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A CRITIQUE OF THE MARKER VARIABLE TECHNIQUE: THE EFFECT OF ALTERNATIVE MARKER VARIABLE CRITERIA

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Abstract

The marker variable technique offers a practical and easy method to address the validity threat on account of common method variance to the findings of individual studies. However, the validity of the marker variable technique has not been established. This paper examines the validity threat to the marker variable technique arising from multiple criteria for the selection of the marker variable proposed in the literature. Our findings show that the conclusions that can be drawn under different criteria are significantly and substantially different, raising doubts about the validity of the marker variable technique. Proposals for developing theoretically grounded criteria for identifying the marker variable correlation are discussed. Importantly, our analysis suggests that the second lowest correlation of the criterion variable may be a more valid method for selecting the marker variable correlation.

Keywords: Common method variance, common method bias, marker variable technique, method-method pair technique.

1 INTRODUCTION

The effect of common method variance (CMV) is a major validity threat to research findings, in particular to survey-based research employing self-report methods of data capture (Doty and Glick 1998; Podsakoff, MacKenzie, Lee and Podsakoff 2003). Recent studies find that CMV is a major validity threat to findings in the information systems (IS) discipline (Burton-Jones 2009; Sharma, Yetton and Crawford 2009). For instance, Sharma et al. (2009) find that spurious correlation due to CMV can inflate a true correlation of zero between constructs to an observed correlation as high as 0.68 between measures of the constructs.

While the CMV-based validity threat is widely acknowledged, it is rarely addressed in research findings (Woszczynski and Whitman 2004). One reason for this has been the absence of a valid technique to estimate the magnitude of CMV-based bias in findings of research studies that do not employ multiple methods. The multitrait-multimethod technique can be employed to correct for the effect of CMV in studies where multiple methods are employed (Campbell and Fiske 1959; Podsakoff et al 2003; Williams, Edwards and Vandenberg 2003). However, social science research, including IS research, typically does not employ multiple methods within individual studies (Doty et al 1998). This raises legitimate, but unanswerable concerns regarding the extent of CMV-based validity threats to the findings of many studies that do not employ multiple methods (Malhotra, Kim and Patil 2006).

The marker variable (MV) technique developed by Lindell and colleagues (2000; 2001) provides a potential solution to this problem. A key feature of the MV technique is its authors' claim that it controls for the effect of CMV in individual studies that do not employ multiple methods. They argue that the MV technique partials out the effect of CMV from correlations obtained in mono-method cross-sectional study designs and returns correlation values that are not contaminated by CMV (Lindell et al 2001). The technique is simple to employ in both a pre-planned and a post hoc analysis. For example, within the IS literature, Malhotra et al. (2006) employ the MV technique in a post hoc analysis and conclude that the extent of bias due to CMV in the IS research domain is not substantial. It is also increasingly being used in IS studies to claim protection against CMV-based validity threats.

However, the validity of the MV technique has not been established and, specifically, Malhotra et al. (2006) repeatedly stress the need to evaluate its validity. It is important to do so before its use becomes prematurely institutionalized and researchers routinely accept findings as valid when they could be substantially inflated by CMV. This is particularly important as a number of concerns have been raised regarding the theoretical validity of the MV technique (Podsakoff et al 2003; Straub and Burton-Jones 2007). Further, a simulation analysis conducted by Richardson, Simmering and Sturman (2009) finds the MV technique to be unreliable and they recommend against its use.

The objective of this paper is to evaluate the validity of the MV technique. Adding to the theoretical critiques and simulation analyses evaluating the validity of the MV technique, this study examines its validity when it is employed in a post hoc analysis. Specifically, it evaluates the impact of a key limitation of the MV technique, the absence of an unambiguous criterion for selecting the MV correlation, on the conclusions that can be drawn from the application of the MV technique.

This paper begins with an overview of the MV technique, followed by a discussion of the alternative criteria for the selection of the MV correlation proposed by Lindell and Whitney. It then tests implications of the alternative criteria on two data sets from IS research. The first data set is the one employed by Sharma et al. (2009) to estimate the effect of CMV on the observed correlation between perceived usefulness and usage in the Technology Acceptance Model literature. The other is the one employed by Malhotra et al. (2006) to illustrate the application of the MV technique. The findings question the validity of the MV technique. Implications for future research and proposals for extending the MV technique to develop a robust set of criteria for selecting the MV correlation are discussed.

