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Multiple Indicators and Multiple Causes (MIMIC) Models as a Mixed-Modeling Technique: A Tutorial and an Annotated Example

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Multiple Indicators and Multiple Causes (MIMIC) Models as a Mixed-Modeling Technique: A Tutorial and an Annotated Example

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Abstract:

Formative modeling of latent constructs has produced great interest and discussion among scholars in recent years. However, confusion exists surrounding researchers' ability to validate these models, especially with covariance-based structural equation modeling (CB-SEM) techniques. With this paper, we help to clarify these issues and explain how formatively modeled constructs can be assessed rigorously by researchers using CB-SEM capabilities. In particular, we explain and provide an applied example of a mixed-modeling technique termed multiple indicators and multiple causes (MIMIC) models. Using this approach, researchers can assess formatively modeled constructs as the final, distal dependent variable in CB-SEM structural models—something previously impossible because of CB-SEM's mathematical identification rules. Moreover, we assert that researchers can use MIMIC models to assess the content validity of a set of formative indicators quantitatively—something considered conventionally only from a qualitative standpoint. The research example we use in this manuscript involving protection-motivated behaviors (PMBs) details the entire process of MIMIC modeling and provides a set of detailed guidelines for researchers to follow when developing new constructs modeled as MIMIC structures.

Keywords: Methodology, Formative Construct Validation, MIMIC Modeling, Covariance-Based SEM, Protection-Motivated Behaviors.

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I. INTRODUCTION

A primary concern for researchers in several fields including information systems (IS) has been to identify the differences between reflective and formative constructs and to assess and validate them appropriately via structural equation modeling (SEM)[1] techniques (Andreev, Heart, Maoz, & Pliskin, 2009; Cenfetelli & Bassellier, 2009; Coltman, Devinney, Midgley, & Venaik, 2008; Diamantopoulos, 2011; Diamantopoulos, Riefler, & Roth, 2008; Petter, Straub, & Rai, 2007; Roberts & Thatcher, 2009; Wilcox, Howell, & Breivik, 2008). Reflective modeling is the more-traditional approach used to assess latent constructs, but formative modeling is an alternative approach that is likened to multiple linear regression in which the individual indicators explain variance in the overall construct, with error residing at the construct level[2] (Diamantopoulos & Winklhofer, 2001). These differences at the conceptual and statistical levels have been the focus of scholarly debate largely because the misspecification of SEM models can lead to erroneous findings, which can then be propagated throughout a field's literature (Bollen, 2007; Collier & Bienstock, 2009; Jarvis, MacKenzie, & Podsakoff, 2003; Petter et al., 2007).

Model misspecification has its roots in several areas, with one of the more prominent areas arising when researchers develop multiple measures for a construct without considering the theory surrounding the construct of interest. That is, researchers might prematurely attempt to design a measure of a construct before they have answered questions such as, "will the items to be developed all tap into the same conceptual domain and thus will they be adequate replacements for one another?" and "does theory suggest that the construct of interest is formed from a variety of individual components, which are not expected to be highly correlated with one another?". Should researchers fail to consider these and other factors, the measures may be misaligned (i.e., misspecified) with theory. Other reasons for misspecification exist, which have been discussed at length by other researchers (Bollen, 2007; Jarvis et al., 2003; MacKenzie, Podsakoff, & Jarvis, 2005; MacKenzie, Podsakoff, & Podsakoff, 2011).

Despite previous academic exchanges and methodologists' arguments for more-stringent assessment and validation efforts of formatively modeled constructs in the IS field (Cenfetelli & Bassellier, 2009; Petter et al., 2007; Ringle, Sarstedt, & Straub, 2012), these techniques are not as mature as those used in traditional, classical measurement (Aguirre-Urreta & Marakas, 2012; Kim, Shin, & Grover, 2010). Moreover, some confusion among IS scholars exists surrounding various SEM techniques and their capabilities in modeling and estimating the statistical parameters of formatively modeled constructs. For example, researchers in over 30 percent of the PLS-based manuscripts published in *MIS Quarterly* explicitly state that they favored PLS because of its capability in modeling and assessing formative constructs (Ringle et al., 2012). Although we note that PLS has this capability, such justification, when offered alone, has likely led some to default to its use in the case of formatively modeled constructs (c.f. Gemino, Reich, & Sauer, 2007). Likewise, researchers have also suggested an inherent weakness in CB-SEM's estimation procedures (Chwelos, Benbasat, & Deter, 2001; Goles, White, Beebe, Dorantes, & Hewitt, 2006; Hsieh, Lai, & Shi, 2006) and even CB-SEM's complete inability to assess formatives (Guo & Barnes, 2012; Hampton-Sosa & Koufaris, 2005; Saraf, Liang, Xue, & Hu, 2012). Little doubt exists that CB-SEM has more stringent assumptions (e.g., residual distributions and sample size constraints) than PLS, but these claims are problematic, not only because they are incorrect, but because they can lead researchers to abandon valuable statistical techniques prematurely. Nowhere is this truer than in the case of when researchers need to assess an overarching theory yet rely on prediction-based methods instead.

In the case of CB-SEM, advanced approaches exist that provide researchers with the ability to rigorously assess and validate formatively modeled constructs. The multiple indicators and multiple causes (MIMIC) model (Diamantopoulos & Winklhofer, 2001; Jöreskog & Goldberger, 1975) is a prime example of such a technique. Specifically, MIMIC models incorporate both formative and reflective components to measure latent constructs. They have been found efficacious in the study of customer equity management (Bruhn, Georgi, & Hadwich, 2008), e-service quality (Collier & Bienstock, 2009), international economies (Dell'Anno, 2007; Dell'Anno, Gómez, & Pardo, 2007; Dobre & Alexandru, 2009), customer market orientation (Cadogan, Souchon, & Procter, 2008), and consumer exit-voice theory (Fornell & Bookstein, 1982), among others. The use of MIMIC models with CB-SEM, however,

[1] In this paper, we use SEM to denote both covariance-based (CB-SEM) and component-based techniques. Of the latter, the partial least squares (PLS) approach is the most dominant in the IS field. Therefore, we use PLS generically to refer to component-based techniques rather than to individual software applications, such as PLS-Graph or SmartPLS.
[2] PLS assumes that this error is equal to zero.

offers both advantages and complexities that need to be examined carefully, especially because few examples can be found in IS literature[3].

Given these opportunities, we explicate the meaning and benefits of MIMIC models in this paper. We also detail how IS researchers can integrate these mixed-model constructs in their theory-testing efforts. Finally, through our development and validation efforts to establish a new construct, we illustrate the process of creating and validating multidimensional MIMIC models, which leads to several key recommendations for IS researchers who wish to develop and use MIMIC models with CB-SEM.

II. REVIEW OF MIMIC MODELS

MIMIC Model Description and Purpose

For this paper, we focus on two important benefits of MIMIC models: (1) mathematical benefits, and (2) the construct validation benefits of formatively modeled constructs. We begin this section by describing MIMIC models and how they assist in achieving model identification in CB-SEM. We then discuss how MIMIC models extend researchers' abilities to assess how well formative indicators capture the domain of the construct under investigation. That is, MIMIC models afford researchers the opportunity to examine—from a quantitative standpoint—the content validity of a formatively modeled construct.

Mathematical Identification

In contrast to reflectively measured constructs, formatively modeled constructs are *always* statistically unidentified in CB-SEM (i.e., the construct and its components produce fewer unique pieces of information than are consumed to estimate all of its free parameters) (Diamantopoulos & Winklhofer, 2001; Hair, Black, Babin, & Anderson, 2009). Such identification issues lead to situations in which only portions of CB-SEM models can be assessed, rather than the models in their entirety (Bollen & Davis, 2009). Consequently, researchers who use CB techniques must carefully plan how the constructs in their theories will be modeled (i.e., reflectively, formatively, or mixed) and assessed quantitatively prior to their data collection efforts. Researchers who disregard this step will likely limit themselves to less-appropriate or less-powerful statistical approaches to evaluate the usefulness of their conceptual models.

A useful way to appease the statistical constraints encountered when using formatively modeled constructs in CB-SEM is to add two or more reflective indicators to the overall construct level. This addition not only allows more unique pieces of information (i.e., non-redundant entries in the sample covariance matrix) to be produced, but it also provides a way for researchers to examine the construct by itself in a measurement model[4]. Without this additional information, formative constructs can only be assessed via their reliance on other constructs in the overall model during structural assessment (Jarvis et al., 2003). Hence, these modified constructs, or MIMIC structures, are among the "simplest, meaningful formative model(s)" (Bagozzi, 2011, p. 272).

