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Call for an Open Discussion on Empirical Viability of Causal Indicators

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Abstract Over the past decade, we have witnessed Serious Debates in MISQ and Other Journals Between Two Camps that have Differing Views on the use of Causal Indicators to Measure Constructs. There is the Camp that advocates Causal Indicators (ADVOCATE) and the Camp that opposes Their Usage (OPPONENT). The Debates have been primarily centered on the OPPONENT's Argument that the Meaning of a Latent Variable is determined by its Outcome Variables. However, Little Effort has been made to Validate the ADVOCATE's Dispute (Against the OPPONENT's Arguments) that the Meaning of a Latent Variable is decided by its Causal Indicators if there is no Misspecification. Our Study precisely examines the Integrity of the Argument. For this, we empirically examine how the two Primary Psychometric Properties-C*omprehensiveness and Interrelationship*-of Causal Indicators Influence Theory Testing between Latent Variables through Three Different Tests (i.e., Comprehensive Test, Interrelationship Test, and Mixed Test). Conducted on Two Different Datasets, Our Analysis Consistently Reveals that Structural Path Coefficients are Hardly Sensitive to the Changes (i.e., Misspecification) in the Properties of Causal Indicators. The Discovery offers Important Evidence that the Sound Theoretical Logic of a Causal Model is not in Sync with the Empirical Mechanism of Parameter Estimation. This Underscores that a Latent Variable Formed by Causal Indicators is *empirically an elusive notion* that is Difficult to Operationalize. As Our Results have Significant Implications on the Integrity of Numerous IS studies which have conducted Theory or Hypothesis Testing Using Causal Indicators, we strongly advocate Open Discussions among Methodologists regarding Our Findings and Their Implications for Both Published IS Research and Future Practices.

Key Words : Causal Indicator, Formative Indicator, Formative Measurement

1. Introduction

Causal or formative indicators have been widely adopted by applied researchers in Information Systems (IS) and broader behavioral science fields [1-2]. At the same time, there have been heated debates regarding the viability of causal indicators among methodologists [3-4]. Howell et al. (2013, p. 44) [5] summed this up as "The past five years have witnessed a plethora of articles on the topic of formative measurement, both in

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the IS area and in other disciplines. This work can best be described as divergent and often contradictory." The debates are between the camp who advocates causal indicators (shortly ADVOCATE) and the camp who opposes their usage (shortly OPPONENT) for theory testing [6-8]. The criticality of the debates stems from the fact that, if the indicators are invalid, subsequent hypothesis testing of theoretical relationships between latent variables (e.g., theory testing) becomes fallacious and will work against the advancement of scholarly research [9].

Previous debates were primarily about the properties of *consequences* (i.e., outcome variables) of latent variables [3]. In this study, we shift our research attention to the two psychometric properties of the *antecedents* (i.e., causal indicators) of a latent variable: *interrelationship and comprehensiveness*, as they constitute key contributors in determining the theoretical meaning of a latent variable [10-11]. The former (i.e., *interrelationship*) is about whether causal indicators representing specific aspects of a latent variable are overlapped in capturing the variable's conceptual domain. The latter (i.e., *comprehensiveness*) is about whether the conceptual domain of a latent variable is adequately covered by its indicators.

By focusing on the two properties of causal indicators, we empirically investigate the validity of ADVOCATE's core dispute against OPPONENT's arguments, which has not been attempted previously. ADVOCATE criticizes that OPPONENT relies on the misspecified causal measurement model to discredit causal indicators, and argue that they are adequate for theory testing if causal measurement models are correctly specified [3]. This ADVOCATE's position implies that there are inevitable differences between the results of theory testing based on correctly specified causal measurement models and their misspecified counterparts because the misspecification should amount to flawed theory testing. Our study precisely examines the ADVOCATE's position. To that end, we compare structural path coefficients of properly specified causal models to those of a set of misspecified causal models for which the properties of causal indicators are artificially manipulated (i.e., changes in the number of and the covariance between causal indicators). If there is little variation of structural path coefficients between the two models, this lends a strong evidence that causal indicators are inadequate for theory testing [5].