2 THE MARKER VARIABLE TECHNIQUE

Systematic covariation in construct scores due to common methods employed to measure the constructs poses a CMV-based validity threat to research findings (Doty et al 1998). Observed scores of measures are composed of three components – systematic variation on account of true score variance, systematic variation on account of method variance and random error variance (Cote and Buckley 1987; Doty et al 1998). When two constructs are measured employing similar methods, they share systematic covariance on account of those common methods. This generates a spurious correlation between the two measures. Following Sharma et al. (2009), formally,

Observed correlation = Construct-level correlation + Spurious correlation due to CMV + Random error

In the presence of CMV, the observed correlation is an inflated estimate of the true relationship between constructs, leading to incorrect conclusions from empirical findings. Underscoring the extent of the problem, in an analysis of published multitrait-multimethod matrices, Doty and Glick (1998, p. 401) observed that CMV inflated observed correlations in all the 316 correlations that they analyzed. Hence, in order to draw valid conclusions from study findings, every bivariate correlation obtained in a study needs to be corrected for the bias due to CMV.

Researchers have responded to the challenge posed by CMV by developing a repertoire of techniques to address the validity threat arising from CMV. Techniques to design studies to minimize the effect of CMV are well established (Burton-Jones 2009; Podsakoff et al 2003). Confirmatory factor analysis-based multitrait-multimethod techniques to control for the effect of CMV in studies employing multiple methods are also well established (Podsakoff et al 2003). Extending this repertoire of techniques, Sharma et al. (2009) develop a technique to evaluate the extent of the CMV-based validity threat to specific theories based on cumulating the findings of multiple studies. However, correcting for the effect of CMV-based bias within individual mono-method studies remains an important methodological challenge (Malhotra et al 2006; Podsakoff et al 2003). The MV technique is intended to fill this important gap.

Lindell and Whitney (2001) developed the MV technique to estimate and control for the effect of CMV within mono-method studies. The MV technique relies on the inclusion of a 'marker variable' in studies: "a scale that is theoretically unrelated to at least one other scale in the questionnaire. So, there is an a priori justification for predicting a zero correlation" (Lindell et al 2001, p. 115). Lindell and Whitney argue that the "smallest correlation among the manifest variables provides a reasonable proxy for CMV" (p. 115). Hence, it can be employed to partial out the effect of CMV from the study and obtain estimates of true construct score correlations unbiased by CMV. Lindell and Whitney also propose that where a marker variable has not been identified a priori, the smallest positive correlation in the correlation matrix is a good proxy for the effect of CMV. Hence, the MV technique can also be applied in post hoc analyses.

The MV technique computes CMV-adjusted correlations as follows (Malhotra et al 2006, Equation 1, p. 1868):

$$r_A = (r_U - r_M) / (1 - r_M)$$

where

r_A = CMV-adjusted estimate of a focal correlation

r_U = Observed value of the focal correlation

r_M = Marker variable correlation for the study.

For instance, if the observed correlation between measures of two constructs is 0.40, and the lowest observed correlation of 0.10 is employed as the marker variable, the CMV-adjusted correlation between the constructs is estimated as (0.40 – 0.10)/(1 – 0.10) = 0.34.

The form of correction offered by the MV technique is intuitively appealing. It is also consistent with theoretical treatments of the effect of CMV. More importantly, it is easy to use and is being widely used to address validity threats due to CMV in many research domains. For instance, in the IS domain the MV technique has been employed by Pavlou, Liang and Xue (2007), Jarvenpaa and Majchrzak (2008), Tiwana (2008), Sun, Bhattacharjee and Ma (2009) and Tiwana and Konsynski (2009) to claim protection against a CMV-based validity threat. However, the validity of the MV technique has not yet been established (Malhotra et al 2006) and, as noted above, concerns have also been raised by Podsakoff et al. (2003), Straub et al. (2007) and Richardson et al. (2009). Given these concerns, it is important to assess the validity of the MV technique before its use becomes accepted practice.

Here, we evaluate the validity of the MV technique by empirically examining the effect of the criteria recommended by Lindell and Whitney (2001) for selecting the MV correlation. Lindell and Whitney acknowledge that the smallest positive correlation may be a biased proxy for the magnitude of the effect of CMV and propose a number of alternative criteria for selecting the MV correlation. For researchers to have confidence in the validity of the MV technique, the conclusions drawn by employing the alternative criteria for selecting the MV correlation should be similar. This is the motivation for this research and for the two research questions examined in this paper:

R1: Do the multiple criteria for selecting the MV correlation generate biased estimates of the magnitude of CMV?

R2: Do the multiple criteria for selecting the MV correlation affect the validity of conclusions that can be drawn from applying the MV technique?

