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Specifying Formatively-measured Constructs In Endogenous Positions In Structural Equation Models: Caveats and Guidelines For Researchers

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The Schumpeter Discussion Papers are a publication of the Schumpeter School of Business and Economics, University of Wuppertal, Germany
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SSBEditor@wiwi.uni-wuppertal.de

SDP 2014-005
ISSN 1867-5352

Impressum
Bergische Universität Wuppertal
Gaußstraße 20
42119 Wuppertal
www.uni-wuppertal.de
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SPECIFYING FORMATIVELY-MEASURED CONSTRUCTS IN
ENDOGENOUS POSITIONS IN STRUCTURAL EQUATION MODELS:
CAVEATS AND GUIDELINES FOR RESEARCHERS

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Final Version: February 13, 2014

Forthcoming: *International Journal of Research in Marketing*

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Acknowledgment: *The authors would like to thank the IJRM Editor, Area Editor, and two anonymous reviewers for helpful comments and suggestions on previous drafts of this paper.*

Abstract

Formatively-measured constructs (FMCs) are increasingly used in marketing research as well as in other disciplines. Although constructs operationalized by means of formative indicators have mostly been placed in exogenous positions in structural equation models, they also frequently occupy structurally endogenous positions. The vast majority of studies specifying endogenously-positioned FMCs have followed the common practice of modeling the impact of antecedent (predictor) constructs *directly* on the focal FMC without specifying *indirect* effects via the formative indicators. However, while widespread even in top journals, this practice is highly problematic as it can lead to biased parameter estimates, erroneous total effects, and questionable conclusions. As a result both theory development and empirically-based managerial recommendations are likely to suffer. Against this background, the authors offer appropriate modeling guidelines to ensure that a conceptually sound and statistically correct model specification is obtained when a FMC occupies an endogenous position. The proposed guidelines are illustrated using both covariance structure analysis (CSA) and partial least squares (PLS) methods and are applied to a real-life empirical example. Implications for researchers are considered and ‘good practice’ recommendations offered.

Keywords: Formatively-measured constructs; Endogenous formative indicators; Covariance structure analysis; Partial least squares

1. Introduction

In recent years, formative measurement models whereby “the direction of causality flows from the indicators to the latent construct, and the indicators, as a group, jointly determine the conceptual and empirical meaning of the construct” (Jarvis, MacKenzie & Podsakoff, 2003, p. 201) have increasingly been used in marketing studies to operationalize constructs as diverse as e-service quality (Collier & Bienstock, 2006), relationship value (Ulaga & Eggert, 2006), retailer equity (Arnett, Laverie & Meiers, 2003) and strategic responsiveness (Nakata, Zhu & Izberk-Bilgin, 2011) to name but a few.

While there exists an impressive body of literature on formative measurement models dealing with such issues as model specification and identification (for a review, see Diamantopoulos, Riefler & Roth, 2008), the focus has, with few exceptions, been on structurally exogenous formatively-measured constructs (FMCs). By ‘structurally exogenous’ we mean that the focal construct is only influenced by its assigned formative indicators but has no further observed causes. FMCs, however, might also occupy an endogenous position in the structural equation model representing a researcher’s theory. Here, in addition to the formative indicators, one or more antecedent constructs are also hypothesized to impact the FMC.

Unfortunately, FMCs cannot be placed in structurally endogenous positions in the same way as their reflectively-measured counterparts, that is, by simply specifying a direct link from the antecedent to the endogenous construct. As will be subsequently demonstrated, doing so and failing to realize that the antecedent construct’s impact on the endogenous FMC should in fact be captured by its indirect effect via the formative indicators, will almost always lead to biased structural parameters, incorrect effect sizes and, ultimately, erroneous study conclusions. As a result, theory development and the generation of empirically-based managerial insights are both likely to suffer.

Although, in recent years, a few authors (Cadogan & Lee, 2013; Temme & Hildebrandt, 2006; Wiley, 2005) have warned against linking FMCs and their antecedents solely by direct construct-level paths (i.e., without further links to the formative indicators), such warnings have remained unheeded as a literature review on the use of endogenous FMCs in top journals demonstrates (see Section 2). The prevalence of misspecification in the literature can partly be attributed to the fact that the (erroneous) practice of modeling the influence of antecedent constructs on endogenous FMCs only by a direct link at the construct level can also be found in methodological papers (e.g., Jarvis et al., 2003; MacCallum & Browne, 1993; MacKenzie, Podsakoff & Jarvis, 2005) and partly to the absence of concrete guidelines on how to correctly model such relationships.