Figure 1 compares a typical formative construct and the same construct altered as a MIMIC model. The formative construct (η_1) consists of five indicators ($x_1 \ldots x_5$), which produce 15 non-redundant elements in the sample covariance matrix (i.e., (n (n + 1)) / 2), yet the model requires 21 degrees of freedom to estimate the structure's relationships (i.e., one path between each indicator and the overall construct ($\gamma_{11} \ldots \gamma_{15}$), the paths representing inter-indicator correlations ($\varphi_1 \ldots \varphi_{10}$), the variances for each of the x indicators, and the error term ζ_1). Adding two reflective or effect items (y_1 and y_2) that are predicted by the overall construct allows the model to become overidentified by 4 degrees of freedom. Specifically, the two reflective and five formative indicators produce 28 nonredundant elements in the variance-covariance matrix, with the entire MIMIC model consuming the original 21

[3] We recognize methodologists' previous efforts to expand researchers' understanding of MIMIC models (Diamantopoulos, 2011; MacKenzie et al., 2005); however, our research pertains to (1) a newly developed, multidimensional IS-centric measure and, (2) design and validation recommendations that take formative and reflective components of the same construct into consideration in a simultaneous fashion. Although formative measurement has been widely adopted in top IS journals (e.g., Cenfetelli & Bassellier, 2009; Diamantopoulos, 2011; Petter et al., 2007; Posey, Roberts, Lowry, Bennett, & Courtney, 2013; Siponen & Vance, 2010), we recognize that not all methodologists agree that formative measurement is desirable and thus that this debate is not fully resolved (Hardin, Chang, & Fuller, 2008a; Hardin, Chang, Fuller, & Torkzadeh, 2011). However, we do not seek to convince methodologists that formative measurement is efficacious. Similarly, we do not mean to enter the debate about the efficacy of CB-SEM versus PLS. Our focus is to explain MIMIC models in CB-SEM to those who see value in formative measurement and are interested in the benefits of this mixed-modeling approach.

[4] We note that there are other possible ways of achieving statistical identification for formative constructs in CB-SEM (Bollen & Davis, 2009); however, we focus on the discussion and development of MIMIC models, which were originally viewed as a single latent construct containing: (1) formative indicators representing the diverse, nonredundant components of the construct; and (2) two or more reflective, interchangeable indicators that reflect the overall construct's nature (Jöreskog & Goldberger, 1975). This understanding allows researchers to use MIMIC models as endogenous constructs without having to specify downstream variables or constructs not theoretically relevant or practically important simply to satisfy these statistical constraints.

degrees of freedom plus a degree of freedom for one of the paths from the construct to the reflective indicators (λ_{11} and λ_{12}) and the error terms on each reflective indicator (ε_1 and ε_2). Typically, only one of the lambdas consumes a degree of freedom since the other will be set to one such that the scale for the construct can be set. Although it is possible to gain one degree of freedom by eliminating the overall error term of the formative construct, leading methodologists strongly discourage this approach (Hair et al., 2009; Petter et al., 2007). We describe *why* this is so in the next section.

Construct Validation

More important than the purely mathematical benefit, however, is the significant advantage of MIMIC models to assist in validating formatively modeled constructs. As Bollen and Ting (2000, p. 4) state:

> *Ideally, to fully validate the usefulness of the latent variable or construct that is influenced by causal indicators, there should be other latent or observed variables that the construct influences so that we can assess whether the construct behaves as hypothesized".*

For this purpose, methodologists have stated that MIMIC analyses may provide a better means of assessing the specification of formative measures in that researchers can evaluate to what degree the formative components relate to the reflective ones (Cenfetelli & Bassellier, 2009; Qureshi & Compeau, 2009).

In a similar validation manner, causal indicators are meant to capture the *entire* domain consumed by the formatively measured construct in which each indicator is designed to represent a unique, non-redundant facet of that domain (Cenfetelli & Bassellier, 2009; Diamantopoulos, 2011; Diamantopoulos & Siguaw, 2006; Petter et al., 2007). However, this coverage needs to be "sufficiently inclusive" (Diamantopoulos & Winklhofer, 2001, p. 272) to capture the essence of the construct (Petter et al., 2007). With the modeling capabilities of CB techniques and the structure afforded by MIMIC models, the construct-level error term noted as ζ_1 has significant meaning when assessing the construct domain:

> *In the MIMIC model, the dependent variable (that which is regressed on the formative indicators) is the shared variance of the reflected variables or constructs. The error term, then, is the shared variance between the outcomes (i.e., the two or more reflective components) not accounted for by the formative indicators* (Wilcox et al., 2008, p. 1224).

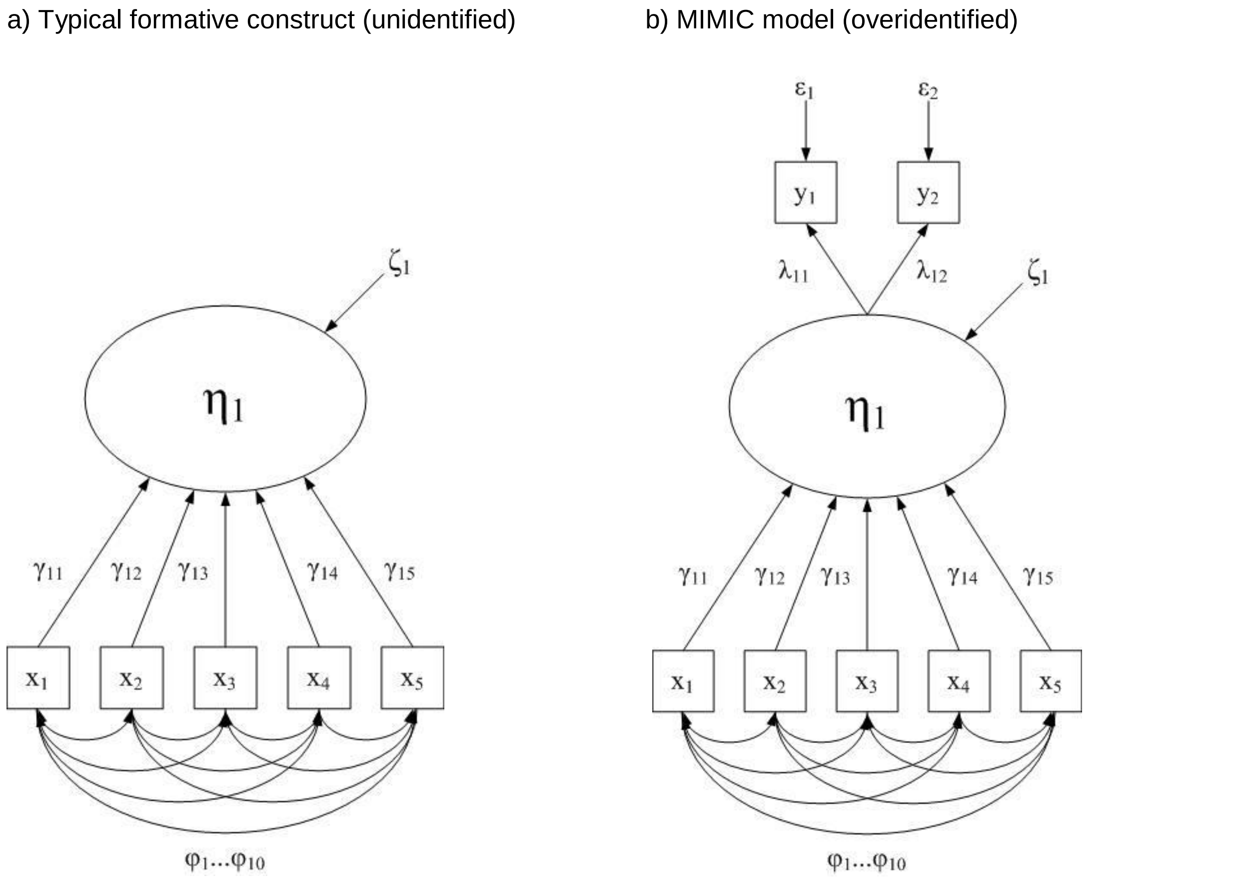

Figure 1. Comparison between a Traditional Formative Construct and a MIMIC Model

Consequently, we assert that researchers' efforts to quantitatively assess how well the formative indicators capture the construct's domain—that is, to produce a content valid set (Cenfetelli & Bassellier, 2009)—are made available via MIMIC models.

For these reasons, MIMIC models provide something that a formatively modeled construct by itself cannot (in addition to mathematical identification)—a quantitative measure of how well the conceptual domain is captured via the formative components. That is, assuming that the reflective component of the MIMIC model adequately represents the concept of interest, then the degree to which the formative indicators explain variance in that component represents a numerical measure by which researchers can assess the amount of the domain covered by the formative indicators. This approach thus is a powerful technique to obtain a quantitative measure of something that has traditionally been assessed by qualitative means (i.e., content validity).

Like others (Bollen, 2007), we argue that the formative and reflective components of a construct are conceptually distinct. This assumption, however, can lead to one of three interpretations, which are mathematically identical, because the same covariance matrices are predicted (MacKenzie et al., 2011). First, a MIMIC model can be viewed as a composite, formatively measured construct that causes reflective indicators. A second interpretation is that a traditional, reflectively modeled construct is affected or influenced by conceptually distinct antecedents. Finally, a third explanation of a MIMIC model is as a single, mixed-model latent construct with both reflective and formative indicators. We concur with previous methodologists (MacKenzie et al., 2011) that this third interpretation is the most appropriate, especially when the construct in question has a multidimensional nature. Moreover, this interpretation lends itself to the study of the MIMIC model as a single, isolated measurement model rather than within an entire structural model, which might not be wholly relevant to the construct of interest given that some formatively measured constructs are positioned as the final endogenous variable in a structural model.

In the following sections, we describe the development and validation of a multidimensional MIMIC model. In this process, we highlight the design and implementation of a higher-order MIMIC model from conception to validation.