3 CHOICE OF MARKER VARIABLE

While the form of correction proposed by the MV technique is consistent with other treatments of CMV, a critical issue is the selection of the MV correlation to be employed to correct the observed correlations. Lindell and Whitney (2001) propose multiple criteria for selecting the MV correlation. Below, we discuss six criteria recommended by Lindell and Whitney for selecting the MV correlation and their rationale for employing each of them.

3.1 Lowest observed correlation

Lindell and Whitney (2001) offer a rigorous justification for an earlier claim by Lindell and Brandt (2000) that “the smallest correlation among the manifest variables provides a reasonable proxy for CMV.” Lindell and Whitney critique an earlier technique proposed by Podsakoff and Todor (1986) who argued that the first factor in a factor analysis of observed item scores is a reasonable proxy for CMV. Lindell and Whitney (2001, p. 114) argue that the first factor is an overly conservative estimate of the CMV effect as it partials out true construct score correlation as well as CMV, resulting in “virtually meaningless results.”

As an alternative to Podsakoff and Todor’s (1985) overly conservative model, Lindell and Whitney (2001) propose an alternative model in which the method factor is assumed to have a constant correlation with all manifest variables. Under that assumption, Lindell and Whitney argue that the lowest observed correlation is the best estimate of CMV for that study. Accordingly, partialing out the lowest observed correlation from all correlations observed in a study provides estimates of construct score correlations that are not biased by CMV. Following from this conclusion, Lindell and Whitney propose using the lowest observed correlation as the criterion for identifying the MV correlation.

3.2 Second lowest observed correlation

While arguing for a robust theoretical basis for employing the lowest observed correlation as a proxy for CMV, Lindell and Whitney (2001, p. 115) also recognize that the “ad hoc selection of the smallest correlation provides an opportunity for capitalizing on chance.” To control for this possibility, Lindell and Whitney (2001) suggest that the second lowest observed correlation could be employed as the MV correlation. Accepting this limitation, Malhotra et al. (2006) employ both the lowest and the second lowest observed correlations criteria in their post hoc analysis of correlation matrices.

3.3 Lowest and second lowest observed correlations of the predictor and criterion variables

Lindell and Whitney (2001) also propose using the lowest and second lowest correlation involving one of the focal variables as the estimate of the MV correlation. They justify this choice on the ground that "there almost always are fewer correlations between the predictors and the criterion than among the predictors, affording less opportunity for capitalization on chance in the selection of the smallest correlation" (Lindell et al 2001, p. 118). Employing the second lowest correlation further reduces the possibility of capitalization on chance.

Finally, Lindell and Whitney recommend conducting sensitivity analysis to estimate the sensitivity of the conclusions to the definition of the MV correlation. They suggest two forms of sensitivity analysis. One employs the "second, third, or *k*th" smallest positive correlation as the marker variable. The other employs the "*p*th percentile points (e.g., 75th, 95th, 99th) of the confidence interval" for the smallest observed correlation". Subsequently, researchers have identified other criteria for the selection of the MV correlation. These include, for example, the mean value of the correlations of the marker variable when it has been included *a priori* in the data collection (Malhotra et al 2006; Podsakoff et al 2003).

The multiplicity of criteria for selecting the MV correlation is an important limitation of the MV technique because Lindell and Whitney (2001) do not provide any theoretical justification for selecting among the criteria. This leaves researchers with no definitive guidance on the choice of the MV correlation. This raises potential validity threats to any conclusions drawn from the application of the MV technique. For example, Malhotra et al.'s (2006, Table 2) sensitivity analysis shows that conclusions drawn from applying the MV technique are different depending on the criteria adopted. This suggests that findings from applying the MV technique may be significantly different across the alternative criteria. This would be a serious limitation to the practical applicability of the MV technique. Here, we conduct a systematic empirical examination to evaluate the effect of the alternative criteria for selecting the MV correlation on the conclusions that can be drawn from applying the MV technique.

4 METHOD

4.1 Sample

This study examines empirically the effect on the conclusions that can be drawn from applying the MV technique when different criteria for selecting the MV correlation are employed. The analysis is conducted on two data sets reported in the literature. One data set is the one employed by Sharma et al. (2009) to estimate the effect of CMV in the cumulative empirical evidence reported for the relationship between perceived usefulness (PU) and Use (U). Sharma et al. conduct a rigorous search of the literature and identify 75 data points reporting the PU-U correlation for inclusion in their analysis. Two comparable meta-analyses of the PU-U relationship have been reported in the literature, one based on 30 data points (Sabherwal, Jeyaraj and Chowa 2006) and the other on 37 data points (Ma and Liu 2004). Therefore, it is a robust sample on which to evaluate the validity of the MV technique.