The results of our tests consistently showed no significant differences in the structural path coefficients between correctly specified and misspecified models, discrediting ADVOCATE's stance and confirming that causal indicators are indeed bias-prone in nature. The finding raises a grave question with regards to the integrity of publications, many in IS, whose research relied on causal indicators. This research has two goals in mind: sharing the dangers of causal indicators with researchers, and calling for open discussions to advance debates among methodologists on this subject matter.

2. Heated Debates

The idea of causal indicators-observable indicators cause or form a latent variable-was initially brought forth about 50 years ago [12-13]. Since then, much effort has been placed on establishing their viability as an alternative to reflective indicators. Edwards and Bagozzi (2000) [14] are among those who established causal indicators as "measures" of a latent variable. The following equation (1) is a *conceptual*, *theoretical*, or *mathematical* representation of the causal measurement model universally agreed by all ADVOCATE and OPPONENT methodologists [4].

$$\eta_1 = \gamma_1 x_1 + \gamma_2 x_2 + \ldots + \gamma_n x_n + \zeta_1 \quad \cdots\cdots\cdots\cdots (1)$$

Consistent with equation (1), Fig. 1 is a graphical display of the measurement model when n = 4. In the measurement model, the four causal indicators (x_1-x_4) define the latent variable (η_1), and thus the associated relationship is reflected by the arrows from the causal indicators to the latent variable. The coefficients (γ_1-γ_4) represent the level of influences the causal indicators have on the latent variable and ζ_1 is a disturbance term that captures all remaining causes of the latent variable unexplained by the causal indicators. The bi-directional arrows indicate covariance between any two causal indicators.

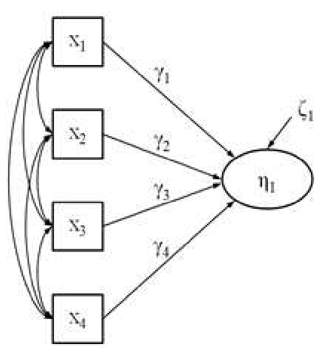

Fig. 1 Causal Measurement Model with Four Indicators

The causal measurement model in Fig. 1 cannot be estimated and the model identification requires addition of at least two outcome variables—latent variables or indicators-to the causal measurement model [15]. ADVOCATE and OPPONENT are in agreement that, for causal indicators to be a reliable alternative to reflective ones, the meaning of a latent variable should be determined only by the causal indicators (and their properties) and not be swayed by the added outcome variables [3,5]. There, however, has been serious debates regarding whether the theoretical premise is sustainable in an empirical setting.

Ironically, the debate was started by ADVOCATE. Jarvis et al. (2003) [15], Podsakoff et al. (2003) [16], and MacKenzie et al. (2005) [17] warned that many studies have been misspecifying causal indicators as reflective ones, resulting in flawed theory testing. Meanwhile, recognizing the increased usage of causal indicators in applied research, Howell et al. (2007) [18] first raised a caution regarding the empirical viability of causal indicators in *Psychological Methods*. They found that causal indicator coefficients (γi) determining the meaning of a latent variable are significantly biased as their estimation depends on other outcome variables. The bias is called *interpretational confounding* and describes a discrepancy between the theoretical and empirical meanings of a latent variable. Based on the result, they argue that the empirical meaning of a latent variable is entirely determined by outcome variables rather than by its causal indicators. Responses by Bagozzi (2007) [19] and Bollen (2007) [20] started the debates. Although Bagozzi (2007) [19] accepts that causal indicators may be appropriate in some cases, he was basically in agreement with Howell et al. (2007) [18] by noting that "R. D. Howell, E. Breivik, and J. B. Wilcox (2007) [18] have recommended that researchers abandon such an approach in favor of reflective measurement. The author agrees with their recommendations (p. 229)." On the other hand, Bollen (2007) [20] disputed Howell et al. (2007) [18] by maintaining that the findings are due to model misspecifications. Further, he notes that "interpretational confounding does not occur if the model is correctly specified whether a researcher has causal or effect indicators (p. 219)."

