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## ESTIMATING THE EFFECT OF COMMON METHOD VARIANCE: THE METHOD–METHOD PAIR TECHNIQUE WITH AN ILLUSTRATION FROM TAM RESEARCH<sup>1</sup>

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### Abstract

*This paper presents a meta-analysis-based technique to estimate the effect of common method variance on the validity of individual theories. The technique explains between-study*

*variance in observed correlations as a function of the susceptibility to common method variance of the methods employed in individual studies. The technique extends to mono-method studies the concept of method variability underpinning the classic multitrait–multimethod technique. The application of the technique is demonstrated by analyzing the effect of common method variance on the observed correlations between perceived usefulness and usage in the technology acceptance model literature. Implications of the technique and the findings for future research are discussed.*

**Keywords:** Common method variance, common method bias, meta-analysis, perceived usefulness, use, system use, usage, technology acceptance model

### Introduction

Artificial covariance between measures due to common methods can inflate observed correlations and provide spurious support for the theories being tested (Campbell and Fiske 1959). The effect of common method variance (CMV) is a major potential validity threat in social sciences research (Doty and Glick 1998; Podsakoff et al. 2003). Doty and Glick illustrate their argument with examples in which the magnitude of CMV is a major validity threat to published findings. However, research, including research within the IS discipline, frequently ignores the effects of CMV (Burton-Jones 2009). Woszczynski and Whitman (2004) estimate that CMV poses a validity threat to over half the studies published in leading IS journals. In contrast, Malhotra et al. (2006) conclude that the extent of bias within the IS domain is not substantial and does not pose a potential validity threat to the

<sup>1</sup>Detmar Straub was the accepting senior editor for this paper. Jonathan Trower served as the associate editor.

**Note:** The appendices for this paper are located at <http://www.misq.org/archivist/appendices/SharmaYettonAppendices.pdf>.

published findings. These two contradictory conclusions leave unanswered a critical question for IS researchers: *Is CMV a major potential validity threat to published findings in the IS literature?*

Addressing this question requires a technique that enables researchers to assess the extent to which CMV affects research findings within individual research domains. However, estimating the effect of CMV within a research domain is a major methodological challenge (Podsakoff et al. 2003). While the multitrait-multimethod (MTMM) technique is generally accepted as the technique of choice to estimate the effect of CMV (Doty and Glick 1998; Podsakoff et al. 2003), social science research, including IS research, typically employs mono-method measurement, for which MTMM-based techniques are not applicable. Instead, other techniques have been employed, including the Harman single-factor test and the marker variable technique (Podsakoff et al. 2003). However, the validity of these techniques remains to be established (Podsakoff et al. 2003; Richardson et al. 2009; Straub and Burton-Jones 2007).

Contributing to the literature on techniques to assess the effect of CMV, this paper draws on the principle of method variability underpinning the MTMM approach (Campbell and Fiske 1959, p. 81) to develop a meta-analysis-based technique to estimate the effect of CMV from the findings of studies employing mono-method measurement. The MTMM approach relies on designing variation in methods and traits within individual studies to assess the convergent and discriminant validity of measures and to assess the impact of CMV on observed findings. In contrast, the present study develops a technique that relies on existing between-studies variation in methods to estimate the effect of CMV. This reframes the challenge from one of designing individual studies that control for CMV to one of validating theory based on a meta-analysis of the cumulative empirical evidence.

The paper begins by reviewing the CMV literature and describing the method-method pair technique. It then illustrates the use of the technique, estimating the effect of CMV on the observed correlations between perceived usefulness (PU) and usage (U) in the technology acceptance model (TAM) literature. The analysis finds that over 56 percent of the variance in observed PU-U correlations can be attributed to method effects. In contrast to the conclusions drawn by Malhotra et al., the findings of this illustration suggest that CMV presents a major potential validity threat to the findings of IS research. Finally, implications for IS research of the method-method pair technique are discussed.

## The Effect of Common Method Variance

It is well accepted that measures employed in social sciences research are subject to a number of measurement errors (Burton-Jones and Gallivan 2007; Podsakoff et al. 2003). A subject's response on a measure can be partitioned into two components, one representing the effect due to the underlying construct and the other representing the effect due to various measurement artifacts (Le et al. 2009, p. 13). These measurement errors introduce biases in estimates of construct-level relationships computed from observed scores (Doty and Glick 1998; Le et al. 2009). In particular, when common or similar methods are employed to measure two variables, measurement errors in the two scores covary, inducing a bias in their correlation (see Figure 1). As a result, observed correlations are inflated.<sup>2</sup>

Podsakoff et al. (2003) identify three components into which observed correlations can be partitioned:

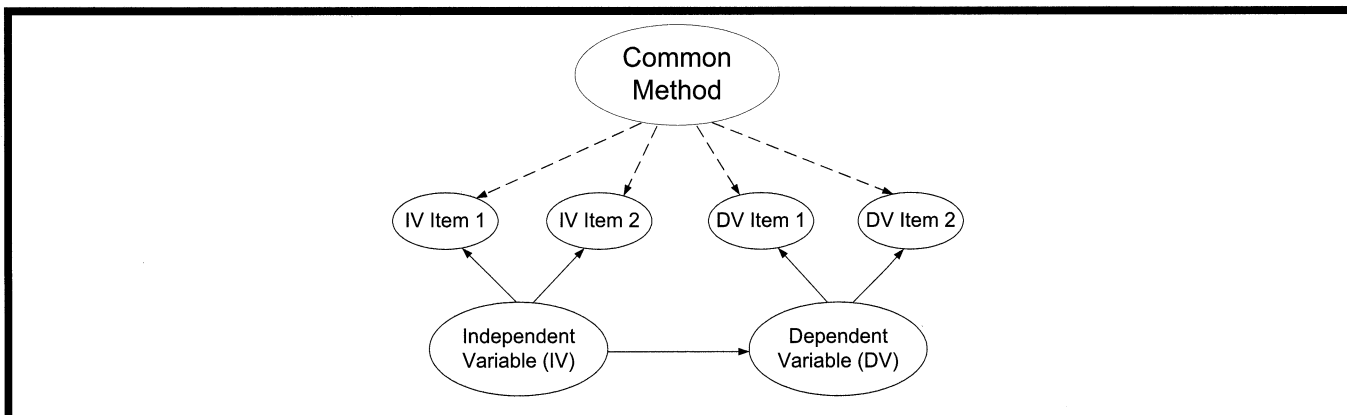
$$\begin{aligned} \text{Observed correlation} &= \text{Construct-level correlation} \\ &+ \text{Spurious correlation due to CMV} + \text{Error} \end{aligned}$$

The error term in the above equation includes all measurement errors other than CMV. While CMV typically inflates observed correlations (Le et al. 2009, p. 13), measurement errors deflate observed correlations. The latter effect can be partially addressed by correcting the observed correlations for the reliabilities of measures (Hunter and Schmidt 2004; Schmidt et al. 2003).