The recommendations that result from the entire process should prove beneficial for researchers whose efforts use both CB-SEM and formatively modeled constructs.

MIMIC Model Development and Validation

For the purposes of an IS-relevant demonstration, we focus on the development of a MIMIC model regarding protection-motivated behaviors (PMBs). PMBs have most recently been defined as the volitional behaviors that organizational insiders can enact to protect (1) organizationally relevant information in their firms, and (2) the computer-based information systems in which information is stored, collected, disseminated, and/or manipulated from information security threats (Posey et al., 2013).

From a methodological standpoint, PMBs are an ideal construct to use for MIMIC models because they are comprised of a wide variety of unique behaviors that are not interchangeable. Organizational insiders, such as full-time employees, may choose to engage in one, many, or all of these beneficial behaviors. If an insider engages in at least one unique behavior in the overall PMB set, then they have engaged in PMB activity. The individual PMB behaviors should thus predict the overall PMB construct, rather than the construct predicting the individual behaviors. Additionally, failure to consider all of the relevant behaviors or behavior sets in the overall PMB construct can change the meaning of PMBs considerably, and the methods by which insiders are motivated to engage in one PMB does not necessarily translate into their motivation to engage in another. For these reasons, the PMB construct should be modeled as formative rather than reflective (Jarvis et al., 2003; Petter et al., 2007), and will serve as a referent construct in elucidating the important validation techniques for MIMIC models. In addition, as we detail later, PMBs are multidimensional in nature: as such, they add complexity and substantial opportunities for learning through these validation efforts. Table 1 describes the general steps in creating and validating MIMIC models.

Aside from providing an ideal mathematical case for MIMIC models, from a conceptual standpoint, variation exists among scholars in the limited amount of research as to what constitutes the protective actions of organizational insiders (Ng, Kankanhalli, & Xu, 2009; Stanton & Stam, 2006; Workman, Bommer, & Straub, 2008). Thus, it is vital to the IS security field's progression to further refine the PMB concept to better assist researchers and practitioners alike in their quest to devise more holistic information security approaches. The development of a new measure via a MIMIC model will provide this possibility.

Content Validation of the PMB Construct

With the choice of PMBs substantiated, we now discuss various efforts used to ensure the content validity of the PMB construct. Moreover, we detail the processes used to validate the new MIMIC model.

Table 1: Process of Creating and Validating MIMIC Models		
Justification/reminders	**Assessment techniques (desired criteria)**	**Significant concerns**
Step 1. Generating and validating items relative to the concept domain		
Items/indicators for both formative and reflective components must be developed according to the construct definition, each with different validation techniques. If the concept is expected to be multidimensional, researchers should assess the legitimacy of creating reflective items for each dimension. If not, the summation of indicators for each dimension can be used. At least two reflective indicators are required; however, three or more are preferred for traditional CB-SEM assessments.	*Possible formative component validation:* Principal components analysis (weights > 0.60). Multidimensional scaling (low stress levels, high dispersion accounted for). Cluster analysis (visible inflection points in Scree plots using agglomerative schedule data). Q-sorting methodology (high inter-judge agreement and Cohen's Kappa). *Possible reflective component validation:* Average variance extracted (> 0.50). Internal consistency (> 0.70). Exploratory factor analysis (loadings > 0.60).	With formatively measured constructs, caution should be used when choosing to remove an indicator due to *quantitative* assessments; if the item(s) is germane to the conceptual domain, the item(s) should be kept for further assessment. Independent samples should be used to establish the two components of the MIMIC model. Validation techniques for formative components are not appropriate for reflective component validation, and vice versa.
Step 2. Initially assess MIMIC model internal validity		
Review the degree of association between the MIMIC components.	Assess the absolute indicator contributions (i.e., zero-order correlations) of each formative item with the averaged reflective component ($p < 0.05$).	Non-significant associations could indicate that the formative indicators do not significantly relate to the construct at the most basic level, and removal could be warranted.
Step 3. Assess potential multicollinearity/significant conceptual overlap using zero-order correlations		
Assess the degree of conceptual overlap among formative indicators to limit potential issues related to multicollinearity.	Assess the inter-item correlations among all of the formative indicators ($r < 0.60$).	High associations indicate potential conceptual overlap; related item(s) should be considered for removal. Formative indicators are not expected to correlate significantly, but there is no reason to expect complete orthogonality among them.
	Regress the summated formative and averaged reflective components on the individual formative components in separate regressions (VIFs < 3.3).	High VIF values could indicate multicollinearity among the formative components. If the sign of the standardized coefficient is opposite of expectations, then the MIMIC model may be multidimensional in nature—validate with theory. Also, a large number of formative indicators might result in unexpected findings, which may be due to the nullification of absolute indicator contributions in the presence of so many other indicators (Cenfetelli & Bassellier, 2009).

Recent research (Posey et al., 2013) provides strong content validity for the PMB concept. Results from qualitative and quantitative techniques verify that PMB is a multidimensional concept composed of 67 individual behaviors, which belong to one of twelve various cluster behavior sets that cover a broad selection of protective behaviors. These behavior types include document protection, legitimate email handling, account protection, protection against unauthorized exposure, and policy-driven awareness and action, among others.

However, because of the importance of content assessments and to ensure that the behaviors specified in previous research adequately captured the domain space defined by PMBs, we issued a survey to panellists (*n* = 200) of an online panel provider from a wide variety of industries and positions. In this survey, we asked them to list several ways that they and their fellow co-workers can protect their organizations' information and information systems from security threats. No new behaviors were elicited from this step that were not already specified by previous, recent research efforts (Posey et al., 2013).

The respondents also indicated (1) the frequency of their engagement in each of the 67 PMBs in the last year on a 7-point scale (1 = never; 7 = always), and (2) which PMBs were and were not applicable to their workplace. Because our PMB measure must be generalizable to a wide variety of occupations and industries, we excluded behaviors that received 25 percent or more "not applicable" responses from the set of PMBs. Eleven behaviors—mostly requiring a highly technical aptitude to perform—met this exclusion criterion, leaving 56 behaviors for further analysis in our study.

Initial Steps in Assessing Construct Validity

Validating formative constructs beyond content validation requires methods different from those used to validate reflective constructs (Cenfetelli & Bassellier, 2009; Hardin, Chang, & Fuller, 2008b; Petter et al., 2007). For example, exploratory factor analysis (EFA) models the variation of individual indicators as being explained by an overall construct, and is therefore appropriate for the initial validation efforts of reflectively modeled constructs (Hair et al., 2009). However, because the variation of formatively modeled constructs is explained by the individual indicators—much like the relationships modeled between independent and dependent variables in linear regression—principal components analysis (PCA) should be used during validation assessments (Petter et al., 2007).

Furthermore, traditional methods of assessing internal consistency, such as Cronbach's α, evaluate the inter-indicator correlations, with the high correlations among the indicators yielding higher levels of consistency (Kerlinger & Lee, 2000; Nunnally, 1978). Although reflective indicators must demonstrate high correlations among each other (i.e., exhibit high conceptual overlap) to be valid internally, the indicators of a formative construct need not meet this criterion, and instead should represent distinct facets of the overall construct being modeled (Bollen & Lennox, 1991; Diamantopoulos & Winklhofer, 2001; Petter et al., 2007). Therefore, internal consistency examinations of formative constructs with Cronbach's α and average variance extracted (AVE) calculations are methodologically inappropriate for formatively modeled constructs (Bagozzi, 1994; Petter et al., 2007).

Because MIMIC models are comprised of both formative and reflective components, researchers' validation efforts must account for both modeling techniques. Immediately prior to the time that the formative components were to be assessed for content validity, we independently developed and assessed a series of reflective items to measure PMBs at an overall level, relative to the definition that Posey et al. (2013) pose. Two IS doctoral students in the US who had experience in research methodology behavioral security research reviewed these 12 items, and they made only minor wording alterations as a result. To ensure that these new reflective items would remain valid across multiple samples, and therefore serve adequately as a reflection of PMBs at an overall, higher-order level, we collected data from two separate panel samples (*n* = 125, *n* = 175), whose composition was very similar to the other samples previously described (i.e., wide variety of industries, positions, experience). The findings from these data collections indicated the appropriateness of five reflective items to serve as the reflective component of the MIMIC structure (see Appendix A). We included these items in the survey instrument that the panel of 200 respondents completed.

As an initial step in validating the internal structure of the formative components of the MIMIC model, we assessed the absolute indicator contributions (i.e., zero-order correlations) between the individual PMBs and the global PMB component created from the average of the five reflective items (Cenfetelli & Bassellier, 2009; Diamantopoulos & Winklhofer, 2001). All but nine of the 56 behaviors exhibited significant associations with the global PMB measure at the 0.05 level of significance. Therefore, the majority of the items in the formative PMB measure exhibited satisfactory initial internal validity[5].

Second, we performed inter-item correlational diagnostics to assess the high correlations among the formative indicators, which correlations can significantly weaken formative measures via multicollinearity (Diamantopoulos & Siguaw, 2006). By this process, we deemed six behaviors to be close replicas of others (i.e., they exhibited

[5] Although these items did not have a significant absolute indicator contribution to the overall PMB component (i.e., $p < 0.05$), they remained in the set for further analysis because we wanted to allow as many unique behaviors to remain in the overall set for content validity purposes, unless they exhibited too much conceptual overlap with other PMBs.

significant conceptual overlap by having $r > 0.60$) and discarded them from the PMB set, which now contained 50 of the 56 widely applicable behaviors.