Before long, the discourse flared up, spreading into various academic disciplines (e.g., Information Systems, Psychology, Management, Marketing, Modeling, etc.), attracting more engagement from many methodologists (Howell et al., 2013) [5] and resulting in special issues from influential journals (see *Journal of Business Research (2008)*, *MIS Quarterly (2011), AMS Review (2013)*, *and Measurement (2014-2015)*). As summarized by Bainter and Bollen (2014) [3], "methodological disagreement concerning causal indicators has centered on the question of whether causal indicators are inherently sensitive to interpretational confounding (p. 125)," debates have been primarily centered on whether the meaning of a latent variable is decided solely by consequences (i.e., outcome variables). According to OPPONENT, a latent variable's meaning is a function of outcome variables rather than causal indicators and, thus, causal indicators should be abandoned, suspended, or avoided (e.g., [1,5,21-25]). Meanwhile, ADVOCATE kept promoting causal indicators by contending that they are the determining source of a latent variable and thus viable for theory testing as long as the estimation is not jeopardized by the misspecification problem [3,8,26-27]. It is not likely that the debate will subside in the near future [28] and applied researchers in IS and other fields largely ignore the controversy with the usage of causal indicators continuing unabated. Therefore, it is urgent to resolve the dispute and maintain the validity of empirical research that leads to positive growth of theoretical knowledge.

In this study, instead of trying to prove the OPPONENT's position that the meaning of a latent variable is determined by its consequences (outcome variables), we concentrate on validating the ADVOCATE's argument that antecedents (causal indicators) of a latent variable determine its meaning and therefore are adequate for theory testing. Subsequent sections are devoted to this empirical validation.

3. Comprehensiveness and Interrelationship

In the causal measurement model of Fig. 1, the variance of the latent variable (η_1) is mathematically a function of variances of causal indicators (x_1-x_4) and covariances between causal indicators (x_1-x_4) (refer to Edwards (2011, p. 374) [22] for detailed formula derivation). That is, the meaning of the latent variable (η_1) is theoretically decided by the degree of causal indicators in covering its conceptual domain (i.e., *comprehensiveness*) and by the level of association between its indicators (i.e., *interrelationship*). Both ADVOCATE and OPPONENT agree that the two properties are fundamental considerations in designing and assessing a causal measurement model [29].

The two properties distinguish causal indicators from reflective indicators. In the reflective measurement model (e.g., [30-32]) a change in the latent variable precedes variations in its indicators. Therefore, all indicators of a reflective measurement model share a common theme and, thus, reflective indicators should be internally consistent and conceptually interchangeable. With the interchangeability of indicators, adding or deleting an indicator should not change the meaning of a latent variable. In the causal measurement model, causal indicators collectively define a latent variable, and thus they do not necessarily share the same theme, are conceptually distinct, and have no preconceived pattern of associations. Since causal indicators form the meaning of a latent variable, its conceptual domain is highly sensitive to indicator properties (i.e., *comprehensiveness and interrelationship*). A change in those properties (e.g., adding or removing an indicator, altering indicator association) modifies the latent variable's meaning [10].

A causal measurement model is correctly specified when its design is grounded on an underlying theory [15,21]. Arbitrary manipulations of the number of indicators and covariances among causal indicators, two fundamental properties that determine the meaning of a latent variable, can cause a misspecified measurement model[6] that is not in conformance with the underlying theory [3,20]. According to ADVOCATE, the meaning of a latent variable defined by misspecified causal indicators should differ from the meaning of the same latent variable defined by correctly specified causal indicators, and therefore have different results in theory testing. In the next section, we examine whether the seemingly apparent theoretical logic of the ADVOCATE position is empirically supported.

4. Empirical Testing

For empirical testing, we utilize the causal model (Fig. 2) and data (see Appendix 1) published in *MIS Quarterly* by Kim et al. (2010) [21] because their model, constructed on a theoretical basis, is correctly specified or at least a properly specified model [5]. The model has a theoretical structure in which four causal indicators (x_1: *connectivity*, x_2: *compatibility*, x_3: *application functionality*, x_4: *data transparency*) defines a latent variable (η_1: IT infrastructure