### Multitrait-Multimethod Techniques

While the existence of CMV is widely acknowledged, techniques used to estimate its effect in individual research domains have limitations. Two broad categories of techniques have been proposed to control for the effect of CMV. One, the MTMM technique, requires researchers to employ multiple traits to operationalize each variable and to employ multiple methods to measure each trait (Campbell and Fiske 1959). The other set of techniques is applicable for studies employing mono-method research designs. This latter set includes the Harman single-factor test and the marker variable

<sup>2</sup>In theory, common method variance could also deflate the observed relationship (Cote and Buckley 1987; Podsakoff et al. 2003), although few studies report observing this effect. Doty and Glick (1998, p. 401) analyzed 316 trait-trait combinations and found that in each of these combinations, CMV inflated the observed correlations.



**Figure 1. Nomological Network of a Relationship Including the Effect of CMV (Adapted from Podsakoff et al. [2003, Figure 3A, Table 5, p. 896] and Le et al. [2009, Figure 1, p. 178])**

technique. However, the validity of these techniques, which are reviewed briefly in Appendix A, has not been established (Podsakoff et al. 2003, p. 893; Richardson et al. 2009; Sharma et al. 2007). Here, we review the MTMM technique, which serves as the point of departure for the meta-analysis-based technique developed in this paper.

The MTMM technique was proposed by Campbell and Fiske (1959) as a means to both assess the convergent and discriminant validity of measures employed in a study, and to address the validity threat arising from CMV. A key principle underpinning the MTMM approach is that variation in methods is essential to estimating the effect of CMV. As Campbell and Fiske comment, “*more than one method must be employed in the validation process*” (p. 81, italics in original). While Campbell and Fiske do not rule out alternative techniques, the MTMM technique has generally come to be associated with employing multiple, maximally dissimilar methods within individual studies to capture each trait (Williams et al. 1989). Analysis of MTMM data, which today generally employs structural equation modeling techniques (Williams et al. 2003), enables researchers to estimate the extent of trait, method, and error variances and to estimate correlations between constructs controlling for method effects and errors in measurement (Millsap 1995; Podsakoff et al. 2003).

Although the MTMM technique of interpreting patterns of correlations in the matrix has been rarely applied within IS research, Straub et al. (2004) identify a number of exceptions. For example, they report that Venkatraman and Ramanujam (1987) employ the MTMM technique to assess convergent validity. Venkatraman and Ramanujam employ two methods of data collection, self-report and archival sources, to measure

three different traits capturing the construct business economic performance, namely, sales growth, profit growth, and profitability. Although Campbell and Fiske originally employed the term *traits* to refer to individual characteristics, which reflects the context of personality research within which they developed the MTMM technique, Venkatraman and Ramanujam’s application reflects more recent trends that apply the MTMM technique to variables other than individual characteristics.

Research based on MTMM techniques reports the extent to which CMV influences research findings in the social sciences (Williams et al. 1989). Analyzing 28 published MTMM matrices, Doty and Glick (1998, p. 394) conclude, “Common methods causes a 26% median bias in observed relationships.” Similarly, Podsakoff et al. (2003, p. 880) review a number of studies that estimate the extent to which CMV influenced published findings. They conclude: “On average, the amount of variance accounted for when common methods variance was present was approximately 35%, versus approximately 11% when it was not present.” Importantly, CMV frequently provides a competing explanation for the observed relationships, compared with the explanations derived from the theory being tested.

A key limitation to employing MTMM techniques is that they require individual studies to employ multiple methods to capture multiple traits representing each construct (Doty and Glick 1998). This places an onerous burden on researchers. As a result, social sciences research relies primarily on mono-method studies in which “each construct is assessed using a single method, such as a scale constructed using Likert-type questionnaire items” (Doty and Glick 1998, p. 377). In the absence of multiple methods, effect sizes reported within

studies cannot be partitioned into construct-level correlations and spurious correlation due to CMV (Doty and Glick 1998; Straub et al. 2004).

Another limitation is that the MTMM approach recommends that the multiple methods employed be maximally dissimilar, or uncorrelated. However, as Campbell and Fiske themselves note, statistical tests of the matrix are problematic, including there being no clear and undisputed metric to rate the similarity/dissimilarity of methods. The extent to which the methods employed to measure variables involved in computing a correlation are similar/dissimilar affects the extent to which the observed correlation is susceptible to the effect of CMV. Therefore, the assumptions made about the similarity/dissimilarity of methods would affect the conclusions based on the analyses of MTMM matrices.

For example, Spector (1987, p. 442) analyzed 10 published MTMM matrices and found little evidence of method variance in the data. He concluded that the potential validity threat from common method variance “may in fact be mythical.” Williams et al. (1989) reexamined the data, assuming that the methods employed in the reported MTMM matrices were not maximally dissimilar. Their analysis finds substantial method variance in the data and they report that “the conclusions reached by Spector (1987) were an artifact of his method and that method variance is real and present [in the data examined]” (Williams et al. 1989, p. 467). These conflicting conclusions highlight the need to develop methods to rate the susceptibility of methods to CMV.

### **A Meta-Analytical Approach for Estimating the Effect of CMV**

Researchers attempting to evaluate the effect of CMV on empirical findings within a theoretical domain are faced with two challenges. One is that the validity of existing techniques to control for CMV in mono-method studies has not been established (Podsakoff et al. 2003; Richardson et al. 2009; Sharma et al. 2007). The other is that few research domains have published enough MTMM matrices to employ MTMM-based techniques.

Instead, some researchers have focused on cumulating available MTMM matrices from multiple domains to estimate the average level of CMV across research domains in the social sciences (Doty and Glick 1998). Other researchers have analyzed the effects of specific factors on CMV. For example, Crampton and Wagner (1994) analyzed the effect of CMV from employing self-report data on 40,000 correlations

reported in published research on organizational behavior and human resources management. Their analysis highlights the effect of CMV on observed correlations but does not enable researchers to estimate the extent of that effect within individual research domains. They conclude that there remains a need for techniques to evaluate the effect of CMV on empirical support for individual theories. This paper addresses that challenge by proposing a meta-analysis-based technique to estimate the effect of CMV within individual research domains.

The technique developed here relies on variation in methods between mono-method studies to explain between-studies variation in effect sizes. Effect sizes reported in mono-method studies include the effects of CMV, whose magnitudes cannot be estimated within each study (Avolio et al. 1991). These effects are a function of the methods employed in the study to measure the independent and dependent variables: “Greater similarity among methods is expected to increase the covariation among methods and thus increase the likelihood of biased results” (Doty and Glick 1998, p. 379). In addition, the effect of CMV increases when the methods employed are more susceptible to method variance, such as self-report Likert scale measures as compared to objective measures (Doty and Glick 1998; Podsakoff et al. 2003).

Here, we propose that between-studies variation in methods can be employed to estimate the effect of CMV from the findings of multiple mono-method studies. This effect is a function of the *method–method pair* employed to measure the dependent and independent variables. Studies vary in the methods employed to measure the variables and, hence, the effect of CMV varies between studies. For example, effect sizes reported in studies employing Likert-type scales to measure both the independent and dependent variables are likely to be subject to a potential CMV-based validity threat. In contrast, studies employing methods that are less susceptible to CMV, including objective measures for both variables, are unlikely to be subject to that validity threat (Podsakoff et al. 2003).

Prior research has identified several method factors that increase the effect of CMV on observed effect sizes. These include, for example, employing abstract constructs and similar response formats, including the scales and anchors employed, to measure variables (Doty and Glick 1998; Podsakoff et al. 2003). In addition, studies that employ the same data source for both the independent and dependent variables and measure them at the same time are subject to a larger CMV-based potential validity threat than studies that employ multiple data sources and/or capture the two variables at different times.