Third, to assess the possibility of multicollinearity among the indicators, we regressed the summated formative PMB measure and the global reflective PMB measure on the 50 independent behaviors in separate linear regressions. Variance inflation factors (VIFs) less than 10 are traditionally viewed as justification for a model's lack of multicollinearity, but methodologists have recently called for a more stringent cut-off of less than 3.3 to be used (Cenfetelli & Bassellier, 2009; Diamantopoulos & Siguaw, 2006; Petter et al., 2007). All of our VIFs were in the specified 3.3 cut-off.

Despite the low VIFs, nearly one-third of the individual regression coefficients exhibited a negative beta coefficient. This seemingly counterintuitive result suggested two potential issues with, or areas that needed to be modified in, the model. First, the sheer number of unique PMBs modeled in the linear regressions allows for a considerable number of absolute indicator contributions (i.e., zero-order correlations) to be nullified in the presence of other significant indicators, with more independent variables leading to more likely occurrences of this issue. That is, these indicators' absolute contributions become minimized when other significant indicators are modeled simultaneously at the same level of analysis (Cenfetelli & Bassellier, 2009).

Second, this finding may also suggest that some small levels of multicollinearity might be present in the model and not adequately captured by the VIFs, and that the construct should be modeled as a higher-order construct to account for the correlations among formative indicators that belong to certain groups within the overall structure (Petter et al., 2007). To eliminate these issues and to coincide with earlier findings (Posey et al., 2013), we modeled the PMBs as a multidimensional construct (Petter et al., 2007; Polites, Roberts, & Thatcher, 2012).

Refining the Multidimensional MIMIC Structure

There are several major types of second-order factors. Type I has reflective first- and second-order components, type II has reflective first-order and formative second-order, and type III has formative first-order and reflective second-order. The MIMIC model produced by our analyses is conceptually equivalent to a type IV alternative second-order factor, in that the first- and second-order components were modeled formatively (Jarvis et al., 2003). We assigned individual behaviors to their first-order constructs based on the findings from earlier PCA and cluster analyses on PMBs that our work builds on (Posey et al., 2013). This multidimensional MIMIC structure of PMBs (i.e., PMBs being formed by 12 individual behavior clusters) was modeled using the CB-SEM program AMOS 16.0, with each first-order construct representing the summated total of their associated PMBs. This initial structure exhibited the following statistics: $\chi^2 = 113.72$, df = 53; CFI = 0.977; RMSEA = 0.056.

These statistical results indicated the MIMIC structure's adequate fit to the dataset (Hair et al., 2009). However, a review of the correlations among the first-order constructs indicated several high correlations that might suggest possible multicollinearity. First, the correlation between the subconstructs co-worker reliance and immediate reporting of suspicious activity was 0.684. We combined these clusters were into a single measure and reassessed the PMB structure ($\chi^2 = 104.01$, df = 49; CFI = 0.977; RMSEA = 0.056). Using the chi-square distribution table, a $\Delta\chi^2 = 9.71$, $\Delta df = 4$ represented a significant change at the 0.05 level of significance. Thus, combining the two clusters into a single cluster was warranted quantitatively. From a qualitative perspective, all of these behaviors were active reporting activities by an organizational insider regarding security issues in the individual's firm. We named this new cluster identification and reporting of security matters.

Second, we found a smaller but still large correlation between the data entry and management and policy-driven awareness and action clusters ($r = 0.617$). We also combined these clusters and followed the steps listed above. The change in the fit statistics (i.e., $\Delta\chi^2 = 10.54$, $\Delta df = 4$) again indicated that combining these two clusters produced a significantly better fit to the data ($\chi^2 = 93.47$, df = 45; CFI = 0.978; RMSEA = 0.054). The behaviors combined in this cluster (e.g., backing up data on a regular basis, changing passwords, etc.) were likely derived from formal policies in organizations. We assigned this new cluster the same name as one of the original clusters, policy-driven awareness and action.

Finally, the wireless installation single-item cluster failed to help form the overall PMB construct significantly. A correlation between this item and the PMB construct also displayed a non-significant association from earlier analyses ($r = 0.098$). On reviewing the statistics from the second data collection, wherein organizational insiders indicated the applicability of individual behaviors, the wireless installation item received a "not applicable" rating of 18 percent. For these reasons, we dropped this item from further analysis and removed it from the MIMIC model.

The final revision to the MIMIC structure produced the following statistics: $\chi^2 = 86.3$, df = 41; CFI = 0.978; RMSEA = 0.055. The squared multiple correlation (SMC) for the PMBs was 0.711, which indicated that the first-order, formative components collectively explained considerable variance in the global PMB measure, and further added to the overall validity of the newly developed measure[6]. Figure 2 displays this finalized structure.

Interpreting the Overall PMB Structure

Leading methodologists on construct measurement (Cenfetelli & Bassellier, 2009; Diamantopoulos & Siguaw, 2006; Petter et al., 2007) have noted that formative constructs may be composed of indicators that exhibit positive and negative weights on their construct. Our multidimensional MIMIC structure was no exception; however, we did not expect these findings and they were seemingly counterintuitive to our initial predictions. For example, both account protection and secure software, email, and Internet use first-order constructs exhibited negative rather than positive standardized beta weights in the PMB MIMIC structure. These findings might lead researchers to make the claim that insiders who do not engage in account protection and secure software, email, and Internet usage actually behave in more protective ways.

In response to these results, we examined whether suppressor effects[7] might be the cause of these negative weights. As we indicate in Table 2, however, the correlations between account protection and secure software, email, and Internet use and the other first-order constructs are not large enough to warrant such a declaration.

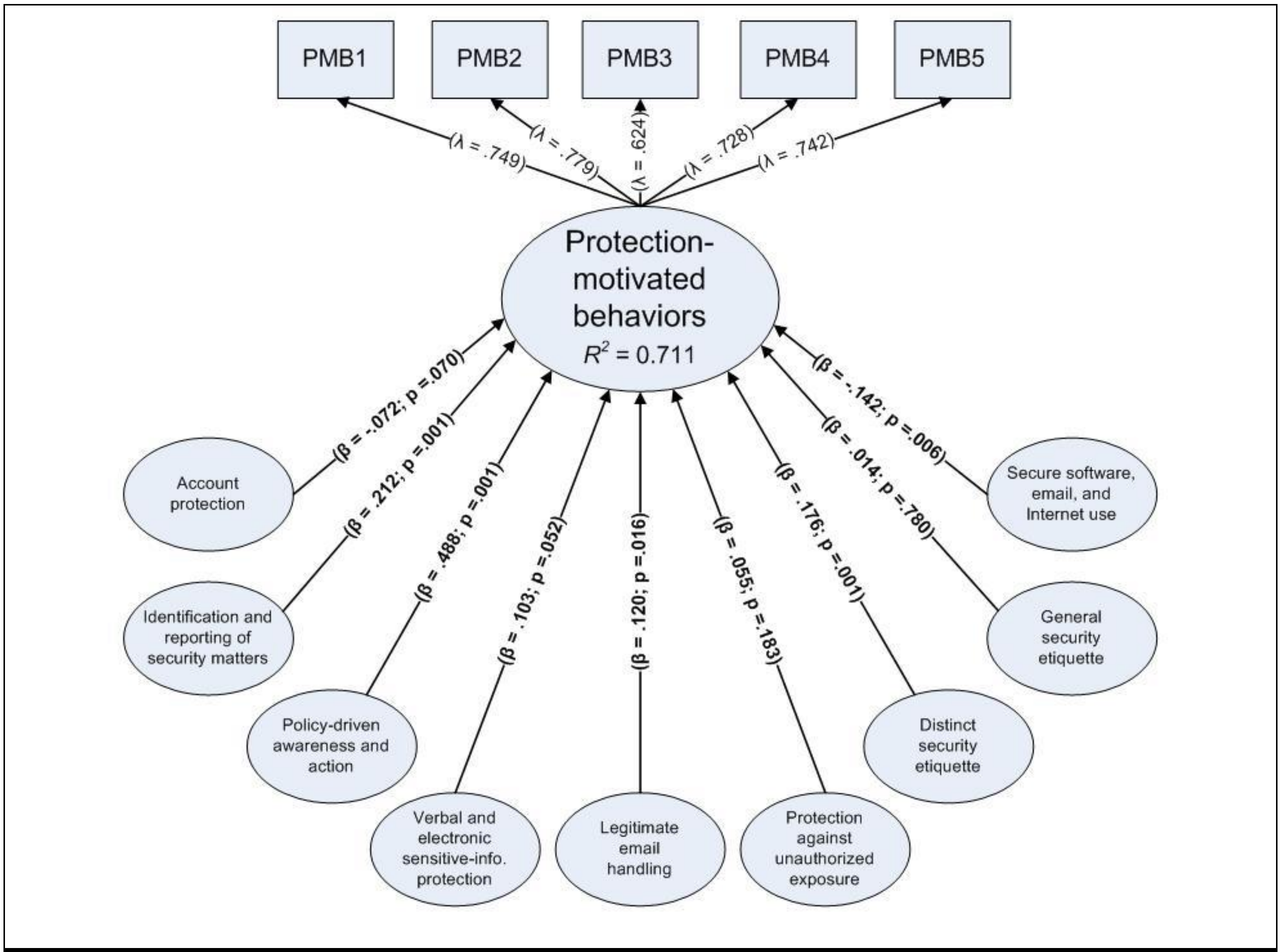

Figure 2. PMB Structure Results

Therefore, we interpreted that both account protection and secure software, email, and Internet use have an absolutely important association with PMBs; however, unlike our predictions, we found that they display negative effects when controlling for the other seven first-order constructs.