Here, we inspected the complete correlation matrices in the studies included in Sharma et al.'s data set and extracted the data required to apply the MV technique. Specifically, we extracted from the correlation matrices the correlations for the six alternative definitions of the MV correlation discussed above, i.e. the lowest observed correlation, the second lowest observed correlation, the lowest and second lowest observed correlations of the predictor variable (PU) and the lowest and second lowest observed correlations of the criterion variable (U). Since some studies did not report the complete correlation matrices, we could obtain the data on all six criteria for only 67 of the 75 data sets employed by Sharma et al. (2009). Three studies that did not report the complete correlation matrices did report all correlations for the criterion variable (U), resulting in 70 data points for the two selection criteria related to the criterion variable.

The other data set is the one employed by Malhotra et al. (2006) to demonstrate the use of the MV technique. It consists of the significant correlations reported in a selected set of 19 studies[1] published in the top two IS journals, MISQ and ISR. We replicate our analysis on this sample to make our findings comparable to their findings. We re-examined the complete correlation matrices reported in those 19 studies, coded the significant criterion variable correlations, replicating the procedure described by Malhotra et al., and extracted the lowest observed correlation, the second lowest observed correlation, the lowest and second lowest observed correlations of the predictor variable and the lowest and second lowest observed correlations of the criterion variable.

4.2 Analysis

To analyze whether the criteria for selecting the MV correlation bias the estimates of the magnitude of CMV (R1), we compared the magnitude of CMV obtained by employing the lowest correlation in the correlation matrix criterion (Criterion 1) against each of the other five criteria. Paired t-tests were employed to conduct the comparisons. Significant differences in the estimates of CMV across the criterion identify bias and unreliability in the findings obtained by applying the MV technique.

To analyze the validity of the conclusions that can be drawn from applying the MV technique (R2), we conducted two analyses. First, we conducted paired t-tests to compare the MV-adjusted correlation obtained by employing Criterion 1 against those obtained by employing each of the other five criteria. Significant differences across the criteria identify bias and unreliability in the conclusions that can be drawn from applying the MV technique. Second, we compared the percentage of observed significant correlations that became non-significant after applying the MV technique across the criteria. Significant differences across the criteria pose a threat to the validity of conclusions that can be drawn from applying the MV technique.

To conduct the above analyses, we first employed the procedure described in Section 2 to compute the MV-adjusted correlations for the six definitions of the MV correlation identified in Section 3. The above analyses were conducted on both samples analyzed in this study.

5 RESULTS AND DISCUSSION

Tables 1 and 2 below report the results of the above analyses for Samples 1 and 2, respectively.

This study finds that the magnitude of the MV correlation is significantly different across the alternative criteria for selecting the MV proposed by Lindell and Whitney (2001). It also finds that the conclusions that can be drawn from applying the MV technique vary significantly across the alternative criteria. The following sections discuss the implications of the findings for the research questions addressed in this study, for the MV technique, for IS research, and proposals for extending the MV technique to improve its validity.

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[1] We are thankful to Sung Kim for providing us with the list of 19 studies employed by Malhotra et al. (2006).

	Criteria for selection of marker variable correlation (r_M)					
	Criterion 1: Lowest correlation in the full correlation matrix (r_{M1Full}) N=67	Criterion 2: Second lowest correlation in the full correlation matrix (r_{M2Full}) N=67	Criterion 3: Lowest correlation of predictor variable in the full correlation matrix (r_{M1IV}) N=67	Criterion 4: Lowest correlation of criterion variable in the full correlation matrix (r_{M1DV}) N=70	Criterion 5: Second lowest correlation of predictor variable in the full correlation matrix (r_{M2IV}) N=67	Criterion 6: Second lowest correlation of criterion variable in the full correlation matrix (r_{M2DV}) N=70
$\overline{r}$ = Mean value of reported correlation between DV and IV	0.37 (Range=0.06-0.68)	0.37 (Range=0.06-0.68)	0.37 (Range=0.06-0.68)	0.38 (Range=0.06-0.68)	0.37 (Range=0.06-0.68)	0.38 (Range=0.06-0.68)
$\overline{r_M}$ = Mean value of marker variable correlation across studies	0.11 (Range=0.00-0.48)	0.16 (Range=0.00-0.68)	0.18 (Range=0.00-0.68)	0.16 (Range=0.00-0.48)	0.28 (Range=0.01-0.69)	0.24 (Range=0.00-0.68)
$\overline{r_A}$ = Mean value of MV-adjusted correlation between DV and IV across studies	0.29 (Range=0.00-0.66)	0.24 (Range=-0.15-0.66)	0.22 (Range=0.00-0.65)	0.25 (Range=0.00-0.66)	0.09 (Range=-0.63-0.64)	0.16 (Range=-0.24-0.66)
Result of paired-samples t-test for difference between mean value of MV correlation using Criterion 1 against other criteria	-N/A-	Difference=0.05 (t=6.58, p<0.000)	Difference=0.07 (t=7.27, p<0.000)	Difference=0.05 (t=5.37, p<0.000)	Difference=0.17 (t=13.85, p<0.000)	Difference=0.14 (t=11.17, p<0.000)
Result of paired-samples t-test for difference between mean MV-adjusted correlation for Criterion 1 against other criteria	-N/A-	Difference=0.06 (t=5.31, p<0.000)	Difference=0.07 (t=6.00, p<0.000)	Difference=0.04 (t=5.02, p<0.000)	Difference=0.20 (t=9.67, p<0.000)	Difference=0.14 (t=9.72, p<0.000)
% of significant correlations turning non-significant	21.5%	35.4%	40.0%	27.7%	60.0%	46.2%