The critical insight here is that observed effect sizes vary with the susceptibility to CMV of the method–method pair employed to measure the focal variables. It follows that the extent of bias due to CMV can be estimated by comparing effect sizes across studies as a function of the method–method pairs employed in those studies. Meta-analysis-based techniques are particularly suited for evaluating the effect of between-studies differences on the findings of individual studies (Erez et al. 1996).

Meta-analysis was developed to systematically cumulate findings from multiple studies, while controlling for the effects of errors and measurement artifacts (Hunter and Schmidt 2004). Estimating the between-studies effect of CMV enables validation of theory based on an evaluation of the cumulative empirical evidence while controlling for CMV. This is an important step in theory development because findings of individual studies are frequently subject to errors and biases that cannot be estimated within those individual studies (Avolio et al. 1991; Hunter and Schmidt 2004). Conclusions based on meta-analytical techniques are more reliable than the findings of any individual study (Hunter and Schmidt 2004).

Drawing on the meta-analysis framework, we propose the method–method pair (MMP) technique to estimate the effect of CMV within individual research domains. The MMP technique takes the MTMM technique as its point of departure. Both techniques rely on variation in methods to partition the variance in effect sizes into construct-level effects and spurious effects due to CMV. However, MTMM techniques do not account for susceptibilities to CMV of the multiple methods employed. In contrast, the MMP technique provides a metric to estimate the susceptibilities of method–method pairs to CMV and a technique to estimate the effect of susceptibilities on observed correlations. Further, in contrast with the MTMM technique, which relies on *designed* variation in methods *within* studies, the MMP technique capitalizes on *realized* variation in methods *between* studies.

The MMP technique makes two contributions to research. One, by reframing the problem of estimating CMV as an application of meta-analysis, it enables researchers to employ the findings of mono-method studies in assessing the effect of CMV. Traditionally, empirical examination of the impact of CMV has been limited to the small minority of studies that report MTMM matrices.

The other contribution is that it enables researchers to examine a specific research domain and estimate the effect of CMV in that domain. The effect of CMV varies across research domains and, therefore, both Cote and Buckley

(1987) and Podsakoff et al. (2003) recommend that each domain be examined individually. In response to their recommendation, the MMP technique estimates the effect of CMV in a research domain as a function of the different methods employed in studies across that domain.

## The Method–Method Pair Technique ■

The influence of CMV on an effect size, for example, a correlation coefficient, is a function of the susceptibility to CMV of the method–method pair employed to measure the dependent and independent variables. Drawing on Podsakoff et al. (2003), the following section develops a metric for the susceptibility of method–method pairs to CMV. We refer to this metric as CMV[MMP] in the rest of this paper. Then, we explain the application of this metric to estimate the effect of CMV within a research domain and, in the next section, illustrate the application of the technique with a worked example from a major research domain within the IS literature.

### **Susceptibility of Method–Method Pairs to CMV**

Estimating CMV[MMP] requires identifying the characteristics of methods that contribute to CMV. Podsakoff et al. (2003, Table 2, p. 882) identify four method characteristics that are potential sources of CMV: source, item characteristics, item constructs and measurement context. For a more complete treatment, see Podsakoff et al.

- *Source* effects arise when data are collected using self-report measures. For example, effect sizes based on self-report measures are biased compared with those based on multi-source measures (Crampton and Wagner 1994; Lowe et al. 1996; Straub et al. 1995). Employing different sources of data, such as peers, external observers, or archival sources, reduces the potential bias due to CMV (Podsakoff et al. 2003).
- *Item characteristic* effects arise when “the manner in which items are presented to respondents [produces] artifactual covariance in the observed relationships” (Podsakoff et al. 2003, p. 883). Such effects can arise when common scale formats are employed to measure variables. For example, employing Likert scales to measure both independent and dependent variables is likely to increase CMV in the observed effect size compared with employing behavioral measures or continuous open-ended scales for at least one of the variables

(Dickinson and Zellinger 1980; Kim and Malhotra 2005). Item characteristic effects also arise when both variables are measured employing items that are abstract, ambiguous, and complex (Cote and Buckley 1987; Crampton and Wagner 1994; Doty and Glick 1998; Podsakoff et al. 2003).

- *Item construct* effects involve the judgment of abstract constructs relating to “internal states or attitudes as experienced through introspection” (Crampton and Wagner 1994, p. 71). Constructs that capture factual and verifiable behaviors are less abstract, compared with constructs that require respondents to engage in more cognitive processing. The latter provide a greater opportunity for respondents to bias their answers in order to remain cognitively consistent (Doty and Glick 1998). Therefore, CMV increases when both variables are measured using abstract items (Podsakoff et al. 2003).
- *Measurement context* effects arise from the context in which measures are obtained (Podsakoff et al. 2003). In particular, concurrent measurement of both independent and dependent variables introduces covariance in the observed relationships (Le et al. 2009). In contrast, temporal separation between the two measurements reduces the effect of CMV (Podsakoff et al. 2003).

Following the above guidelines, we estimate CMV[MMP] based on four method characteristics: data sources, scale format, item abstractness, and temporal separation between measurements. Of these, the first three are properties of instruments. The fourth, temporal separation, is a property of the manner in which the instruments are administered. Accordingly, we identify two dimensions of CMV[MMP]: CMV[MMP-I] (instrument) and CMV[MMP-T] (temporal separation). The rest of this paper is focused on the effect of CMV [MMP-I]. We return to CMV [MMP-T] in the “Discussion.”

Here, we rank order CMV[MMP-I] for four method–method pairs. The case examined here is the special case in which one of the methods is a self-report perceptually anchored measure, while the other variable is measured employing each of the four measurement methods, including a perceptually anchored measure, presented in Table 1. The more general case, where measurement methods vary for both the dependent and independent variables, is more complex. We return to this issue in the “Discussion” section, where we generalize the technique to rank CMV[MMP-I] for the 10 distinct method–method pairs formed by different combinations of the four methods presented in Table 1.

Consider the following four method–method pairs:

- Correlations of a self-report *perceptually anchored* measure with a *system-captured* measure are based on the method–method pair that is least susceptible to CMV. System-captured, as compared with perceptually anchored, measures come from very different sources, are in different response formats, are factual and verifiable, and do not require any cognitive processing by respondents.
- Correlations of a self-report *perceptually anchored* measure with a *behavioral continuous* measure are susceptible to CMV because both are self-report measures. However, their response formats are different. Behavioral continuous measures employ open-ended numerical measures of behavior while the former employs perceptually anchored scales. Further, the items employed in behavioral continuous measures, such as hours of use, are less abstract than perceptually anchored scale measures and, hence, less susceptible to CMV.
- Correlations of a self-report *perceptually anchored* measure with a *behaviorally anchored* measure are more susceptible to CMV than correlations based on perceptually anchored and behaviorally continuous method–method pairs. Both methods in the former method–method pair are self-report measures. In addition, both generally employ a similar response format. However, the scale anchors employed are different. The latter generally employs behavioral anchors such as “not at all–very often” and “never–more than once day,” whereas the former generally employs “disagree–agree” anchors. Further, behaviorally anchored items (for example: “How often do you use this system?”) are less abstract than perceptually anchored items.
- Correlations of a self-report *perceptually anchored* measure with another *perceptually anchored* measure are the most susceptible to CMV. Both are self-report measures, employ similar response formats, have similar scale anchors, and are more abstract than behaviorally anchored items.