[6] It is possible to obtain an actual squared multiple correlation of the overall construct because CB-SEM techniques allow the construct-level error term to be modeled and freely estimated.

[7] Suppressor effects are effects that cause relative contributions (i.e., beta weights) to become inverted because an indicator (or first-order construct, in our case) shares more variance with another first-order construct than the overall second-order construct (Cenfetelli & Bassellier, 2009).

Additionally, two clusters exhibited the expected positive weights in the MIMIC model but were non-significant at the 0.05 level of significance[8]. These clusters were protection against unauthorized exposure and general security etiquette. Again, we ruled out suppressor effects and checked for potential multicollinearity among the first-order constructs. The VIFs were below the 3.3 criteria, and the other combinations of clusters exhibiting moderately high correlations with each other (i.e., secure software, email, and Internet use combined with legitimate email handling, and general security etiquette combined with distinct security etiquette) failed to produce significant $\Delta\chi^2$ tests—ruling out multicollinearity. With the evidence of the absolute importance of these first-order constructs shown in Appendix B and the elimination of possible suppressor or conceptual overlap explanations, we concluded that protection against unauthorized exposure and general security etiquette do not significantly explain the variance in the overall PMBs above the variance already explained by the other first-order constructs (Cenfetelli & Bassellier, 2009). However, we kept these subcomponents in the MIMIC model because of their absolute importance in statistical terms and their high relevance to information security and the concept of PMBs in practical terms.

Table 2: Correlational Analysis of the Internal MIMIC Structure

Variable	Mean	SD	α	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1. Overall PMBs—Reflective Component	50.19	1.61	0.84										
2. Overall PMBs—Formative Component	253.25	33.09	N/A	.693**									
3. Account protection	19.10	2.53	N/A	.018	.271**								
4. Identification and reporting of security matters	20.37	8.04	N/A	.599**	.738**	.005							
5. Policy-driven awareness and action	61.45	11.64	N/A	.720**	.835**	.079	.583**						
6. Verbal and electronic sensitive-information protection	42.40	5.18	N/A	.466**	.720**	.282**	.382**	.502**					
7. Legitimate email handling	17.31	3.19	N/A	.413**	.654**	.205**	.324**	.414**	.517**				
8. Protection against unauthorized exposure	13.31	1.38	N/A	.156**	.300**	.265**	.014	.150**	.390**	.306**			
9. Distinct security etiquette	15.11	5.22	N/A	.600**	.732**	.045	.496**	.612**	.435**	.403**	.101		
10. General security etiquette	35.91	5.32	N/A	.430**	.682**	.204**	.369**	.475**	.477**	.424**	.274**	.529**	
11. Secure software, email, and Internet use	27.51	5.39	N/A	.255**	.646**	.269**	.363**	.271**	.523**	.599**	.236**	.321**	.426**

Assessing the Nomological Validity of PMBs

The assessment of the nomological validity of any newly developed measure—though surprisingly rare—is an important initial step in establishing construct validity (Bagozzi, 1980; Straub, Boudreau, & Gefen, 2004). Nomological validity requires one to analyze the intercorrelations between an overall measure and its proposed antecedents, correlates, and consequences to determine if they are greater than zero (MacKenzie et al., 2005). We used another independent panel sample (n = 250) for the nomological validity assessment to determine the reliability of the MIMIC model, and to determine any patterns among the formative components and the intercorrelations for the newly created measures. However, because the nomological validity assessment was not central our goals, we place these details and the rationale for various antecedents, correlates, and a consequence of PMBs in Appendix B.

III. DISCUSSION

In this paper, we assist IS researchers in their understanding of (1) formative construct modeling in CB-SEM, (2) MIMIC models and their mathematical and construct validation benefits, and (3) how multidimensional MIMIC models might be applied in a meaningful IS context. Subsequently, one important contribution is the discussion of

[8] Verbal and electronic sensitive-information protection exhibited a standardized beta weight with a p-value of 0.052, which was justified as close enough to the chosen cutoff value of 0.05.

the various steps involved in validating newly developed constructs and their MIMIC structures. Here, we discuss these contributions in more detail.

First and foremost, our efforts provide a detailed example of advanced measurement development for complex, mixed-model constructs using the most recent methodological advancements (Cenfetelli & Bassellier, 2009; Diamantopoulos et al., 2008; Hair et al., 2009; Petter et al., 2007). Namely, we advance IS researchers' understanding of MIMIC models by developing and analyzing the multidimensional PMB construct using CB-SEM and the program AMOS. When researchers use CB-SEM techniques and the overall dependent variable is modeled formatively, MIMIC models become a necessity to estimate the entire model adequately. As we note in Section 2, the problem is that formative constructs are unidentified by nature (Diamantopoulos & Winklhofer, 2001). Using MIMIC models allows researchers to overcome this identification issue by using reflective items at the global level of the construct of interest to add the requisite degrees of freedom (Barki, Titah, & Boffo, 2007; Cenfetelli & Bassellier, 2009; Diamantopoulos & Winklhofer, 2001; Jöreskog & Goldberger, 1975). Our MIMIC model is one of the few empirical examples in the IS literature that uses such a powerful mixed-modeling approach (Barki et al., 2007; Wells, Parboteeah, & Valacich, 2011). We also believe it to be the first MIMIC model of a multidimensional nature in the IS field, though previous efforts exist that offer guidance on the operationalization of multidimensional constructs in SEM (Wright, Campbell, Thatcher, & Roberts, 2012). Our efforts and subsequent recommendations should prove useful for future measurement development efforts—especially as researchers continue to focus on formative and reflective measurement model distinctions and better address the significant differences between covariance- and component-based SEM techniques (Cenfetelli & Bassellier, 2009).

We also highlight the various difficulties that researchers might encounter when using non-traditional measurement techniques in CB-SEM. As we show in Section 2, the analysis of any construct with formative components has many quantitative facets; however, researchers must not overlook the fact that these data-driven techniques must be coupled with common sense and content-based decisions. MIMIC models are comprised of both formative and reflective components, so this validation process is more intricate than traditional approaches. Again, Table 1 contains this information.

Overall, we conclude that the benefits of MIMIC models outweigh the difficulties associated with these intricacies. These models are highly beneficial when attempting to assess the content validity quantitatively—a precursor to construct validity—of a formatively modeled construct. For example, if each formative indicator captures a unique, non-redundant portion of the overall construct, and the reflective items adequately reflect the construct at the overall level, then the SMC from the CB-SEM measurement model provides an indication of the variance not accounted for by the formative components. In our context, more than 70 percent of the variance in the PMBs was explained by unique behaviors. Although the theoretical goal of any formatively modeled construct is to have the components explain 100 percent of the variance in the construct, researchers must realize that such attainment is likely to never occur in practice—at least when studying complex behavioral, psychological, or emotional phenomena. Importantly, these assessments can be performed in a single measurement model, rather than relying on other components in a complete structural assessment in CB-SEM. As a beginning heuristic, we suggest that 50 percent coverage be considered the absolute minimum to argue for the validity of a formatively modeled construct.

Our paper leads to some promising possibilities for future research. First, with an increased understanding of MIMIC models in CB-SEM, researchers can compare these models directly with redundancy models in PLS. Though these two models are similar conceptually[9], analyzing how both algorithms empirically assess SMC and R^2 values for their respective overall constructs would be an important step in furthering academicians' knowledge about quantitative content-validity estimations for each approach.

Likewise, methodologists should evaluate the negative impacts of the model under specification (i.e., missing but important formative components of a construct) and misspecification with respect to construct dimensionality. Exactly how detrimental are missing formative components to CB-SEM's estimation of the model parameters? When a construct's nature is multidimensional, yet the MIMIC model is not specified as such, what influence does this misspecification have on both the measurement and structural models? Furthermore, does this influence vary depending on the MIMIC model's location (i.e., exogenous, endogenous, or both) in the overall structural model?

Finally, we realize that some researchers might wonder why the academic community should consider modeling a construct as formative when reflective measurement for the same construct is available. To this concern, we assert that theoretical development cannot occur for the formative components of a construct if they are not modeled. We

[9] Because PLS does not allow for disturbance terms on latent constructs, redundancy analyses are modeled as formative constructs being exogenous to their reflective counterparts.

argue that this is especially the case in multidimensional constructs. In our review of PMBs, one would not have been able to ascertain the patterns among the formative components (see Table B.2 in Appendix B) had they not been included in the nomological validity assessments. Specifically, while the individual formative components and their associated behaviors are important facets of the higher-order PMB construct, they exhibit varying relationships with the external constructs in the nomological assessment. This fine-grained detail provides the impetus for the theoretical development of why these patterns emerged, and the findings could then be leveraged in designing organizational interventions to promote change in employee behavior. Had the nomological assessment been carried out with only the overall reflective component, this information would have remained hidden. Additionally, research findings on a single formative component (e.g., single behavior type) could be generalized to those exhibiting similar nomological networks to aid in determining the scope of various research efforts.