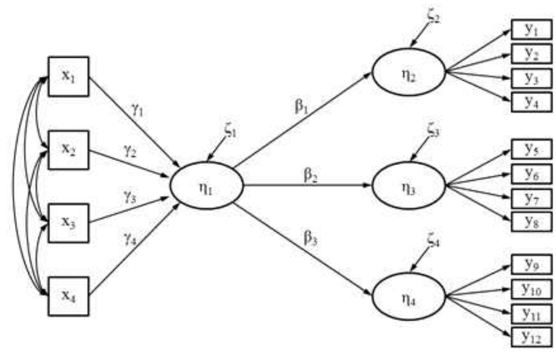

Fig. 2 Correctly Specified Causal Model

flexibility) and subsequently the latent variable influences three reflective latent variables (η_2: *financial performance,* η_3: IT *performance,* η_4: *process performance*) (refer to Kim et al. (2010) [21] for more details). For reliable comparisons, we apply the same scaling technique to all estimated models. That is, consistent with Diamantopoulos (2011) [4], the first structural path coefficient ($\beta 1$ in Fig. 2) is fixed at one and the first reflective indicator's loading of each endogenous latent variable (y_1, y_5, and y_9 in Fig. 2) is fixed to unity. LISREL 8.52 is used for model estimation. To examine if causal indicators are adequate for theory testing, three different tests (i.e., comprehensive test, interrelationship test, and mixed test) are performed in succession.

5. Comprehensiveness Test

The comprehensiveness test probes the influence of dropping one or more causal indicators on structural path coefficients of β_1, β_2, and β_3. For this, we first estimate the correctly specified causal model (Fig. 2). Then,

6) According to Bainter and Bollen (2014) [3], in the case of a causal model, misspecification can be caused by various reasons including omitted (or unneeded) paths, variables, dimensions, or correlations among disturbances or exogenous variables.

Table 1 Comprehensiveness Test

	Correctly specified model	Misspecified models with dropped indicators			
		x_1	x_1,x_4	x_2,x_3,x_4	x_1,x_2,x_3,x_4
Weight					
γ_1	0.320	*Dropped*	*Dropped*	**0.451**	*Dropped*
γ_2	0.160	0.179	**0.228**	*Dropped*	*Dropped*
γ_3	0.313	**0.387**	**0.432**	*Dropped*	*Dropped*
γ_4	0.206	0.224	*Dropped*	*Dropped*	*Dropped*
Error variance					
ζ_1	0.560	**0.652**	**0.694**	**0.796**	**1.000***
Path					
β_1	0.486	0.496	0.501	0.486	0.501
β_2	0.863	0.851	0.837	0.863	0.839
β_3	0.726	0.730	0.741	0.725	0.738
Fit index					
Chi-square (df)	164.903 (95)	144.391 (84)	136.524 (73)	137.590 (62)	116.123 (51)
RMSEA	0.055	0.055	0.060	0.071	0.073
TLI	0.980	0.982	0.981	0.976	0.977

*the standardized variance of η_1.

a set of misspecified causal models are formed by systematically dropping causal indicators—one at a time, two at a time, three at a time, and then four altogether—for empirical estimation. In total, 15 misspecified causal models—sum of 4, 6, 4, and 1 causal models, each having 3, 2, 1, and 0 causal indicators respectively—are estimated. Then, the resulting coefficients of the correctly specified and misspecified causal models are compared.

The estimates of the misspecified causal models belonging to each "causal indicator group" (e.g., those with three causal indicators) are similar and, for brevity, one estimate from each causal indicator group is shown in Table 1[7)]. It reveals that dropping causal indicators results in increased error variances and changes of weights between causal indicators and their latent variable (i.e., those with more than 0.05 increase are highlighted in yellow). The gap between the correctly specified causal model and the "x_2, x_3, x_4 - dropped" causal model was especially large (e.g., 0.131 for γ_1 and 0.236 for ζ_1). As more causal indicators are dropped, the error variance, as expected, increases as well.

The structural paths between the latent variables, meanwhile, unraveled a consistent pattern in which there was little discrepancy between the correctly specified and misspecified causal models. The largest difference was merely 0.015, 0.026, and 0.015 for β_1, β_2, and β_3 respectively. One particularly troubling outcome is that the model with no causal indicator (i.e., all four causal indicators were dropped)—practically, a confirmatory factor model—has structural path coefficients roughly equivalent to those of the correctly specified causal model. This seems to constitute convincing evidence that the misspecification of causal indicators in terms of their comprehensiveness has little or no effect on the estimation of structural paths.

6. Interrelationship Test

The interrelationship test investigates how

7) Some misspecified models—including the one with the (x_2, x_4) exclusion—fail to converge.