Table 2 rank orders CMV[MMP-I], the expected CMV for a specific method–method pair, for the above special case, where the independent variable is always measured on a perceptually anchored scale and the dependent variable is measured with each of the four methods in Table 1. The method–method pair most susceptible to CMV is when the dependent



**Table 1. Classification of Four Measurement Methods Employed in the IS Literature (Adapted from Rai et al. (2002) and Kim and Malhotra (2005))**

Method Type	Definition
System-Captured	Actual data are obtained from historical records and other objective sources, including usage records captured by a computer system.  Example items: Computer generated records of “time spent on the computer” or “number of web-pages accessed” or “number of software packages or functions used.”
Behavioral Continuous	Items refer to specific behaviors or actions that people have carried out. Responses are generally captured on a continuous open-ended scale.  Example items: “How many e-mail messages do you send on a typical day?”; “How many hours did you spend last week on this system?”; “What percentage of your time did you spend on this application?”
Behaviorally Anchored	Items refer to specific actions that people have carried out. Responses are generally captured on scales with behavioral anchors, such as “Never–More than once a day.”  Example items: “How often do you use this system?” captured on a scale with anchors ranging from “Not at all” to “Very often.”
Perceptually Anchored	Items that capture responses generally on “Agree–Disagree” Likert scales or on semantic differential scales.  Example items: “I use the system regularly” rated on an “Agree–Disagree” Likert scale.

**Table 2. Rank Order of CMV[MMP-I] for Method–Method Pairs**

Method–Method Pair	Susceptibility to CMV Due to Data Source (Respondent)	Susceptibility to CMV Due to Response Format (Scales and Anchors)	Susceptibility to CMV Due to Abstractness of Measures	CMV[MMP-I]
Perceptually Anchored and System-Captured	Very low	Very low	Very low	Very low
Perceptually Anchored and Behavioral Continuous	Very high	Low	Low	Low
Perceptually Anchored and Behaviorally Anchored	Very high	High	High	High
Perceptually Anchored and Perceptually Anchored	Very high	Very high	Very high	Very high

variable is measured using perceptually anchored scales. In contrast, the method–method pair least susceptible to CMV is when the dependent variable is measured using a system-captured measure. The rank ordering of CMV[MMP-I] in Table 2 is consistent with Podsakoff et al.’s (2003, p. 885)

conclusion that: “Method biases are likely to be particularly powerful in studies in which the data for the predictor and criterion variables are obtained from the same person, in the same measurement context, using the same item context and similar item characteristics.”

### Estimating the Effect of CMV

Following Erez et al. (1996, Equation 9, p. 287), a general random effects model explaining variation in correlations observed in multiple studies is given by

$$r_i = \rho + u_i + e_i$$

where

$r_i$  = Observed correlation reported in Study  $i$  ( $i = 1$  to  $k$ , where  $k$  is the number of studies)

$\rho$  = The population correlation coefficient for the entire population of studies

$u_i$  = Effect of between-studies differences on the correlation coefficient of Study  $i$

$e_i$  = Within-studies error

Both  $e_i$  and  $u_i$  are normally and independently distributed with a mean of zero

The technique proposed here explains variation in between-studies correlations as a function of CMV[MMP-I]. A random effects ANOVA model partitions the observed variance in effect sizes into two components: “within-studies (i.e., due to error) and between-studies (i.e., due to differences among studies) variance” (Erez et al. 1996, Equation 3, p. 279). Formally,

$$\text{Var}(r_i) = \text{Var}(u_i + e_i) = \sigma^2 + \Gamma^2$$

where

$u_i$  = Effect of between-studies differences on the correlation coefficient of Study  $i$  ( $i = 1$  to  $k$ , where  $k$  is the number of studies)

$e_i$  = Within-studies error

Both  $e_i$  and  $u_i$  are normally and independently distributed with a mean of zero

Variance of  $e_i$  ( $\sigma^2$ ) is the within-study variance or sampling error

Variance of  $u_i$  ( $\Gamma^2$ ) is the between-studies variance

The first component accounts for within-studies variance that influences correlations reported in individual studies (Erez et al. 1996). It is estimated as per the formula for sampling error proposed by Hunter and Schmidt (2004). The second component accounts for the between-studies variance (Erez et al. 1996).

### An Illustration

We illustrate the application of the MMP technique by estimating the effect of CMV on the observed correlations

between perceived usefulness (PU) and usage (U) reported in the technology acceptance model (TAM) literature. This is an important relationship in the nomological networks within the broad research domain of IT usage, including diffusion of innovation theory (Rogers 1983), TAM (Venkatesh and Davis 2000), and expectation-disconfirmation theory (Bhattacharjee and Premkumar 2004).

The TAM domain is chosen for three reasons. First, TAM has been subject to extensive investigation and the findings are generally accepted to be valid (Benbasat and Barki 2007). Therefore, any CMV-based threat to those findings would raise serious questions about IS research findings in general. Second, Straub and Burton-Jones (2007) speculate that empirical support for TAM is subject to a validity threat on account of CMV. Third, specific characteristics of the research in this domain make it simple to illustrate the technique. Specifically, with PU typically measured on a perceptually anchored scale, CMV[MMP-I] is rank ordered as presented in Table 2. Formally, we investigate the following two hypotheses:

**Hypothesis 1:** The observed effect size (e.g., correlation) between perceived usefulness and usage is a function of the method–method pair employed.

**Hypothesis 2:** The magnitudes of the observed effect sizes (e.g., correlations) of perceived usefulness (PU) on usage (U) for different method–method pairs are in the following order (from lowest to highest):

- (a) Mean effect size (correlation) (perceptually anchored method for PU with system-captured method for U),
- (b) Mean effect size (correlation) (perceptually anchored method for PU with behavioral continuous method for U),
- (c) Mean effect size (correlation) (perceptually anchored method for PU with behaviorally anchored method for U),
- (d) Mean effect size (correlation) (perceptually anchored method for PU with perceptually anchored method for U).

Hypothesis 1 is tested using a random effects ANOVA model, with the observed correlation as the dependent variable and CMV[MMP-I] as the independent variable. Hypothesis 2 is tested using planned contrasts.

### Sample

Following the procedure described by Hunter and Schmidt (1990, 2004) and by Glass et al. (1981) and adopted, for

example, by Dennis et al. (2001), Kohli and Devaraj (2003), and Sharma and Yetton (2003, 2007), the sample for this meta-analysis consists of empirical studies reported in journals, conference proceedings, and unpublished dissertations that examine the theoretical effect under investigation.

Studies published before 2001 were located through several literature searches. Sources searched include ABI/INFORM, Sociological Abstracts, and Dissertation Abstracts; manual searches of back issues of major journals in the IS literature, including *Information Systems Research*, *MIS Quarterly*, *Management Science*, *Journal of Management Information Systems*, and *Decision Science*; and the bibliographies of existing works. The databases were searched using terms including perceived usefulness, use, relative advantage, and TAM. Dissertation abstracts are specifically included in the search in order to overcome the potential bias of higher effect sizes associated with journal articles, commonly referred to as the “file-drawer problem” (Hunter and Schmidt 2004; Rosenthal 1979).