Table 1: CMV-Corrected Correlations Under Different Criteria to Select Marker Variable (Sample 1)

	Criteria for selection of marker variable correlation (r_M)					
	Criterion 1: Lowest correlation in the full correlation matrix (r_{M1Full})	Criterion 2: Second lowest correlation in the full correlation matrix (r_{M2Full})	Criterion 3: Lowest correlation of predictor variable in the full correlation matrix (r_{M1IV})	Criterion 4: Lowest correlation of criterion variable in the full correlation matrix (r_{M1DV})	Criterion 5: Second lowest correlation of predictor variable in the full correlation matrix (r_{M2IV})	Criterion 6: Second lowest correlation of criterion variable in the full correlation matrix (r_{M2DV})
$\overline{r}$ = Mean value of reported correlation between DV and IV	0.33 (Range=0.14-0.72)	0.33 (Range=0.14-0.72)	0.33 (Range=0.14-0.72)	0.33 (Range=0.14-0.72)	0.33 (Range=0.14-0.72)	0.33 (Range=0.14-0.72)
$\overline{r_M}$ = Mean value of marker variable correlation across studies	0.08 (Range=0.00-0.41)	0.11 (Range=0.02-0.42)	0.12 (Range=0.00-0.42)	0.13 (Range=0.02-0.41)	0.18 (Range=0.02-0.59)	0.20 (Range=0.05-0.53)
$\overline{r_A}$ = Mean value of MV-adjusted correlation between DV and IV across studies	0.28 (Range=0.00-0.68)	0.25 (Range=-0.09-0.67)	0.24 (Range=0.00-0.67)	0.23 (Range=0.00-0.66)	0.18 (Range=-0.30-0.65)	0.16 (Range=-0.42-0.63)
Result of paired-samples t-test for difference between mean value of MV correlation using Criterion 1 against other criteria	-N/A-	Difference=0.03 (t=20.39, $p<0.000$)	Difference=0.05 (t=9.68, $p<0.000$)	Difference=0.06 (t=12.49, $p<0.000$)	Difference=0.11 (t=16.99, $p<0.000$)	Difference=0.13 (t=17.79, $p<0.000$)
Result of paired-samples t-test for difference between mean MV-adjusted correlation for Criterion 1 against other criteria	-N/A-	Difference=0.03 (t=18.03, $p<0.000$)	Difference=0.04 (t=9.32, $p<0.000$)	Difference=0.05 (t=11.55, $p<0.000$)	Difference=0.09 (t=16.33, $p<0.000$)	Difference=0.12 (t=16.26, $p<0.000$)
% of significant correlations turning non-significant	17.3%	23.8%	22.2%	27.0%	42.2%	47.0%

Table 2: CMV-Corrected Correlations Under Different Criteria to Select Marker Variable (Sample 2, N=186)

5.1 Estimates of the magnitude of the MV correlation (R1)

A critical step in applying the MV technique is selecting an observed correlation that is a reasonable proxy for CMV. Lindell and Whitney (2001) argue that the smallest manifest correlation is a reasonable proxy for CMV. However, they also acknowledge the limitations of this criterion and propose a number of alternative criteria. This study analyzes six criteria proposed by Lindell and Whitney to analyze the effect of alternative criteria on the magnitude of the MV correlation.