The purpose of the current paper is to offer such guidelines so as to enable marketing researchers to correctly assess the influence of explanatory variables on FMCs under both covariance structure analysis (CSA) and partial least squares (PLS) perspectives. In doing so, we highlight several conceptual and methodological issues and also present an empirical illustration of ‘good practice’.

2. Misspecification of Endogenously-Positioned FMCs

Figure 1 shows how endogenous FMCs are typically modeled in empirical literature. Here η_1 is the FMC with formative indicators x_4 and x_5 , while ξ_1 is the antecedent construct with reflective indicators x_1 - x_3 . The relationship between ξ_1 and η_1 is captured by γ_1 . The constructs η_2 and η_3 are hypothesized reflectively-measured outcomes of the FMC. Given that ξ_1 , x_4 and x_5 are all exogenous, they are all allowed to covary, as indicated by covariances ϕ_{14} , ϕ_{15} and ϕ_{45} (MacCallum & Browne, 1993).

INSERT FIGURE 1 ABOUT HERE

Modeling the influence of ξ_1 on η_1 along the lines shown in Figure 1 (i.e., by specifying a direct path between the two constructs only) is intuitively appealing as it simply mimics the way such effects are specified in both CSA and PLS path modeling when a reflectively-measured construct acts as the dependent variable. However, when the latter is an FMC such an approach creates a logical inconsistency because “a change in the value of a formative latent variable cannot occur independently of a change in the value of one or more of its indicators” (Cadogan & Lee, 2013, pp. 234-235). This condition is clearly not fulfilled in the model in Figure 1 because the antecedent construct (ξ_1) impacts the FMC (η_1) *without* impacting any of the formative indicators (x_4, x_5). Thus, the specification mistakenly assumes that η_1 completely mediates the impact of ξ_1 on η_1 and η_3 independently from the FMC’s formative indicators. As the latter remain exogenous but are allowed to covary both with each other and with ξ_1 , the direct effect γ_{11} in fact only captures the antecedent variable’s *incremental* impact conditioned on the formative indicators. Consequently, if the formative measurement model has been correctly specified, *no* direct influence of ξ_1 on η_1 will emerge (i.e., within sampling error, $\gamma_{11} = 0$), resulting in a total effect of zero. Given a true non-zero total effect, this specification will considerably underestimate the impact of ξ_1 on η_1 and invariably lead to wrong conclusions.

Unfortunately, the practice of linking antecedent constructs to a FMC only by direct construct-level paths is widespread in the literature. A review of articles (47 in all) involving endogenous FMCs in six top-tier marketing journals during 2006-2012 (see Table 1) revealed that the overwhelming majority (94%) incorrectly specified the effects of antecedent variables on endogenous FMCs at the construct level only, that is, by directly linking the predictor construct(s) to the FMC. Our review covered the following journals: *International Journal of*

Research in Marketing (IJRM), Journal of the Academy of Marketing Science (JAMS), Journal of Marketing (JM), Journal of Marketing Research (JMR), Journal of Service Research (JSR), and Marketing Science (MS). A full list of the reviewed articles can be found in the online appendix.

INSERT TABLE 1 ABOUT HERE

As can be seen from Table 1, the reviewed studies have been classified according to (a) whether aggregation of formative indicators was undertaken prior to estimation, and (b) whether the latter was performed with CSA, PLS or regression-based approaches. Both dimensions – handling of formative indicators prior to analysis and estimation method – have a substantial influence on the distortions resulting from incorrectly specifying the links between FMCs and their antecedents. Roughly one-third of the articles used disaggregated formative measurement models, however, in each of these studies the direct ‘construct-level only’ effects specified for the relationships between antecedent constructs and FMCs were interpreted as total effects. More specifically, in CSA, the direct effect was erroneously not regarded as an incremental/additional effect but as the only (i.e., total) effect of the antecedent construct on the FMC. Likewise, in PLS path modeling, direct links have been misinterpreted as representing the total impact of the antecedent construct(s) on the FMC which – as vividly demonstrated by our empirical illustration in Section 4 – is inappropriate. The remaining two-third of the articles formed composites prior to CSA or regression-type analysis. Although – at least in principle – this approach allows to correctly estimate total effects (see Section 3.3 for the necessary conditions), the prevailing practice of aggregating equally-weighted formative indicators casts serious doubt on whether such effects have indeed been correctly estimated in the corresponding empirical studies.