For the period 2001–2004, we adopted two search strategies. One was to examine all references cited in the meta-analyses of TAM by King and He (2006), Ma and Liu (2004), and Sabherwal et al. (2006). This was supplemented by a manual search of key journals and conference proceedings in the field. This search strategy ensures a broad coverage of published as well as unpublished studies.

A more comprehensive search would involve searching Dissertation Abstracts for the period 2001–2004, contacting authors of studies that examine the PU-U relationship but do not report the correlation or an equivalent metric, and soliciting unpublished studies through various professional forums. However, since the focus of this study is to estimate the effect of CMV and not to estimate the magnitude of the PU-U correlation, the limited search strategy employed is appropriate.

Studies were selected for inclusion if they satisfied two criteria. One criterion is that they report the PU-U correlation, or a statistic that could be converted to a correlation (for procedures to convert other common statistics to correlations, see Wu and Lederer 2009; Wolf 1986). The other is that they report the measures employed to operationalize both PU and U. The studies included in this illustration are listed in Appendix B.

The most frequent reason for excluding a study from the sample was that it did not report the PU-U correlation, or a metric that could be converted into a correlation. In particular, a number of studies investigated the relationship between perceived usefulness and behavioral intention but did

not investigate the relationship between PU and U (see, for example, Gefen et al. 2003; Karahanna et al. 1999). In addition, a few studies reported path coefficients but did not report the correlation matrix (see, for example, Gefen and Straub 1997; Straub et al. 1995). Both types of studies were excluded from the meta-analysis.

This search procedure identified 76 data points from 50 publications for inclusion in the meta-analysis. (See Appendix B for an analysis of potential validity threat from including multiple data points from a single publication.) In contrast, Sabherwal et al.’s meta-analysis includes 30 data sets for the PU-U correlation, King and He do not report a meta-analysis of the PU-U correlation but report a meta-analysis of the relationship between PU and behavioral intention based on 67 data sets, and Ma and Liu’s meta-analysis of the relationship between PU and technology acceptance is based on 37 datasets from 21 publications.

One observation was identified as an outlier and is not included in further analysis. This observation reports a correlation value of -0.32. It is the only negative correlation in the sample and is more than six standard deviations away from the mean. It is also identified as an outlier by various tests including studentized residuals, Cook’s distance, influence statistics, and leverage (Pedhazur and Schmelkin 1991). As a result, the number of data sets included in further analysis is 75, whereas the literature search identified 76 data sets for inclusion in the meta-analysis.

Table 3 presents a meta-analysis of the PU-U correlation, following the procedure recommended by Hunter and Schmidt (2004). The large fail-safe N (390 publications), estimated as the number of “missing” publications reporting nonsignificant correlations required to bring the mean correlation down to 0.05, suggests that the sample does not suffer from the file drawer problem (Hunter and Schmidt 2004, p. 500; Rosenthal 1979). The mean value of the correlation is  $r = 0.36$ , with a 95 percent credibility interval<sup>3</sup> of 0.06 to 0.66. Sampling variance accounts for 17.8 percent of the variance in the PU-U correlation, with 82.2 percent of the variance remaining unexplained. The large unexplained variance and the wide credibility interval support the search for moderator variables in the population (Hunter and Schmidt 2004). The significant Q statistic ( $Q = 310.6$ ,  $p \leq 0.01$ ) also supports the search for moderator variables (Lipsey and Wilson 2001).

<sup>3</sup>The credibility interval in meta-analysis refers to the distribution of means in the population. It is computed based on the population variance (see Table 3). Credibility intervals support judgments regarding the variability of the mean across the population and the presence or absence of moderator variables. In contrast, confidence intervals for the mean are based on the standard error of the mean and support judgments regarding the magnitude of the mean.

**Table 3. Meta-Analysis of the Correlation Between Perceived Usefulness and Usage**

Number of data sets	75
Mean correlation <sup>†</sup>	0.36
95% credibility interval	0.06 to 0.66
Range of correlation values	0.04 to 0.68
Fail-safe N	390
Average sample size per study	153.43
Observed variance (S.D.)	0.028 (0.168)
Sampling variance (S.D.)	0.005 (0.071)
Population variance <sup>‡</sup> (S.D.)	0.023 (0.152)
% of observed variance explained by sampling variance	17.8%
% of observed variance unexplained by sampling variance	82.2%

<sup>†</sup>The mean correlation reported here is sample-size-weighted mean of the observed correlations. The mean correlation after correcting correlations reported in individual primary studies for reliability of PU and applying inverse variance weights (Hunter and Schmidt 2004, p. 124) is  $r = 0.38$ . The mean value of reliability (see Appendix B for details of reliability data) of perceived usefulness is used where reliability data are not available. Data for reliability of usage are available for only 26 of the 75 data sets; hence, the reported correlations are not corrected for reliability of usage. See Appendix B for a discussion of this issue.

<sup>‡</sup>Observed variance is the variance in correlation values across studies. Sampling variance is the variance in correlation values across studies that could be attributed to sampling errors, calculated as per Hunter and Schmidt (2004). Population variance = Observed variance – Sampling variance.

### Measures of Perceived Usefulness and Usage

As shown in Table 2, CMV[MMP-I] is a function of how U, the dependent variable, is measured in each study. This is because all the studies in the sample employ perceptually anchored scales to measure PU. This is similar to the context discussed above to explain the technique.

### Categorizing Usage Measures

The operationalization of U employed in each study included in the illustration was classified as belonging to one of the four categories defined in Table 1. Since CMV operates at the item level rather than at the construct level, this rating was carried out at the item level. Items employed to measure U were obtained from each individual study and each item was rated into one of the four categories described in Table 1. Item-level ratings were then aggregated to categorize the measure employed in each primary study. This procedure identified an additional category, labeled “mixed behavioral continuous and behaviorally anchored” containing both behavioral continuous and behaviorally anchored items. This category is ranked medium on the CMV[MMP-I] scale in Table 4.

Two authors and one trained rater, working independently, categorized each survey item for 28 studies included in the

meta-analysis. Cohen’s kappa for inter-rater reliability among the three raters (Fleiss 1971) is 0.91 ( $p \leq 0.01$ ). The differences were resolved by discussion. Given the high level of inter-rater reliability and the recurrence of items across studies, the remaining studies were categorized by two authors. They agreed on all item classifications. Appendix B classifies each study included in this meta-analysis. Table 4 presents the frequency of studies belonging to each category.

### Control Variables

The hypotheses developed above explain variance in observed correlations as a function of MMP. Prior research suggests a number of other factors that could account for variance in observed PU-U correlations. To address the validity threat arising from the exclusion of potentially significant factors, four factors were investigated. These are publication type, respondent type, PU operationalization type, and voluntariness.