We concur that, although some constructs might not be inherently formative or reflective (Wilcox et al., 2008), others provide a clearer indication of which measurement approach is more appropriate (Podsakoff, MacKenzie, Podsakoff, & Lee, 2003). This indication is derived from the nature of the construct under investigation, and should ultimately guide researchers in their modeling approach. The nature of PMBs and their nuances, as we discuss earlier, quite clearly lend themselves to formative rather than reflective measurement. Add to this the likelihood that the PMB construct will typically be evaluated by researchers as a main dependent variable (i.e., endogenous variable) in structural equation models, modeling the construct as a MIMIC structure becomes a necessity in order to assess all of the free parameters in the entire CB model (Bollen & Davis, 2009).

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APPENDIX A: MEASUREMENT ITEM DETAIL

Reflective PMB Items

The five reflective items used for the MIMIC model were:

PMB1: I actively attempted to protect my organization's information and computerized information systems.

PMB2: I tried to safeguard my organization's information and information systems from their information security threats.

PMB3: I took committed action to prevent information security threats to my firm's information and computer systems from being successful.

PMB4: I purposefully defended my organization from information security threats to its information and computerized information systems.

PMB5: I earnestly attempted to keep my organization's information and computer systems from harm produced by information security threats.

Formative PMB Clusters and Items

Table A.1: Formative PMB Clusters and Items	
Cluster name	**Cluster items**
Account protection	AP1: I wrote my system login information down. (R)
	AP2: I gave my computer-system account information to unauthorized individuals. (R)
	AP3: I performed work on a computer workstation with a co-worker's account information or under a co-worker's login session. (R)
Policy-driven awareness and action	PDAA1: I properly destroyed unneeded data residing on the computer system or my computer workstation.
	PDAA2: I properly destroyed and disposed of all unneeded sensitive documents.
	PDAA3: I performed a "double check" of my work to make certain that the sensitive information I entered into the computer system was accurately coded.
	PDAA4: I stored sensitive corporate information on protected media or locations (e.g., a protected server).
	PDAA5: I backed up important data and documents on a regular basis.
	PDAA6: I used shortcuts in the computer system that would be against the organization's accepted security protocol. (R)
	PDAA7: I fully read and paid close attention to security newsletters sent by my organization's department that is responsible for information-security matters.
	PDAA8: I stored information according to the retention policies specified by my organization.
	PDAA9: I created strong passwords (i.e., passwords having a combination of lower- and upper-case letters, numbers, and special characters).
	PDAA10: I changed my passwords according to my organization's security guidelines.
	PDAA11: I used wireless and/or wired networks not approved by my organization for off-site network access. (R)
Verbal and electronic sensitive-information protection	VESP1: I disclosed sensitive company information to unauthorized individuals. (R)
	VESP2: I put sensitive information in emails or other forms of electronic communication (e.g., instant messages) when I was unauthorized to do so. (R)
	VESP3: I displayed sensitive documents in public (e.g., airplane or airport). (R)
	VESP4: I verbally discussed sensitive information in areas where unauthorized persons may have been located (e.g., a hallway, an elevator). (R)
	VESP5: I accessed information in the computer system that was not required for my job. (R)
	VESP6: Prior to speaking with someone about sensitive company information, I made sure the other individual(s) had legitimate access to that information.
	VESP7: I verified an individual's identity prior to releasing sensitive information to them.

Table A.1: Formative PMB Clusters and Items (cont.)	
Cluster name	**Cluster items**
Legitimate email handling	LEH1: I responded to emails that did not have a legitimate business request. (R)
	LEH2: I opened emails that I believed had a chance of containing a virus or other potentially malicious components. (R)
	LEH3: When compiling a new email message, I double-checked the list of recipients in the "To:", "CC:", and "BCC:" fields before I actually sent the email to verify that only the intended recipients would receive the communication.
Protection against unauthorized exposure	PUE1: I allowed unauthorized individuals to do my work for me. (R)
	PUE2: I allowed individuals to look over my shoulder when I work on sensitive documents. (R)
Distinct security etiquette	DSE1: I set my computer workstation's screen saver to password protect (i.e., requires a password once the screen saver detects user activity to regain access to the workstation).
	DSE2: I cleared sensitive information off my desk or computer before allowing someone entrance into my office or leaving at the end of the workday.
	DSE3: I locked sensitive, physical documents in a secure location when they were not in use.
General security etiquette	GSE1: I properly logged into and out of computer systems at work.
	GSE2: I logged out of the computer system as soon as I was done using it.
	GSE3: I left active computers unattended. (R)
	GSE4: I allowed unauthorized individuals to utilize my computer workstation or other electronic devices issued to me by my organization. (R)
	GSE5: I brought a laptop, USB drive, or other electronic device from home and attached it to my organization's corporate network without authorization to do so. (R)
	GSE6: I locked my workstation when leaving my office space so that the workstation could not be accessed by other individuals.
Secure software, email, and Internet use	SEIU1: I installed software on my computer workstation when not authorized to do so. (R)
	SEIU2: I immediately applied software updates to my computer workstation when notified of the update by an authorized individual or department within my organization.
	SEIU3: I forwarded email spam to co-workers. (R)
	SEIU4: I used corporate email for non-work-related activities. (R)
	SEIU5: While at work, I utilized the Internet for non-work-related tasks. (R)
Identification and reporting of security matters	IRSM1: I informed my co-workers if I believed that the co-worker was engaging in behaviors not accepted by our company's information-security guidelines and policies.
	IRSM2: I notified my co-workers of new, important security information of which I became aware.
	IRSM3: I reminded my fellow co-workers of information security guidelines and protocols adopted by our organization.
	IRSM4: If I identified something that looked out of the ordinary in my work environment, I immediately reported it to the proper organizational authorities.
	IRSM5: I immediately reported a co-worker's negligent information-security behavior to the proper organizational authorities.
(R) = Reverse worded	

APPENDIX B: ESTABLISHING NOMOLOGICAL VALIDITY OF THE PMB CONSTRUCT

This appendix provides rationale for why we included several antecedents, correlates, and a consequence to be tested in the nomological validity assessment of PMBs and its first-order components—again, focusing on positive and negative antecedents, positive and negative correlates, and consequence of PMBs. Figure B.1 displays the suggested framework for performing this requisite step. After establishing these constructs, we then used an external panel to further test and refine PMBs for nomological validity.

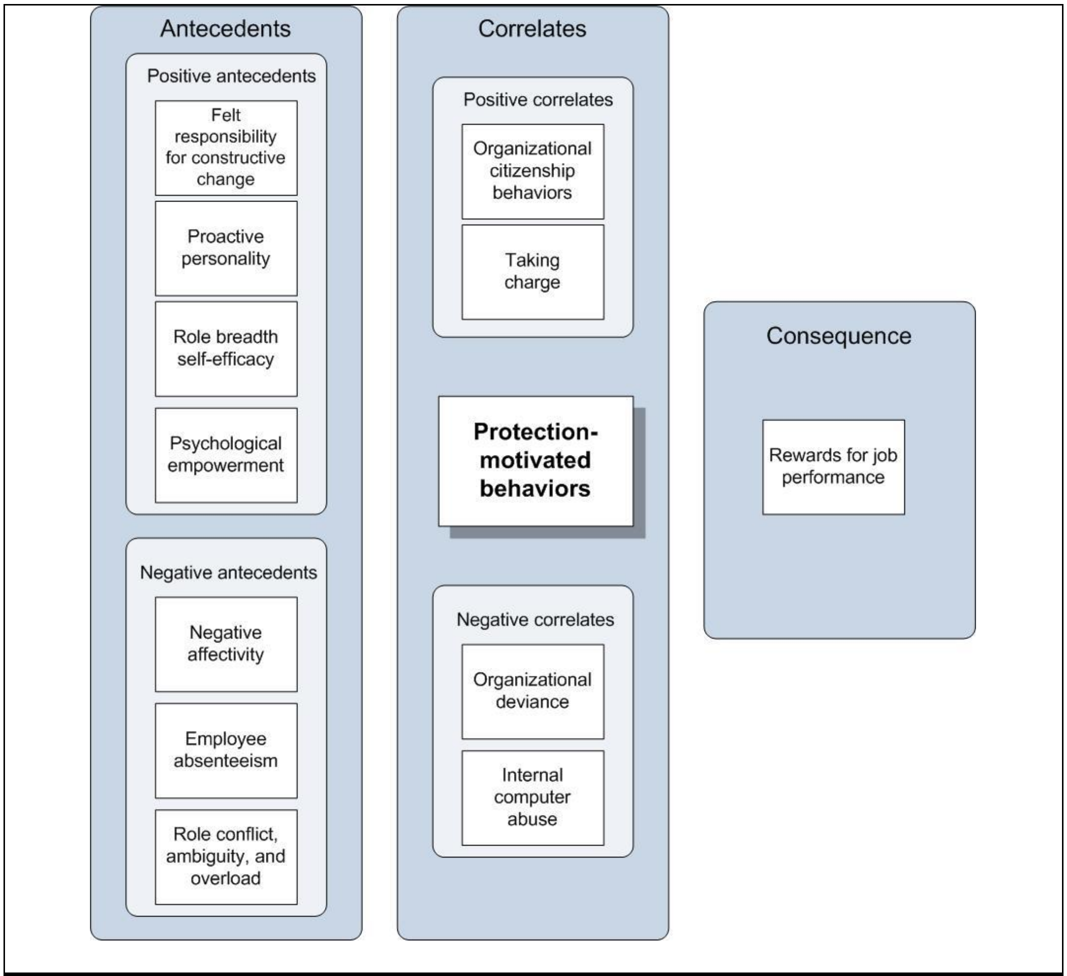

Figure B.1. Structure Used to Assess the Nomological Validity of PMBs

Predicting the Antecedents of PMBs

As a first step in evaluating the nomological validity of PMBs, we proposed several antecedents that other academic fields have shown to influence the degree to which organizational employees engage in positive workplace behaviors. This set of antecedents—consisting of both positive and negative precursors—provides a foundation from which potential psychological and environmental motivators can be derived in future research. We discuss positive antecedents first, which include felt responsibility for constructive change, proactive personality, role-breadth self-efficacy, and psychological empowerment. We then discuss the negative antecedents, which include negative affectivity; employee absenteeism; and role conflict, ambiguity, and overload.