Table 3 summarizes the magnitudes of the MV correlations across all six criteria for the two samples examined. For both samples, all estimates of the MV correlation obtained by employing the lowest manifest correlation as the criterion for selecting the MV are lower than the corresponding values obtained by employing each of the other five criteria (all differences are significant at $p \leq 0.001$). This identifies significant bias and unreliability in the magnitude of the CMV effect estimated by the different criteria.

The divergence or, more specifically, the lack of consistency in estimates of the MV correlation across criteria leads us to conclude that estimates of the MV correlation vary significantly across the alternative criteria identified by Lindell and Whitney (2001). This pattern is observed in both samples. Since Lindell and Whitney argue for the plausibility of each of the six criteria, it is not possible for researchers to estimate which of those estimates is a reasonable proxy for the magnitude of CMV biasing a study. This is an important limitation of the MV technique that makes it difficult for researchers to defend the choices they make.

	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6
Sample 1	0.11	**0.16**	**0.18**	**0.16**	**0.28**	**0.24**
Sample 2	0.08	**0.11**	**0.12**	**0.13**	**0.18**	**0.20**
All correlations marked in bold are significantly different ($p \leq 0.001$) from the corresponding estimate under Criterion 1						

Table 3: MV Correlations Under Different Criteria to Select the MV

5.2 Effect on conclusions drawn from applying the MV technique (R2)

Table 3 shows the unreliability of estimates for the MV correlation depending on the criterion employed. However, that may not be enough to question the validity of the MV technique if, despite those differences, the conclusions drawn from applying the MV technique are similar across the different criteria employed.

Table 4 summarizes the magnitudes of the MV-adjusted correlations across all six criteria for the two samples examined. For both samples, the estimate of the MV-adjusted correlation obtained by employing the lowest manifest correlation as the criterion for selecting the MV is higher than the corresponding values obtained by employing each of the other five criteria (all differences are significant at $p \leq 0.001$).

	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6
Sample 1	0.29	**0.24**	**0.22**	**0.25**	**0.09**	**0.16**
Sample 2	0.28	**0.25**	**0.24**	**0.23**	**0.18**	**0.16**
All correlations marked in bold are significantly different ($p < 0.001$) from the corresponding estimate under Criterion 1						

Table 4: MV-adjusted Correlations Under Different Criteria to Select the MV

The findings reported in Table 4 show that estimates of the MV-adjusted correlation vary significantly across the alternative criteria. This pattern is consistent across both samples. For Sample 1, the variance explained by estimates of the MV-adjusted correlations range from 13.7% (r = 0.37, uncorrected) to 8.5% (r = 0.29, Criterion 1) and 0.01% (r = 0.09, Criterion 5). For Sample 2, the corresponding figures are 10.9% (r = 0.33, uncorrected) to 7.6% (r = 0.28, Criterion 1) and 2.5% (r = 0.16, Criterion 6). MV-adjusted correlations are not only significantly different, but are also substantively different across the criteria. Given such large differences across criteria, it is difficult to see how researchers can draw valid conclusions from applying the MV technique.

Conclusions drawn by analyzing the percentage of significant uncorrected correlations turning non-significant across different criteria (Table 5) are identical. For Sample 1, 21.54% of observed correlations that were significant turn non-significant when Criteria 1 is applied, while the corresponding figure is 60% when Criterion 5 is applied. Similarly, for Sample 2, the percentage varies from 17.3% (Criterion 1) to 47.03% (Criterion 6).

The validity threat posed by this pattern of findings is that researchers are unable to specify the Type I and Type II error rates for whatever criteria they employ. If the criterion for selecting the MV correlation is too liberal, the Type I error rate (accepting a correlation as significant when in fact it is not) could be unacceptable high. Conversely, if the criterion is too conservative, the Type II error rate (accepting a correlation as non-significant when in fact it is significant) could be unacceptably high. However, researchers have no way of knowing whether the criterion they have employed is too liberal or too conservative. In the face of this uncertainty, it is difficult for researchers to defend the validity of their findings.