Publication type refers to whether a study was published in a journal ( $n = 51$ ), or a dissertation or conference proceedings ( $n = 24$ ). This addresses the file drawer problem arising from an expectation that effect sizes reported in refereed journals are higher than those reported in unpublished studies and less heavily refereed conference proceedings (Hunter and Schmidt 2004). Table 5 reports a nonsignificant effect of publication

**Table 4. Number of Primary Studies in Each Usage Measure Category**

Category of Usage Measure	CMV[MMP-1]	Number of Data Sets in Category
System-captured	Very low	7
Behavioral Continuous	Low	18
Mixed Behavioral Continuous and Behaviorally Anchored	Medium	6
Behaviorally Anchored	High	31
Perceptually Anchored	Very high	13
Total		75

**Table 5. Test of Between-Studies Factors**

Factor	Sum of Squares	df	Mean Square	F	Variance Explained (Eta Squared)	Significance (p value, two-tail)
Publication Type	2.19	1	2.19	1.21	0.65%	0.276
Respondent Type	9.07	1	9.07	5.00	2.71%	0.029
Perceived Usefulness Type	14.30	1	14.30	7.88	4.27%	0.007
CMV[MMP-1]	187.84	4	46.96	25.90	56.09%	0.000
Error	121.49	67	1.81		36.28%	

type on the PU-U correlation. This further confirms the conclusion drawn from the large fail-safe N that the file drawer problem does not pose a potential validity threat to the findings reported in the next section (Hunter and Schmidt 2004; Rosenthal 1979).

Respondent type refers to whether the primary study was conducted on a student population ( $n = 21$ ) or a nonstudent population ( $n = 54$ ). Including this control variable addresses the concern that the responses of students differ from those of nonstudents. PU operationalization type refers to whether PU was captured using Davis's (1989) perceived usefulness instrument ( $n = 57$ ) or Rogers's (1983) relative advantage or other similar instrument ( $n = 18$ ). Both measures capture a common underlying construct (Fichman 1992; Igbaria et al. 1996; Moore and Benbasat 1991) and both are measured on perceptually anchored scales. Including this control variable addresses the potential validity threat that different measures of PU could bias the reported correlations. These two controls have a significant effect on the PU-U correlation, accounting for 6.9 percent of the variance in Table 5.

Finally, a recent meta-analysis by Wu and Lederer (2009) reports that voluntariness does not moderate the PU-U relationship. In addition, the total variance in PU-U correlations explained by CMV[MMP-1], respondent type, PU operationa-

lization type, and sampling error, exceeds 80 percent. This suggests that all major moderator variables are included in the model (Hunter and Schmidt 2004). So, voluntariness is not included as a control variable in the test of H1 and H2.

### Findings

Table 5 reports the results of a random effects ANOVA, in which Hypothesis 1 is supported: *The observed correlation between perceived usefulness and usage is a function of the method-method pair employed.* CMV[MMP-1] explains 56.09 percent ( $p \leq 0.05$ ) of the between-studies variance in PU-U correlations.<sup>4</sup>

Table 6 reports the results of the planned contrasts analysis, in which Hypothesis 2 is supported: *The magnitudes of the observed correlations between perceived usefulness and usage*

<sup>4</sup>This analysis is conducted after correcting the observed correlations for the reliability of PU. Each data point is weighted by its inverse variance weight. The inverse variance weight employed for each study is its sample size adjusted for the reliability of PU (Hunter and Schmidt 2004, pp. 122-132). The results are similar when uncorrected correlation values are employed in this analysis, with CMV[MMP-1] explaining 54.5% of the between-studies variance,  $F = 24.29$ ,  $p < 0.05$ .

**Table 6. Planned Contrasts Analysis**

Category of Usage Measure <sup>†</sup>	Mean Correlation between Perceived Usefulness and Usage	Contrast	Significance (p value, two-tail) <sup>‡</sup>
System-captured (CMV[MMP-I] = Very Low)	0.16		
Behavioral Continuous (CMV[MMP-I] = Low)	0.29	0.29 vs. 0.16	$p \leq 0.020$
Behaviorally Anchored (CMV[MMP-I] = High)	0.42	0.42 vs. 0.29	$p \leq 0.015$
Perceptually Anchored (CMV[MMP-I] = Very High)	0.59	0.59 vs. 0.42	$p \leq 0.015$

<sup>†</sup>The fifth category of usage identified during the rating process, mixed behavioral continuous and behaviorally anchored (CMV[MMP-I] = Medium) is excluded from this analysis as no contrasts are hypothesized for this category. Mean correlation for this category is 0.38, which lies between the values for CMV[MMP-I] = Low and High.

<sup>‡</sup>Since the three contrasts (-1, 1, 0, 0; 0, -1, 1, 0; and 0, 0, -1, 1) are non-orthogonal, a Bonferroni adjustment is applied to the tests of individual contrasts to achieve an overall Type I error rate  $\leq 0.05$  (Pedhazur and Schmelkin 1991, p. 485).

for different method–method pairs are in the hypothesized order. All the hypothesized planned contrasts are significant ( $p \leq 0.02$ ).

This study explains 81.5 percent of the variance in the observed PU-U correlations, with sampling error explaining 17.8 percent of the observed variance (Table 3), CMV[MMP-I] explaining 56.1 percent of the between-studies variance in Table 5, and the control variables in Table 5 explaining 7.6 percent of the between-studies variance. The observed PU-U correlations are a function of CMV, explained by the different method–method pairs employed to measure the observed correlations.

## Discussion

This paper develops a meta-analysis-based technique to evaluate the effect of CMV within specific research domains. The technique is based on the cumulative findings of mono-method studies in a research domain and an estimation of susceptibility to CMV of the different method–method pairs employed in individual studies. The technique is generic and can be employed in both IS and non-IS research domains.

CMV has long been recognized as a potential validity threat to findings in the social sciences (Podsakoff et al. 2003). Recommendations to mitigate that threat have focused on the design and analysis of individual studies. Implicitly, they focus on the question: *How should researchers design individual studies and analyze their findings to ensure that the*

*findings are not subject to a potential CMV-based validity threat?* For example, researchers are advised both to use multiple methods and to control for CMV when estimating parameters (Podsakoff et al. 2003). However, these protocols are rarely followed in practice and findings in social sciences research are frequently subject to a potential CMV-based validity threat (Doty and Glick 1998; Williams et al. 1989; Williams et al. 2003).

This paper reframes the research effort to address CMV in two ways. First, it changes the focus from minimizing the effect of CMV within an individual study to assessing the effect of CMV on the findings of multiple studies. Second, it evaluates potential CMV-based validity threats to individual theories rather than the potential CMV-based threat to social science research in general.

The MMP technique is illustrated by investigating the effect of CMV in the TAM literature. Specifically, it examines the PU-U relationship. The results show that observed PU-U correlations are a function of the method–method pair employed to measure those correlations. The average correlations for the four method–method pairs investigated range from  $r = 0.16$  to  $r = 0.59$ , with CMV explaining 56.09 percent of the between-studies variance in observed correlations. The findings show that observed PU-U correlations increase as the method–method pair employed to measure the correlation becomes more susceptible to CMV. The application of the MMP technique reveals that CMV substantially inflates observed PU-U correlations and poses a strong CMV-based validity threat to the evidence supporting the PU-U relationship in TAM research.