Table 2 Interrelationship Test

	Correctly specified model	Misspecified models (changes in indicator covariance): 0.6 increase of all covariances	0.6 increase of $(x_1,x_2),(x_1,x_3),(x_1,x_4)$	0.6 increase of $(x_1,x_2),(x_1,x_3),(x_1,x_4)$ & 0.3 decrease of $(x_2,x_4),(x_3,x_4)$
Weight				
γ_1	0.320	**0.232**	**0.120**	**0.034**
γ_2	0.160	**0.039**	0.156	0.182
γ_3	0.313	0.308	0.335	**0.394**
γ_4	0.206	**0.080**	0.195	**0.295**
Error variance				
ζ_1	0.560	**0.694**	**0.645**	0.606
Path				
β_1	0.486	0.493	0.492	0.493
β_2	0.863	0.846	0.855	0.856
β_3	0.726	0.737	0.729	0.727
Fit index				
Chi-square (df)	164.903 (95)	172.677 (95)	168.780 (95)	172.639 (95)
RMSEA	0.055	0.058	0.057	0.058
TLI	0.980	0.979	0.980	0.979

changes in covariances between causal indicators, as another form of measurement model misspecification, influence structural path coefficients. For this, causal models are estimated after misspecifying covariances between causal indicators in various manners (e.g., increase all covariances, decrease all covariances, increase and decrease combined). All of the resulting estimates indicated their similitude and, again for brevity, a subset of them is presented in Table 2. As shown, alterations in covariances between causal indicators lead to moderations in the error variance[8] and their weights. Those larger than 0.05 in difference are highlighted in yellow. When compared to the correctly specified causal model, the misspecified causal models have larger gaps. For example, the gap for γ_1 is 0.286 (= 0.320 - 0.034; "0.6 increase & 0.3 decrease" model) and that for ζ_1 is 0.134 (= 0.694 - 0.560; "0.6 increase" model). Just as with the comprehensiveness test, however, the association (i.e., structural paths) between the latent variables revealed a consistent pattern of little difference between the correctly specified and misspecified causal models. The largest difference was a meager 0.007, 0.017, and 0.011 for β_1, β_2, and β_3 respectively. This is an indication that the misspecification of causal indicators in terms of their interrelationships has little bearing on the strength of structural paths.

8) Increase (or decrease) of all covariances between causal indicators led to decreased (or increased) error variances consistently.

7. Mixed Test

For the test, we first increased all covariances between causal indicators by 0.6 from the correctly specified ones, resulting in a new misspecified model. Then, from the new model, a set of further misspecified causal models are formed following the same approach as that of the comprehensiveness test

Table 3 Mixed Test

	Correctly specified model	Misspecified models with dropped indicators			
		x_1	x_1,x_4	x_2,x_3,x_4	x_1,x_2,x_3,x_4
Weight					
γ_1	0.320	*Dropped*	*Dropped*	**0.451**	*Dropped*
γ_2	0.160	**0.050**	**0.082**	*Dropped*	*Dropped*
γ_3	0.313	**0.418**	**0.460**	*Dropped*	*Dropped*
γ_4	0.206	**0.107**	*Dropped*	*Dropped*	*Dropped*
Error variance					
ζ_1	0.560	**0.728**	**0.733**	**0.796**	**1.000***
Path					
β_1	0.486	0.500	0.503	0.486	0.501
β_2	0.863	0.834	0.827	0.863	0.839
β_3	0.726	0.744	0.750	0.725	0.738
Fit index					
Chi-square (df)	164.903 (95)	149.848 (84)	137.670 (73)	137.590 (62)	116.123 (51)
RMSEA	0.055	0.057	0.061	0.071	0.073
TLI	0.980	0.981	0.981	0.976	0.977

*the standardized variance of η_1.

(i.e., dropping causal indicators one at a time, two at a time, three at a time, and then four altogether) for empirical model estimation. Table 3 displays partial results of the mixed test, which are not much different from those of the two previous tests. That is, the acute misspecification changed indicator weights and error variance of the latent variable, especially large increases in error variance, but it still has little bearing on structural paths. The largest difference between the correctly specified and misspecified models was just 0.017, 0.036, and 0.024 for β_1, β_2, and β_3 respectively.