Three papers (Melancon, Noble & Noble, 2011; Roggeveen, Tsiros & Grewal, 2012; Seiders, Voss, Godfrey & Grewal, 2007) are notable exceptions from the mainstream approach in that they at least estimate individual effects of antecedent variables on *each* of the formative components. However, none of these studies documents results for a complete structural model in which the effects of antecedent variables on the FMC are mediated by its formative components. Instead, total effects were determined based on a regression of a composite score for the FMC on the antecedent variables.

In the next section, we provide the correct specification for evaluating effects on FMCs for the three most typical cases: disaggregated formative measures in CSA, disaggregated formative measures in PLS and aggregated formative measures in CSA or regression.

3. Correct Specification of Endogenously-Positioned FMCs

3.1 Disaggregated formative measures in CSA

Figure 2 displays the correct specification in CSA for assessing the impact of the antecedent construct ξ_1 on the FMC (now denoted as η_3). In contrast to the misspecified model in Figure 1, there are now direct effects (represented by γ_{11} and γ_{21}) from ξ_1 on the formative indicators thus making the latter variables endogenous (Temme & Hildebrandt, 2006). This is achieved through the introduction of the pseudo-latent variables η_1 and η_2 which enable the formative indicators of η_3 (now denoted as y_1 and y_2) to function as endogenous variables; note in this context that $\lambda_{11} = \lambda_{22} = 1$ and $\varepsilon_1 = \varepsilon_2 = 0$, which implies that $y_1 \equiv \eta_1$ and $y_2 \equiv \eta_2$. Similar to the common specification of free covariances between exogenous formative indicators (MacCallum & Browne, 1993), the error terms of the two pseudo-latent variables η_1 and η_2 are allowed to correlate (i.e., $\psi_{12} \neq 0$). Following Bollen and Davis (2009), identification of the

formative measurement model is established by, first, specifying direct effects from η_3 on the two reflectively-measured outcome constructs η_4 and η_5 , and, second, by fixing one of these outgoing paths to unity (i.e., $\beta_{43} = 1$). If we proceed from the full mediation hypothesis implied by a correctly specified formative measurement model (i.e., that the influence of any remote cause has to be *completely* channeled through the formative indicators), the exogenous latent variable ξ_1 impacts η_3 (i.e., the FMC) only indirectly via its influence on the two pseudo-latent variables η_1 and η_2 (model without the dashed path γ_{31} in Figure 2). In this specific case, the total effect of ξ_1 on η_3 equals the sum of the exogenous latent variable's indirect effects on η_3 via η_1 and η_2 , that is, $\gamma_{\text{total}} = \gamma_{11} \beta_{31} + \gamma_{21} \beta_{32}$. Note, in this context, that if, upon estimation of this model a significant modification index is obtained pointing to an (additional) direct effect from ξ_1 on η_3 , this would be indicative of misspecification of the formative measurement model *itself* in that at least one relevant formative indicator (correlated with ξ_1) has been omitted. Given that, in practice, formative measurement models are sometimes specified somewhat incorrectly, it seems prudent to include an *additional* direct path to the FMC (model including the dashed path γ_{31} in Figure 2) which will pick up the antecedent variable's effect on the FMC via any missing formative indicators. In such an extended model, the total effects amounts to $\gamma_{\text{total}} = \gamma_{11} \beta_{31} + \gamma_{21} \beta_{32} + \gamma_{31}$. Of course, if the direct path turns to be *non-significant* (i.e., within sampling error, $\gamma_{31} = 0$), it could be subsequently eliminated; indeed, such a non-significant effect would enhance confidence in the FMC's measurement model.

