies, *MIS Quarterly* published two (Sharma & Yetton, 2003; Wu & Lederer, 2009), *Information Systems Research* published one (Kohli & Devaraj, 2003), and *Management Science* published one (Sabherwal et al., 2006). Therefore, we call for more future meta-analysis studies that test theory-guided research hypotheses or models.

4 Conclusion

Because meta-analysis can provide helpful insight into a research topic, it has become a widely accepted research tool. For this same reason, more and more IS researchers have begun to use meta-analyses to retrieve knowledge from many single empirical studies. Although meta-analyses represent a powerful tool for advancing cumulative knowledge, the complex issues and techniques involved in the methodology may confuse IS researchers. In an effort to address these complexities, we discuss the procedures, issues, and techniques that pertain to properly performing a meta-analysis in IS field. By doing so, we help to identify the key meta-analysis procedures, improve our understanding of the associated issues, and advance the accuracy of applying meta-analytic techniques.

Moreover, to make the paper more empirical and practical, we also introduce IS researchers to software tools for efficiently synthesizing and analyzing the data in Table 1. Such information may furnish another important contribution to the IS field because novel researchers may have very limited knowledge on how to use software tools to help conduct a meta-analysis. Finally, we call for more hypothesis- or model-testing meta-analysis studies in the future because such empirical meta-analysis studies usually provide more enlightening and path-breaking findings and can often contribute more novelties to the IS field. To sum up, we believe that any empirical research should focus on constructing a cumulative base of knowledge upon which future researchers may build. We also believe that meta-analysis is an irreplaceable tool to facilitate that journey.

[1] Two other studies, Montazemi and Wang (1988/89) and Schepers and Wetzels (2007), have also identified moderators, but without developing research hypotheses. These two studies were not counted into the five studies discussed here. Thus, the total number of data synthesis and/or analysis studies could be 20 (i.e., 9+4+5+2). This is because one study, Benbasat and Lim (1993), can be dual-counted toward two groups (examine explained variances and identify moderators with hypotheses; see Appendix A).

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Appendix

Table A1. Meta-analysis Studies Reviewed for This Research

Paper	Main data synthesis or analysis methods	Theory involved
Benbasat & Lim. (1993)	Examine explained variances to identify moderators and test hypotheses	Group support systems (GSS) framework
He & King (2008)	Correlation analysis	System success model
Henry et al. (2015)	Correlation analysis	Organizational control theory
Hwang & Thorn (1999)	Correlation analysis	System success model
Khechine, Lakhal, & Ndjambou (2016)	Correlation analysis	Unified theory of acceptance and use of technology
King & He (2006)	Correlation analysis	Technology acceptance model
Kohli & Devaraj (2003)	Identify moderators by testing research hypotheses	No theory involved
Lee et al. (2003)	Examine explained variances	Technology acceptance model
Ma & Liu (2004)	Correlation analysis	Technology acceptance model
Mahmood et al. (2001)	Correlation analysis	System success model
Masoner, Lang, & Melcher (2011)	Correlation analysis	System success model
Montazemi & Wang (1988)	Identify moderators	No theory involved
Sabherwal et al. (2006)	Test a research model and hypotheses	System success model
Saeed et al. (2003)	Correlation analysis	Technology acceptance model, theory of reasoned action, theory of planned behavior, innovation Diffusion theory, flow theory
Schepers & Wetzels (2007)	Identify moderators	Technology acceptance model
Sharma & Yetton (2003)	Identify moderators by testing research hypotheses	Diffusion theory, technology acceptance model
Sharma, Yetton, & Crawford (2009)	Correlation analysis	Technology acceptance model
Wu & Lederer (2009)	Identify moderators by testing research hypotheses	Technology acceptance model, the theory of apparent mental causation
Wu & Du (2012)	Examine explained variances	Technology acceptance model, system success model
Yousafzai et al. (200b7)	Identify moderators and examine explained variances	Technology acceptance model
Haried & Dai (2011)	No data synthesis or analysis	No theory involved
Ramaprasad & Syn (2013)	No data synthesis or analysis	No theory involved
Yousafzai et al. (2007a)	No data synthesis or analysis	Technology acceptance model

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