	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6
Sample 1	21.5%	35.4%	40.0%	27.7%	60.0%	46.2%
Sample 2	17.3%	23.8%	22.2%	27.0%	42.2%	47.0%

Table 5: Percentage of Significant Uncorrected Correlations Turning Non-significant Under Different Criteria to Select the MV

5.3 Comparison with previous findings

While Lindell and Whitney (2001) do not offer a basis on which to choose one criterion over another, comparing the findings of this study with other studies employing different techniques to estimate construct-level correlations controlling for the effect of CMV can offer some guidance. In particular, Sharma et al. (2009) employ the meta-analysis-based method-method pair technique to estimate the magnitude of the PU-U correlation controlling for the effect of CMV. Since Sharma et al.'s technique estimates the effect of CMV considering the specific methods employed, their estimate of the PU-U correlation is considered theoretically robust. Sharma at al.'s findings for the CMV-corrected PU-U correlation are comparable to the findings of Sample 1 (Table 1) of this study. The criterion for choosing the MV correlation that returns a CMV-corrected PU-U correlation closest to that estimated by Sharma et al. is considered the most robust.

Analyzing the cumulative empirical evidence and controlling for the effect of CMV across studies, Sharma et al. (2009, Figure 2, p. 487) estimate that the CMV-adjusted correlation between PU and U lies between 0.15 and 0.20. Inspecting Table 1, the only estimate of CMV-adjusted correlation for the PU-U relationship employing the MV technique that falls within this range is r = 0.16, which is obtained when Criterion 6 (second lowest correlation of the criterion variable) is employed.

Comparing the findings of the MV technique with Sharma et al.'s technique suggests that, on average, Criterion 6 (second lowest correlation of the criterion variable) provides a better proxy of the effect of CMV than the other criteria. This finding is consistent with Podsakoff et al.'s (2003) critique that the MV technique ignores the methods employed to measure the focal variables. It is also consistent with Lindell and Whitney's (2001) critique that employing a correlation involving the criterion variable as the MV reduces the possibility of capitalization on chance. Adding to the rationales for employing the second lowest correlation of the criterion variable as the MV, we argue that since the extent of CMV-based bias depends on the methods employed (see Sharma et al.'s (2009) findings), a theoretically robust MV correlation should employ methods that mirror the focal correlation being corrected. The second lowest correlation involving the criterion variable meets both the criteria identified here – reducing the possibility of capitalization on chance and reflecting the methods employed to measure the focal correlation. We conclude that the second lowest correlation of the criterion variable is a better proxy for the CMV effect than the other criteria identified by Lindell and Whitney.

5.4 Recommendations for future research

The findings of this study support Podsakoff et al. (2003) and Richardson et al.'s (2009) conclusions that the MV technique is an unreliable technique to apply. Conclusions drawn by employing different criteria for selecting the MV correlation vary significantly and substantially. Future research should examine whether a theoretically sound approach for selecting the MV correlation is feasible.

However, the MV technique fills an important need as it provides a technique to control for the effect of CMV in the findings of individual studies employing mono-method techniques of data collection. To our knowledge, no other technique fulfils this need. This is important as the majority of studies in IS, and in the broader social sciences are mono-method studies. In the absence of a technique such as the MV technique, the vast majority of empirical evidence in those fields remains beyond the reach of techniques to empirically examine the effect of CMV. We concur with Lindell and Whitney (2001, p. 119) that the MV technique is "superior to overlooking CMV effects altogether, which seems to be a very common way of addressing the problem." We also concur with Malhotra et al. (2006, p. 1881) that the MV technique "is one of the most practical tools available for assessing and controlling for CMV." However, in the absence of a valid criterion for identifying the MV correlation, there remains a strong validity threat to the conclusions drawn from applying the MV technique.

Following from the findings of this study, we recommend that researchers employ the second lowest correlation of the criterion variable as the MV correlation. We also recommend that individual studies report the findings based on both observed and CMV-controlled correlations.

An important issue for future research is to extend the MV technique to identify a MV correlation that is a good proxy for CMV. Comparing the findings of this study with those of Sharma et al. (2009) offers a direction for this research. In particular, we recommend that future research examine the relationship between the methods employed to measure a focal correlation and the criteria for selecting the MV correlation that offers a good proxy for the effect of CMV.

5.5 Limitations and validity threats

One validity threat to the findings of this study is that it conducts twenty t-tests, raising concerns about the overall Type I error rate. To maintain an overall Type I error rate of 0.05, Bonferroni adjustment suggests that each t-test should be significant at $p \leq 0.0025$. An examination of Tables 1 and 2 reveals that each t-test is significant at $p \leq 0.001$, suggesting that the results are unlikely to be due to an inflation of the overall error rate.

6 CONCLUSIONS

This study finds that the alternative criteria for selecting the MV correlation identified by Lindell and Whitney (2001) result in conclusions that are significantly and substantially different. This raises doubts about the validity and utility of employing the MV technique. The protection from CMV claimed by employing the MV technique may be mythical. However, the MV technique fulfils an important need as it enables researchers to assess and control for the effect of CMV within the findings of individual mono-method studies. Our analysis finds that the second lowest correlation of the criterion variable may be a more valid criterion for identifying the MV correlation than the other criteria examined. We suggest directions for future research to extend the MV technique to identify a valid criterion for identifying the MV correlation within individual studies.