INSERT FIGURE 2 ABOUT HERE

3.2 Disaggregated formative measures in PLS

Correctly specifying the same model in PLS (see Figure 3) leads to a similar model structure as in CSA with two fundamental differences. First, introducing η_1 and η_2 as pseudo-latent variables for the formative indicators, leaves η_3 (i.e., the focal FMC) without indicators. Since such a model cannot be estimated in current implementations of the PLS approach (e.g., SmartPLS or PLS Graph), an additional reflective indicator (shown as y_9 in Figure 3) needs to be assigned to η_3 . Second, unlike CSA, PLS does not allow disturbance terms to be correlated; thus the covariance between ζ_1 and ζ_2 is zero ($\psi_{12} = 0$).

As was the case for CSA, it is recommended to also include a direct path from ξ_1 to η_3 (shown as the dashed path γ_{31} in Figure 3) to account for the antecedent construct's impact on the FMC via any omitted indicators. This is particularly important in PLS as the lack of model fit diagnostics such as modification indexes, can result in misspecifications remaining undetected.

INSERT FIGURE 3 ABOUT HERE

3.3 Aggregated formative measures in regression

As previously noted in Table 1, formative indicators are often aggregated and the resulting composites used as dependent variables in subsequent regression analyses. The key reason for doing so is because “lack of parsimony when modeling formative indicators as separate constructs is an issue” (Howell, Breivik & Wilcox, 2007, p. 215; see also Cadogan & Lee, 2013). However, there is a clear downside to aggregation in that potential relationships of interest between an antecedent variable and the *individual* indicators of a FMC cannot be explicitly assessed. Thus one cannot trace the separate paths from the antecedent construct to the FMC via the formative indicators and draw inferences as to which indicators are mostly affected

and how. This is an important shortcoming of aggregation not least because it is entirely possible that the same predictor construct can impact some formative indicators positively and others negatively; in this case, aggregating indicators can completely mask the impact of the antecedent construct on the FMC. Furthermore, potentially omitted formative indicators will not be detected if aggregation is used (since there will be only a single path linking the antecedent construct with the composite).

With the above caveats in mind, let us assume that the FMC in Figure 2 is now represented by the composite variable C_3 (instead of the formative latent variable η_3), completely determined by the two formative indicators y_1 and y_2 (i.e., $\zeta_3 = 0$). Assuming mean-centering of y_1 and y_2 and given specific, a priori fixed β -weights, aggregation leads to the following linear composite:

$$C_3 = \beta_{31}y_1 + \beta_{32}y_2 \quad (1)$$

For each formative indicator, the impact of the mean-centered antecedent variable ξ_1 is specified by the following regression equation:

$$y_i = \gamma_i \xi_1 + \zeta_i, \quad (2)$$

where $i = 1, 2$.

The total effect of ξ_1 on C_3 is then captured by the slope parameter (referred to as γ_{total}) in the corresponding regression of C_3 on ξ_1 which can be estimated as follows:

$$\begin{aligned} \gamma_{\text{total}} &= \frac{\text{Cov}(C_3, \xi_1)}{\text{Var}(\xi_1)} \\ &= \frac{E[(\beta_{31}y_1 + \beta_{32}y_2)\xi_1]}{\text{Var}(\xi_1)} \end{aligned} \quad (3)$$

Substituting Equation (2) for the two formative indicators in Equation (3) and invoking the common assumption that the predictor ξ_1 is not correlated with the disturbances ζ_1 and ζ_2 yields:

$$\begin{aligned}\gamma_{\text{total}} &= \frac{E\{[(\gamma_{11}\beta_{31} + \gamma_{21}\beta_{32})\xi_1 + (\beta_{31}\zeta_1 + \beta_{32}\zeta_2)]\xi_1\}}{\text{Var}(\xi_1)} \\ &= \frac{(\gamma_{11}\beta_{31} + \gamma_{21}\beta_{32})\text{Var}(\xi_1)}{\text{Var}(\xi_1)} \\ &= \gamma_{11}\beta_{31} + \gamma_{21}\beta_{32}\end{aligned}\quad (4)$$

Thus, as long as the β -weights for the formative indicators are correctly determined, regressing C_3 on ξ_1 yields an unbiased estimate of the total effect of ξ_1 on C_3 via the formative indicators (note that this conclusion may not apply to the FMC η_3 if some of the indicators have been omitted). Even in this case, however, the shortcomings of aggregation noted earlier still apply and, therefore, we urge researchers to opt for disaggregated modeling of endogenous formative indicators along the lines discussed in Sections 3.1 and 3.2.