The technique developed here complements existing techniques to minimize the potential CMV-based validity threat within mono-method studies. In addition, we identify two important implications for the design of individual studies. First, we recommend that researchers employ behavioral continuous measures with open-ended numerical scales. Within the studies examined, these measures are found to be subject to a significantly lower potential CMV-based validity threat than are perceptually and behaviorally anchored scales, which are frequently employed in survey instruments. In addition, they are not as difficult to employ as system-captured measures.

Second, we recommend that researchers employ multiple methods between studies. The technique developed here relies on between-studies variation in methods to assess the effect of CMV. However, this involves a potential trade-off. Employing previously validated measures increases the validity of measures employed in individual studies. Employing a different method from those employed in previous studies enables the estimation of method effects in the cumulative empirical record (Boudreau et al. 2001). This need not be a trade-off because a construct can be operationalized by multiple reliable instruments employing different methods (Straub and Burton-Jones 2007).

However, even when following best practice, the findings of individual studies are subject to errors and biases that cannot be evaluated within studies, including the effect of CMV. Meta-analysis is currently the most rigorous technique available to estimate and correct for such errors and biases (Hunter and Schmidt 2004). Judgments regarding the validity of theories should be based on an evaluation of the cumulative empirical evidence, rather than the findings of any individual study, however well designed (Hunter and Schmidt 2004).

A key advantage of the MMP technique over the typical MTMM methodology is that it can be applied to any research domain in which two conditions are satisfied. One is that there are sufficient studies to support a meta-analysis. The other is that those studies employ different measurement methods, ranging from low to high CMV[MMP]. Both conditions are frequently satisfied.

In addition, existing meta-analysis studies in the social sciences could be reanalyzed to estimate the effect of CMV in observed findings. This would enable an *ex post* analysis of the effect of CMV in individual research domains. In the absence of techniques that can control for the effect of CMV within mono-method studies, an *ex post* analysis based on the MMP technique developed here would provide the best assessment of the extent of bias due to CMV within each research domain. This would directly address the long-held

concerns about the effect of CMV on the results reported in the social science literature.

Below, we discuss the limitations of the MMP technique. We then extend the MMP technique to the general case, where both the independent and dependent variables are measured using multiple methods. Finally, the implications of the findings for IS research are discussed.

## Limitations

The MMP technique developed and illustrated in this paper is subject to a number of limitations and validity threats. Four of these are considered here. First, the illustration above is a limited special case of the technique because the method employed to measure PU is the same across all studies. This simplifies the rank ordering of CMV[MMP-I]. Here, we relax this constraint and define the rank ordering of CMV[MMP-I] when the methods employed to measure both focal variables vary across studies. This begins to generalize the MMP technique to other research domains.

The effect of CMV on an observed correlation is a function of the method–method pair employed to measure that correlation. Table 7 identifies the 10 unique method–method pairs for the four measurement methods described in Table 1. The susceptibility of a method–method pair to CMV is a function of two factors. One is the susceptibility of a method to CMV. The other is the combination of methods in a method–method pair and the effect of that combination on the pair's susceptibility to CMV.

Two assumptions rank order the 10 method–method pairs' susceptibility to CMV. One is that the susceptibility of a method to CMV increases from objective (system-captured) measures to perceptually anchored measures and can be rank ordered as follows (Cote and Buckley 1987; Doty and Glick 1998):

Perceptually Anchored > Behaviorally Anchored >  
Behavioral Continuous > Objective Measure

The other assumption is that the susceptibility of a method–method pair to CMV is determined by the measurement method less susceptible to CMV. Formally,

$$\begin{aligned} \text{CMV}_{\text{BB}} &= \text{CMV}_{\text{PB}} \\ \text{CMV}_{\text{CC}} &= \text{CMV}_{\text{BC}} = \text{CMV}_{\text{PC}} \\ \text{CMV}_{\text{OO}} &= \text{CMV}_{\text{CO}} = \text{CMV}_{\text{BO}} = \text{CMV}_{\text{PO}} \end{aligned}$$

Integrating the two assumptions, CMV[MMP-I] for each cell is rank ordered as follows:

**Table 7. Susceptibility of Method–Method Pairs to CMV**

			CMV <sub>PP</sub>	Perceptually Anchored (PA)
		CMV <sub>BB</sub>	CMV <sub>PB</sub>	Behaviorally Anchored (BA)
	CMV <sub>CC</sub>	CMV <sub>BC</sub>	CMV <sub>PC</sub>	Behavioral Continuous (CB)
CMV <sub>OO</sub>	CMV <sub>CO</sub>	CMV <sub>BO</sub>	CMV <sub>PO</sub>	Objective Measure (OM)
OM	CB	BA	PA	

**Note:** CMV<sub>BB</sub> refers to the susceptibility to CMV between a Behaviorally Anchored (B) measure and another Behaviorally Anchored (B) measure; CMV<sub>PB</sub> refers to the susceptibility to CMV between a Perceptually Anchored (P) measure and a Behaviorally Anchored (B) measure; and so on.

CMV<sub>OO</sub> = CMV<sub>CO</sub> = CMV<sub>BO</sub> = CMV<sub>PO</sub> = Very low  
 CMV<sub>CC</sub> = CMV<sub>BC</sub> = CMV<sub>PC</sub> = Low  
 CMV<sub>BB</sub> = CMV<sub>PB</sub> = High  
 CMV<sub>PP</sub> = Very high

Assuming that CMV[MMP-I] is bounded by the susceptibility to CMV of the two methods in the method–method pair, Appendix E presents some alternative assumptions to rank order the method–method pairs in Table 7. However, the rank ordering of CMV[MMP-I] is an empirical question that should be investigated in future research.

A second limitation is that the MMP technique models the influence of CMV on the observed correlation as a function of the susceptibility to CMV of the method–method pair, with CMV[MMP] partitioned into two components: CMV[MMP-I] and CMV[MMP-T]. However, we do not formally model their relationship. In the TAM-based illustration above, this is not investigated as only three data sets in the meta-analysis sample employ temporal separation. This issue should be addressed in future research.

A related limitation is that system-captured measures confound source-based CMV effects and temporal separation-based CMV effects. This arises from the fact that system-captured and other objective measures frequently aggregate archival data over a period of time (see, for example, Straub et al. 1995; Szajna 1996). Researchers need to develop techniques to separate the confounding effects of CMV and transient error (Le et al. 2009). In the present study, we investigated this confounding effect by repeating the analysis excluding the system-captured data points. The results of this analysis are presented in Appendix C. H1 and H2 are supported even when these data points are excluded from the analysis.