Felt responsibility for constructive change (FRCC): FRCC represents "an individual's belief that he or she is personally obligated to bring about constructive change" (Morrison & Phelps, 1999, p. 407). Employees who feel responsible for their work are more likely to produce higher-quality output (Hackman & Oldham, 1975) and are more likely to engage in positive behaviors such as continuous improvement and extra-role efforts (Fuller, Marler, & Hester, 2006; Morrison & Phelps, 1999; Pearce & Gregersen, 1991). Likewise, many employees who engage in PMBs do so because they believe they have a personal responsibility to protect their organization's information and computerized information systems from security threats. Therefore, we predict:

> **H1.** *The stronger an employee's FRCC, the more likely the employee will be to perform PMBs within their organization.*

Proactive personality: proactive personality represents an individual's relatively stable drive to affect change in the workplace (Bateman & Crant, 1993). Individuals exhibiting a proactive personality "scan for opportunities, show initiative, take action, and persevere until they reach closure by bringing change" (Bateman & Crant, 1993, p. 105). This perseverance leads individuals with a proactive demeanour to achieve high levels of job performance (Crant, 1995; Thompson, 2005) and career success (Seibert, Crant, & Kraimer, 1999).

Organizations desire insiders who actively scan their environments and endure the stresses of daily organizational life well. From an information security perspective, individuals who attempt to protect organizational information assets effectively must do so from ever-increasing numbers and types of security threats in both physical and digital domains (Ponemon, 2010; Richardson, 2007). Therefore, we predict that:

> **H2.** *The stronger an employee's proactive personality, the more likely the employee will be to perform PMBs within their organization.*

Role breadth self-efficacy (RBSE): RBSE "refers to employees' perceived capability of carrying out a broader and more proactive set of work tasks that extend beyond prescribed technical requirements" (Parker, 1998, p. 835). These perceptions are important because modern work environments encourage diversified employee activity (Judge, Jackson, Shaw, Scott, & Rich, 2007; Parker, 2000). As organizations continually invest in various methods of dealing with information security threats, employees must be able to adapt quickly to a diverse set of circumstances and job requirements. Given that PMBs represent a wide variety of specialized proactive behaviors, we predict that:

> **H3.** *The stronger an employee's RBSE, the more likely the employee will be to perform PMBs within their organization.*

Psychological empowerment: psychological empowerment represents an active rather than passive orientation to one's work role and is composed of four unique components: (1) meaning (the degree to which the work role meshes with the individual's beliefs, values, and behaviors), (2) competence (synonymous with self-efficacy, this represents an individual's belief of capability of performing a specified task), (3) self-determination (the degree to which individuals believe they have choice in their engagement of organizational behaviors), and (4) impact (the degree to which individuals perceive that their efforts in the workplace have the ability to influence the overall outcomes of their organization (Spreitzer, 1995; Thomas & Velthouse, 1990). Research has shown that empowered individuals are more committed to their organizations (Avolio, Zhu, Koh, & Bhatia, 2004), have more innovative leadership characteristics (Spreitzer, de Janasz, & Quinn, 1999), and are more likely to perform creatively and engage in organizational citizenship behaviors (Alge, Ballinger, Tangirala, & Oakley, 2006). In summary, we predict that psychological empowerment increases propensity to perform PMBs as follows:

> **H4.** *The stronger an employee's sense of psychological empowerment—as represented by (a) meaning, (b) competence, (c) self-determination, and (d) impact—the more likely the employee will be to perform PMBs within their organization.*

Negative affectivity (NA): negative affectivity is the disposition to experience negative emotions independent of contextual stressors (Watson & Clark, 1984; Watson & Pennebaker, 1989). Individuals with high negative affectivity tend to concentrate on the negative aspects of themselves and their environment (Watson & Clark, 1984). They also tend to experience decreased satisfaction in their jobs (Connolly & Viswesvaran, 2000), more stress (Moyle, 1995), and increased work-family conflict (Stoeva, Chiu, & Greenhaus, 2002); and they engage in more deviant behaviors (Aquino, Lewis, & Bradfield, 1999). In addition, research has found negative relationships between negative affectivity and both organizational citizenship (Hui, Law, & Chen, 1999) and prosocial behaviors (George, 1990). Therefore, we expect that employees with high negative affectivity will expend little effort in protecting their organizations from information security threats simply because they may not see the need to protect something (e.g., the organization) or someone (e.g., the organization's customers). Thus, we predict that:

> **H5.** *The stronger an employee's negative affectivity (NA), the less likely the employee will be to perform PMBs within their organization.*

Employee absenteeism: employee absenteeism is linked to decreased employee performance, increased turnover, and significant organizational expense (Harrison & Martocchio, 1998). Individuals who are employed in dangerous or harsh environments, yet are frequently absent for safety meetings due to absenteeism, become lackadaisical with their organizations' safety procedures, which increases the occurrences of workplace accidents (Goodman & Garber, 1988). Using this concept, employees with less absenteeism are more likely to display both knowledge and dedication to PMBs in their organizations. Thus, we predict that:

H6. The more an employee exhibits absenteeism, the less likely the employee will be to perform PMBs within their organization.

Role conflict, ambiguity, and overload: organizational insiders in today's work environment experience (1) conflict between various tasks that each require employees' attention (i.e., role conflict), (2) uncertainties regarding what is expected of them (i.e., role ambiguity), and (3) potential burdens of being given too many tasks and demands simultaneously (i.e., role overload). These role issues have been linked with decreased job involvement and increased anxiety among other outcomes (Bedeian & Armenakis, 1981; Rizzo, House, & Lirtzman, 1970; Tubre & Collins, 2000). Accordingly, insiders who experience role conflict, ambiguity, and overload are not likely to engage in PMBs. We thus predict that:

H7. *The stronger an employee's perceived (a) role conflict, (b), role ambiguity, and (c) role overload, the less likely the employee will be to perform PMBs in their organization.*

Predicting the Correlates of PMBs

Another important consideration in establishing the nomological validity of new constructs is to assess how they relate to other similar and dissimilar constructs (MacKenzie et al., 2005), also known as positive and negative correlates, respectively. For this purpose, we chose to include other behavior sets that are important to organizations, which we term correlates of PMBs. We assessed both positive- and negative-oriented correlates in order to strengthen our analysis. The positive correlates include organizational citizenship behaviors and taking charge. The negative correlates include workplace deviance and internal computer abuse.

Organizational citizenship behaviors (OCBs): OCBs are "individual behavior that is discretionary, not directly or explicitly recognized by the formal reward system, and in the aggregate promotes the efficient and effective functioning of the organization" (Organ, Podsakoff, & MacKenzie, 2006, p. 3). Forms of OCBs have been shown to increase performance quantity and quality (Podsakoff, Ahearne, & MacKenzie, 1997) and general organizational effectiveness (Podsakoff, MacKenzie, Paine, & Bachrach, 2000). Despite being originally conceptualized as comprising several individual concepts (Organ, 1988), researchers frequently examine OCBs along two dimensions: OCBs directed toward individuals (OCBIs) and OCBs directed toward organizations (OCBOs) (Aryee, Budhwar, & Chen, 2002; Lee & Allen, 2002; Podsakoff, Whiting, Podsakoff, & Blume, 2009; Williams & Anderson, 1991).

Because PMBs and OCBs are activities designed to promote the effectiveness of an organization, we expect them to be positively correlated. Furthermore, because many PMBs involve protective behaviors that require interactions with co-workers, both the individual and organizational components of OCBs should be correlated with PMBs, as follows:

H8. *PMBs are positively correlated with (a) OCBOs and (b) OCBIs.*

Taking charge: taking charge encapsulates the volitional, extra-role behaviors of employees to effect positive change in the workplace through modifications to work execution (Morrison & Phelps, 1999). These efforts are focused on changing the status quo by attempting to increase organizational effectiveness rather than personal gain. Organizations experience beneficial results when employees feel they have a duty or obligation to watch out for the welfare of the organization (Moon, Kamdar, Mayer, & Takeuchi, 2008).