References

Burton-Jones, A. Minimizing Method Bias through Programmatic Research, MIS Quarterly (33:3) 2009, pp 445-471.

Campbell, D.T., and Fiske, D.W. Convergent and Discriminant Validation by the Multitratit-Multimethod Matrix, Psychological Bulletin (56:2) 1959, pp 81-105.

Cote, J.A., and Buckley, M.R. Estimating Trait, Method, and Error Variance: Generalizing Across 70 Construct Validation Studies, Journal of Marketing Research (24:3) 1987, pp 315-318.

Doty, D.H., and Glick, W.H. Common Methods Bias: Does Common Methods Variance Really Bias Results?, Organizational Research Methods (1:4) 1998, pp 374-406.

Jarvenpaa, S.L., and Majchrzak, A. Knowledge Collaboration Among Professionals Protecting National Security: Role of Transactive Memories in Ego-Centered Knowledge Networks, Organization Science (19:2) 2008, pp 260-276.

Lindell, M.K., and Brandt, C.J. Climate Quality and Climate Consensus as Mediators of the Relationship between Organizational Antecedents and Outcomes, Journal of Applied Psychology (85:3) 2000, pp 331-348.

Lindell, M.K., and Whitney, D.J. Accounting for Common Method Variance in Cross-sectional Research Designs, Journal of Applied Psychology (86:1) 2001, pp 114-121.

Ma, Q., and Liu, L. The technology acceptance model: A meta-analysis of empirical findings, Journal of End User Computing (16:1) 2004, pp 59-72.

Malhotra, N.K., Kim, S.S., and Patil, A. Common Method Variance in IS Research: A Comparison of Alternative Approaches and a Reanalysis of Past Research, Management Science (52:12) 2006, pp 1865-1883.

Pavlou, P.A., Liang, H., and Xue, Y. Understanding and Mitigating Uncertainty in Online Exchange Relationships: A Principal-Agent Perspective, MIS Quarterly (31:1) 2007, pp 105-136.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y., and Podsakoff, N.P. Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies, Journal of Applied Psychology (88:5) 2003, pp 879-903.

Podsakoff, P.M., and Todor, W.D. Relationships Between Leader Reward and Punishment Behavior and Group Processes and Productivity, Journal of Management (11:1), Spring85 1985, p 55.

Podsakoff, P.M., and Todor, W.D. Relationships between leader reward and punishment behavior and group processes and productivity, Journal of Management (11:1) 1986, pp 55-73.

Richardson, H.A., Simmering, M.J., and Sturman, M.C. A Tale of Three Perspectives: Examining Post Hoc Statistical Techniques for Detection and Correction of Common Method Variance, Organizational Research Methods (12:4) 2009, pp 762-800.

Sabherwal, R., Jeyaraj, A., and Chowa, C. Information System Success: Individual and Organizational Determinants, Management Science (52:12) 2006, pp 1849-1860.

Sharma, R., Yetton, P.W., and Crawford, J. Estimating the Effect of Common Method Variance: The Method-Method Pair Technique with an Illustration from TAM Research, MIS Quarterly (33:3) 2009, pp 473-490.

Straub, D.W.J., and Burton-Jones, A. Veni, Vidi, Vici: Breaking the TAM Logjam, Journal of the Association for Information Systems (8:4) 2007, pp 223-229.

Sun, Y., Bhattacharjee, A., and Ma, Q. Extending technology usage to work settings: The role of perceived work compatibility in ERP implementation, Information & Management (46:6), August 2009, pp 351-356.

Tiwana, A. Does technological modularity substitute for control? A study of alliance performance in software outsourcing, Strategic Management Journal (29) 2008, pp 769-780.

Tiwana, A., and Konsynski, B. Complementarities Between Organizational IT Architecture and Governance Structure, Information Systems Research (Forthcoming) 2009.

Williams, L.J., Edwards, J.R., and Vandenberg, R.J. Recent Advances in Causal Modeling Methods for Organizational and Management Research, Journal of Management (29:6) 2003, pp 903-936.

Woszczynski, A.B., and Whitman, M.E. The Problem of Common Method Variance in IS Research, in: The Handbook of Information Systems Research, A.B. Woszczynski and M.E. Whitman (eds.), Hershey, PA, 2004, pp. 66-77.