Third, further work is needed on techniques to estimate the magnitude of construct-level correlations controlling for CMV and other measurement errors. This is an important

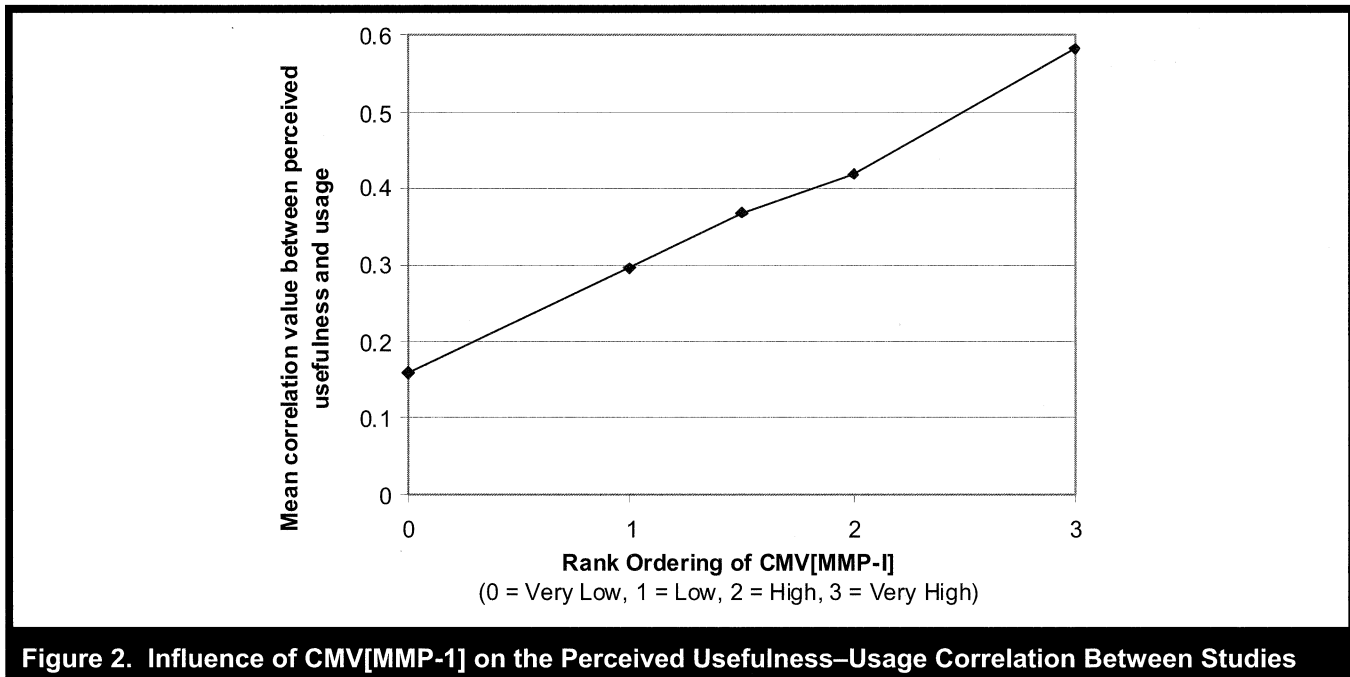
research question as the validity of a theory rests on the magnitude of this correlation. The intercept, when observed correlations are regressed against CMV[MMP], is an estimate of the construct-level correlation controlling for CMV. However, this estimate is subject to a number of measurement errors that need to be corrected in order to obtain a valid estimate of the construct-level correlation (Hunter and Schmidt 2004; Le et al. 2009; Schmidt et al. 2003). This issue is beyond the scope of this paper but is addressed briefly in Appendix C.

Fourth, the technique assumes the existence of equivalent measures of constructs that are measured employing different methods. Scholars have questioned the assumption of trait–method dichotomy that underpins the MTMM technique (see, for example, Cronbach 1995). Trait and method are considered so intertwined that a method of measuring a trait is considered implied in its definition. Consequently, such scholars do not consider trait and method to be distinct. Instead, like Cronbach, they prefer to refer to trait–method units. Cronbach argues that: “Aspects of method become part of a substantive construct as the construct is refined” (p. 155). Researchers need to consider the definitions of constructs and methods as they investigate the effects of method on cumulative findings within a research stream.

**Implications for IS Research**

The findings of this study have specific implications for IS research. The estimates of CMV in the TAM research domain reported in the illustration above are consistent with those obtained from the analysis of MTMM-based studies in the social sciences. For example, Podsakoff et al. report, as quoted at the beginning of this paper: “On average, the amount of variance accounted for when common method variance was present was approximately 35 percent, versus approximately 11 percent when it was not present” (p. 880).





**Figure 2. Influence of CMV[MMP-1] on the Perceived Usefulness–Usage Correlation Between Studies**

The results presented here are similar. Table 6 reports that the mean PU-U correlation, when both are measured on perceptually anchored scales and subject to high CMV, is  $r = 0.59$ , explaining 35 percent of the variance. In contrast, when U is measured on a behavioral continuous scale and subject to low CMV, the correlation is  $r = 0.29$ , explaining 8.4 percent of the variance. There is no evidence here to suggest that, as claimed by Malhotra et al., the IS research domain is subject to less CMV than the broader social sciences.<sup>5</sup> Instead, the magnitudes of the effects of CMV are similar in the TAM illustration and Podsakoff et al.'s general findings.

In addition, inspecting Figure 2, the expected PU-U correlation, controlling for CMV, is low. As discussed in Appendix C, the intercept obtained when the observed correlations are regressed against CMV[MMP] is an estimate of the construct-level correlation controlling for CMV. In Figure 2, this intercept is between 0.15 and 0.20. When controlling for publication type, respondent type, and PU operationalization type, Appendix C reports that the intercept<sup>6</sup> is  $r = 0.01$  (ns). In comparison, the weighted average value of the observed

PU-U correlation is  $r = 0.36$ , as reported in Table 3. The effect of CMV can potentially suggest a strong relationship even when the underlying correlation is very weak. For instance, in the TAM research examined here, when both PU and U are measured employing perceptually anchored methods, the effect of CMV and other measurement errors can inflate the true PU-U correlation of  $r = 0.01$  to an observed correlation as high as 0.68 (see “Range of Correlation Values” in Table 3).

Two conclusions can be drawn from these findings. One is that CMV is a powerful predictor of the observed PU-U correlations when U is measured on a behaviorally anchored or perceptually anchored scale. The other is that support for TAM is subject to a major potential validity threat from CMV, because a significant PU-U correlation is a necessary but not sufficient condition for behavioral intention to mediate the relation between PU and U (Baron and Kenny 1986).

The findings in Figure 2 (and Appendix C) support the critique of TAM research by Straub et al. (1995) and Szajna (1996), challenging the strong belief by Benbasat and Barki (2007) and others that empirical support for TAM is unassailable. Whereas, Straub et al. and Szajna base their conclusions on only one study, the findings presented above are based on a systematic evaluation of 75 published TAM datasets. While this is an illustration of the MMP technique and not a meta-analysis of the complete TAM model, inspecting

<sup>5</sup>Appendix D presents a comparison of the MMP technique and findings presented here with that of the marker variable technique employed by Malhotra et al.

<sup>6</sup>See Appendix C for the results and for details of the technique employed to estimate the construct-level correlation controlling for the effect of CMV.

Figure 2 raises the critical question: What are the implications of the findings for the full nomological network of TAM? This should be the subject of future research.

## Conclusion

This paper develops a meta-analysis-based method–method pair technique for estimating the effect of common method variance in individual research domains by analyzing the cumulative findings of mono-method studies. In an illustration of the MMP technique employing data from IS research, the magnitude of the CMV effect is of the same order of magnitude as that estimated in the social sciences using MTMM techniques. The MMP technique is applicable to research in the social sciences and is not restricted to IS research. It can be employed to resolve challenges to existing theories where CMV is a potential major validity threat, including research domains dominated by mono-method studies. The challenges could be particularly strong where empirical support for theories relies primarily on studies employing perceptually or behaviorally anchored measures. The contribution to both research and practice of resolving such challenges could be substantial.

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