Similar to taking charge, PMBs are conceptualized as being fostered by feelings of personal responsibility for an organization's information security needs. Employees may find certain aspects of their job that they feel need to be redesigned in order to facilitate such protective efforts. Thus, we predict that:

H9. *PMBs are positively correlated with taking charge.*

Workplace deviance: workplace deviance is "voluntary behavior that violates significant organizational norms and in so doing threatens the well-being of the organization, its members, or both" (Robinson & Bennett, 1995, p. 556). Workplace deviance encapsulates behaviors such as taking property from work without permission, falsification of receipts to receive more reimbursement than is requisite, mistreating co-workers, discussing confidential company information with unauthorized persons, and neglecting to follow a superior's instructions (Bennett & Robinson, 2000). Workplace deviance behaviors are thus categorized into those focused on harming an organization (i.e., organizational deviance) and those targeting specific individuals (i.e., interpersonal deviance). Given these examples, PMBs represent behaviors that are the antithesis of workplace deviance, and thus this is the focus of our nomological validity check. We would expect that deviant employees are less likely to engage in PMBs than non-deviant employees. Consequently, we predict the following:

H10: *PMBs are negatively correlated with (a) organizational deviance and (b) interpersonal deviance.*

Internal computer abuse: internal computer abuse has been a costly proposition for many organizations (Moore, Cappelli, & Trzeciak, 2008). Internal computer abuse is "the unauthorized and deliberate misuse of assets of the local organizational information system by individuals" (Straub, 1990, p. 257). Because internal computer abuse is a form of organizational deviance manifested via technology (Posey, Bennett, Roberts, & Lowry, 2011), it is likely that deviant employees are more likely to commit it and to engage in fewer PMBs than non-deviant employees. We thus predict that:

H11. *PMBs are negatively correlated with internal computer abuse.*

Predicting Consequences of PMBs

In finalizing the structure of a new construct's nomological validity, it is important to assess any potential outcomes of the construct's proposed antecedents and correlates. Much like its correlates, however, researchers will most likely use PMB activity as their main dependent variable of interest. This fact proved a difficult barrier in our finding of potential outcomes of PMBs; however, we were able to find one construct that had been used—though quite rarely—with the correlates of PMBs: rewards for job performance, which we explain as follows.

Rewards for job performance: *e*mployees exhibiting positive behaviors in their organizations (e.g., OCBs, extra-role behaviors) are often given higher performance evaluations and rewards for achievement than those who do not (Organ et al., 2006; Podsakoff et al., 2009). Therefore, individuals who make considerable efforts to perform PMBs are more likely to be viewed as a vital resource to organizations, which should translate into higher performance evaluations than those received by individuals who are less protection oriented.

H12. *PMBs are positively correlated with rewards for job performance.*

VALIDITY OF PMBS

Given our proposed nomological validity hypotheses, we then tested these with a new survey. We acquired responses to this survey via another independent sample (n = 365) from a professional marketing research firm. We used validated measures to assess the constructs of interest (see Table B.1). We shortened the individual instruments, if possible, in their number of items to reduce the overall length of the survey. We used factor loadings for reflective measures published in the original developmental pieces to make these decisions, and included the highest loading items.

The next step was to examine the nomological validity of PMBs. First, we assessed the constructs for internal consistency. Unfortunately, the items used to capture organizational citizenship behaviors targeted at organizations failed to meet an acceptable level of internal consistency and thus could not be used in further analyses. Table B.2 displays the means, standard deviations, Cronbach's α's, and inter-construct correlations of the other constructs hypothesized to exhibit significant associations with PMBs. Importantly, the correlations with the PMB construct were performed with both the summated formative and averaged reflective measures of PMBs to obtain a better perspective of the nomological network.

As Table B.2 shows, many of the hypotheses were empirically supported. Proactive personality, RBSE, and the components of psychological empowerment (i.e., meaning, competence, self-determination, and impact) were significant members of the PMB nomological network (H1–H4d, respectively). However, role ambiguity (H7b) was the only negative antecedent that exhibited a significant association with both the formative and reflective measures of PMBs; the remainder of the proposed negative antecedents did not. In addition to the antecedents, all of the correlates exhibited their proposed associations with PMBs. OCBIs were significantly and positively correlated with both the formative (r = .294) and reflective (r = .290) measures of PMBs, and taking charge exhibited significant associations with both the formative (r = .295) and reflective (r = .377) measures of PMBs as well. Likewise, the technology form of deviance (i.e., internal computer abuse) demonstrated the highest negative correlation with PMBs (r = -.430). Both organizational and interpersonal forms of deviance also displayed strong but lower associations with PMBs (r = -.365 and r = -.318, respectively), which supported H10a and H10b.

Table B.1: Measures Used to Assess the Nomological Validity of PMBs
Antecedents
Felt responsibility for constructive change (Morrison & Phelps, 1999)
Proactive personality (Bateman & Crant, 1993)
Role breadth self-efficacy (Parker, 1998)
Psychological empowerment (Spreitzer, 1995)
Negative affectivity (Watson, Clark, & Tellegen, 1988)
Employee absenteeism (Gellatly, 1995)
Role conflict (Peterson et al., 1995)
Role ambiguity (Peterson et al., 1995)
Role overload (Peterson et al., 1995)
Correlates
Organizational citizenship behaviors (Williams & Anderson, 1991)
Taking charge (Morrison & Phelps, 1999)
Organizational deviance (Bennett & Robinson, 2000)
Internal computer abuse (Posey et al., 2011)
Consequence
Rewards for job performance (Welbourne et al., 1998)

The lone consequence included in the model of PMBs was rewards for job performance (H12). As Table B.2 shows, this construct demonstrated significant, positive associations with both the formative (r = .180) and reflective (r = .211) measures of PMBs. Therefore, Hypothesis 12 was empirically supported. While formal hypotheses were not created for each of the first-order PMB dimensions, note that differences exist in the associations among these first-order constructs and the variables used during the nomological validity tests. Since formative measures' indicators need not covary, their indicators' antecedents and consequences are expected to be different (Diamantopoulos & Winklhofer, 2001). Our analysis regarding PMBs is a prime example of this expected result. Table B.2 highlights the pattern of these correlations.

Table B.2: Patterns from Nomological Validity Tests of PMBs														
Variable	**Mean**	**SD**	**α**	**PMBR**	**PMBF**	**AP**	**IRSM**	**PDAA**	**VESP**	**LEH**	**PUE**	**DSE**	**GSE**	**SEIU**
H1: FRCC	4.84	1.15	0.79	.319**	.332**	.048	.272**	.424**	.188**	.155**	.073	.204**	.119*	.040
H2: Proactive personality	5.09	1.08	0.87	.218**	.221**	.046	.205**	.283**	.121*	.136**	.025	.160**	.190**	.096
H3: RBSE	3.66	0.90	0.93	.197**	.146*	.020	.197**	.272**	.099	.036	-.040	.127*	.044	.013
H4a: Meaning	5.60	1.45	0.95	.212**	.181**	-.060	.224**	.208**	.102	.073	.031	.112*	.106	.066
H4b: Competence	6.41	0.72	0.84	.160**	.199**	-.009	.139**	.253**	.191**	.026	.091	.128*	.144**	.004
H4c: Self-determination	5.66	1.30	0.88	.175**	.109	.012	.133*	.208**	.059	.013	.052	.113*	.072	-.078
H4d: Impact	4.86	1.57	0.88	.183**	.131*	-.023	.218**	.196**	.042	.094	.030	.082	.063	.023
H5: NA	3.08	0.85	0.87	-.063	-.179**	-.107*	-.042	-.111*	-.144**	-.182**	-.113*	-.088	-.094	-.184**
H6: Absenteeism	6.60	13.07	N/A	-.003	-.011	-.136*	.014	.024	.005	.029	.017	-.019	.021	-.068
H7a: Role conflict	3.98	1.43	0.73	.051	.003	-.068	.122*	.047	-.129*	-.077	-.215**	.010	-.066	-.214**
H7b: Role ambiguity	5.54	1.23	0.83	-.147**	-.270**	-.050	-.180**	-.163**	-.190**	-.154**	-.142**	-.196**	-.157**	-.142**
H7c: Role overload	3.43	1.60	0.88	-.033	-.017	-.021	.071	-.017	-.077	.008	-.165**	-.080	-.109*	-.061
H8: OCBs—individual	5.24	1.19	0.69	.290**	.294**	-.031	.340**	.348**	.221**	.185**	.105*	.288**	.171**	.043
H9: Taking charge	5.10	1.31	0.92	.377**	.295**	-.102	.370**	.400**	.105	.091	.000	.181**	.097	.025
H10a: Deviance—organizational	1.92	1.04	0.70	-.182**	-.365**	-.181**	-.166**	-.164**	-.309**	-.301**	-.220**	-.151**	-.360**	-.451**
H10b: Deviance—individual	1.76	0.89	0.75	-.187**	-.318**	-.261**	-.083	-.181**	-.316**	-.274**	-.183**	-.153**	-.339**	-.346**
H11: Computer abuse	13.89	5.25	N/A	-.184**	-.430**	-.317**	-.072	-.176**	-.500**	-.459**	-.433**	-.174**	-.425**	-.493**
H12: Rewards for job performance	6.55	0.66	0.87	.211**	.180**	.012	.129*	.237**	.232**	.070	.126*	.165**	.136*	.002
Note: *** p < 0.001, ** p < 0.01, * p < 0.05														

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