For further validation of the findings in their reliability, we replicated the same test procedure using the survey data gathered on a correctly specified model, which was published in *MIS Quarterly* by Diamantopoulos (2011) [4], and obtained equivalent results[9]. The revealed patterns are, therefore, highly convincing.

8. Discussions

Theoretically, the meaning of a latent variable should be formed by its causal indicators [22], and thus the theoretical relationship between a casual latent variable and particular outcome variables should naturally be a function of causal indicators' properties (e.g., comprehensiveness and interrelationship). This theoretical logic should be empirically supported for causal indicators to become a reliable alternative to reflective indicators. That is, an arbitrary alteration of causal indicators' properties (i.e., misspecification) should be adequately reflected in the relationship (i.e., structural path coefficients) between implicated latent variables. Nonetheless, our empirical analysis consistently shows that structural path coefficients are hardly sensitive to misspecifications in causal indicators, even

9) For brevity of our manuscript, the results obtained based on the survey data in Diamantopoulos (2011) [4] are not included here. They are available from the first author on request.

Table 4 Additional Test

	Correctly specified model	Changes in outcome indicator covariance: 0.3 decrease of (η_2,η_3)	0.3 decrease of (η_1,η_2), (η_2,η_3)	0.3 decrease of (η_1,η_3), (η_2,η_3)	0.2 decrease of (η_1,η_2), (η_2,η_3), (η_1,η_3)
Weight					
γ_1	0.320	**0.378**	**0.441**	**0.411**	**0.403**
γ_2	0.160	0.192	**0.219**	0.208	0.200
γ_3	0.313	**0.392**	**0.459**	**0.422**	**0.413**
γ_4	0.206	0.243	**0.280**	**0.264**	**0.257**
Error variance					
ζ_1	0.560	**0.358**	**0.132**	**0.247**	**0.282**
Path					
β_1	0.486	0.475	**0.338**	**0.390**	**0.362**
β_2	0.863	**0.696**	**0.608**	**0.667**	**0.677**
β_3	0.726	**0.555**	**0.523**	**0.519**	**0.570**
Fit index					
Chi-square (df=95)	164.903	181.113	171.900	179.606	158.549
RMSEA	0.055	0.062	0.058	0.061	0.053
TLI	0.980	0.972	0.973	0.972	0.978

Note: (η_i, η_j) means covariance between the indicators η_i and η_j.

when they were entirely removed from the measurement model (see Table 1 and 3). This discovery offers convincing evidence that the sound theoretical logic of a causal model is not in sync with the empirical mechanism of parameter estimation.

If so, what operational mechanism is in play in estimating the causal model? To answer this, we bring up the fact that the empirical results above can be explained in terms of another empirically indistinguishable model [18]. That is, the estimation results in Fig. 2 can be interpreted in terms of the four predictors (x_1-x_4) influencing the second-order latent variable (η_1) composed of three first-order reflective latent variables (η_2, η_3, and η_4). Then, it is not surprising at all that the changes in the four predictors' properties alter both the paths (γ_1-γ_4) from the predictors to the second-order latent variable (η_1) and the η_1's disturbance term (ζ_1). Likewise, it is also natural that (β_1-β_3), representing reflective relationships between the second-order latent variable (η_1) and the three first-order reflective latent variables (η_2, η_3, and η_4), do not react to the changed properties of predictors (x_1-x_4) but to those of outcome variables' indicators (y_1-y_{12}).

To see if this alternative explanation is empirically supported—in other words, whether β_1-β_3 are sensitive to the change in covariances between outcome reflective indicators (y_1-y_{12})—we performed an additional test. For this, causal models are estimated after the covariances between outcome reflective indicators are moderated in various combinations and the results are compared with those of the correctly specified model. For brevity, Table 4 displays a subset of the empirical test. As shown, the estimates, β_1-β_3, sensitively react to the covariances between outcome reflective indicators (i.e., those with more than 0.05 increase are highlighted). This leads us to argue that causal models, although anchored on sound theories, are inevitably vulnerable to bias in their empirical estimation [21].

With this empirical evidence, the following summarizes the empirical-level functions of variables and parameters in Fig. 2 that are severed from the functions intended at the theoretical-level. First, predictors, x_1-x_4, are not causal indicators, but predictors of the outcome latent variable (η_1) and, subsequently, γ_1-γ_4 become structural path coefficients. In this light, a latent variable formed by causal indicators is empirically an elusive notion that is difficult to operationalize. Second, practically, η_1 is not a causal latent variable but a common factor that, as a second-order latent variable, explains covariances among outcome reflective indicators (y_1-y_{12}) [5]. Then, ζ_1 is not unmeasured causal indicators, but all unmodeled sources of covariance among the outcome reflective indicators (e.g., omitted predictors and covariates). Our findings are consistent with Borsboom, a highly respected psychometrician, and his colleagues, who state, "….causal indicators are *entirely superfluous* to the measurement and identification of the latent variable" ([25], p. 60).

Our findings indicate that the ADVOCATE's theoretical argument–adequacy of correctly specified causal indicators in defining the meaning of a latent variable and conducting theory testing–cannot be empirically sustained. They send a clear message to applied researchers with regards to the risks of causal indicators in testing hypotheses, and caution that the integrity of many empirical findings (i.e., theory testing results) in IS research that rely on causal indicators are subject to questions and reevaluations. Numerous IS publications have adopted causal indicators, but the reassessment of their findings appears to be necessary. Furthermore, causal indicators should be avoided until a reliable solution is found.

9. Conclusion

Consistent with other researchers, we agree that latent variables (e.g., social interaction or exposure to media violence) defined by causal indicators exist at the conceptual or theoretical level [7,26]. On the other hand, we are confident that a causal model with causal indicators is not empirically tenable. This is consistent with Lee et al. (2013) [1], who question the ontology of a latent variable named on the basis of its causal indicators. In this light, we would like to call for open discussion among methodologists on this vitally important subject. Causal indicators are used extensively in IS research and this work could cast aspersions on their results and conclusions. We also believe that our work can become an anchor point of the open discussion. Furthermore, we would like to invite and challenge scholars to perform replication research using data available from this study (see Appendix 1), from Diamantopoulus' work (2011) [4], and from other sources of causal indicator research. The active participation from scholars through the empirical testing of various theories grounded on causal indicators is arguably the only way that we can put this heated debate behind us.

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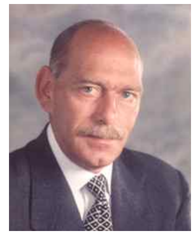

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Appendix 1 Covariance Matrix (Source: Kim et al., 2010 [5])

Input	y_1	y_2	y_3	y_4	y_5	y_6	y_7	y_8	y_9	y_{10}	y_{11}	y_{12}	x_1	x_2	x_3	x_4
y_1	2.294															
y_2	1.864	2.236														
y_3	1.531	1.795	2.200													
y_4	1.693	1.916	1.846	2.224												
y_5	0.442	0.458	0.484	0.473	1.103											
y_6	0.525	0.589	0.549	0.567	0.824	1.113										
y_7	0.408	0.439	0.450	0.458	0.621	0.726	1.029									
y_8	0.438	0.485	0.507	0.497	0.729	0.789	0.750	0.942								
y_9	0.570	0.489	0.388	0.493	0.670	0.602	0.391	0.523	1.520							
y_{10}	0.532	0.508	0.419	0.632	0.624	0.542	0.414	0.462	0.995	1.332						
y_{11}	0.540	0.508	0.406	0.541	0.618	0.558	0.420	0.490	0.895	0.972	1.413					
y_{12}	0.397	0.397	0.326	0.415	0.608	0.516	0.405	0.482	0.829	0.863	0.915	1.230				
x_1	0.427	0.411	0.229	0.343	0.626	0.576	0.347	0.490	0.578	0.394	0.442	0.520	2.226			
x_2	0.421	0.403	0.275	0.380	0.500	0.440	0.428	0.456	0.394	0.304	0.277	0.497	0.349	2.375		
x_3	0.477	0.504	0.367	0.468	0.511	0.505	0.446	0.455	0.468	0.481	0.517	0.561	0.503	0.706	1.758	
x_4	0.321	0.330	0.302	0.279	0.391	0.504	0.423	0.381	0.323	0.351	0.278	0.389	0.283	0.627	0.490	2.035

Note: IT Infrastructure flexibility (x_1-x_4), Financial Performance (y_1-y_4), IT Performance (y_5-y_8), and Process Performance (y_9-y_{12}).