4. Empirical Illustration

We now illustrate the steps involved in modeling a structurally endogenous FMC by using real data from a survey of students' satisfaction with the university cafeteria ($n = 181$). By comparing the results under both incorrect (i.e., direct effect at the construct level only – Model 1) versus correct specifications (i.e., indirect effects via the formative indicators *plus* a direct effect at the construct level – Model 2), we empirically highlight the substantial discrepancies in the study implications arising from the two models. Furthermore, we show that CSA and PLS produce vastly different results if the antecedent variable's effect on the FMC is incorrectly modeled.

Our illustrative model (shown in Figure 4) proposes that the importance price plays in students' decisions on where to go for a meal (hereafter simply referred to as 'price importance') has an impact on their satisfaction with the university's cafeteria (hereafter simply called 'satisfaction'). Satisfaction is conceptualized as a FMC, whereby satisfaction with the (1) taste and (2) healthiness of the meals, (3) the variety of meals offered each day, (4) the cafeteria's cleanliness, and (5) the prices charged by the cafeteria function as formative indicators. Additionally, satisfaction is measured by two reflective items (overall satisfaction; right choice); all indicators of satisfaction are measured on 5-point rating scales, with larger values implying more favorable judgments. The exogenous antecedent variable price importance is measured by a single item, whereby larger values on a 4-point rating scale indicate higher importance of price. The relevant parameter estimates under both methods of estimation are shown in Table 2.

INSERT FIGURE 4 ABOUT HERE

INSERT TABLE 2 ABOUT HERE

4.1 Estimation results – Model 1

In Model 1, the antecedent variable price importance impacts satisfaction only directly, that is, the five formative indicators remain exogenous variables. Thus, the corresponding CSA specification drops the paths γ_{11} to γ_{51} and only models the path γ_{61} ; the formative indicators are allowed to covary freely both with each other and with the antecedent construct, ξ_1 . A scale for the FMC was established by appropriately constraining its variance to unity as suggested by Franke, Preacher and Rigdon (2008), while linking the FMC to the two reflective items ensured that the model was identified (e.g., Bollen & Davis, 2009). In the PLS specification, Mode B was

chosen for the outer model in light of satisfaction's conceptualization as a FMC (e.g., Hair et al., 2013).

CSA estimation of Model 1 provides an excellent overall fit ($\chi^2 = 7.37$, $df = 5$, $p = 0.195$; RMSEA = 0.051; CFI = 0.992; NNFI = 0.979; SRMR = 0.017). The parameter estimates suggest that the importance price plays in students' food-related decisions has no significant impact on their satisfaction with the university cafeteria ($\gamma_{\text{direct}} = \gamma_{61} = 0.03$, $p < 0.58$). In contrast, PLS estimation suggests a strong positive relation between price importance and satisfaction ($\gamma_{\text{direct}} = \gamma_{61} = 0.31$, $p < 0.0001$). Marked differences also emerge for the formative indicator weights. Whereas in the CSA model all weights are positive and highly significant, only two formative indicators (satisfaction with price and taste) are significantly linked to satisfaction in the PLS model. Furthermore, price satisfaction has a *negative* weight which is clearly counterintuitive as it suggests that increasing students' satisfaction with the prices charged would decrease their overall satisfaction level.

The highly divergent CSA and PLS results for Model 1 can be largely attributed to the fact that CSA and PLS optimize very different criteria during parameter estimation (e.g., see Henseler & Sarstedt, 2013). Whereas CSA minimizes a global fit function based on some distance between the observed and the model-implied covariance matrix, PLS maximizes a correlation-based criterion. Specifically, the PLS solution is equivalent to the results of a canonical correlation analysis where 'price importance' is the predictor and 'satisfaction' is the dependent canonical variate. Thus, the formative indicator weights γ_{11} to γ_{51} are determined such that the correlation (i.e., the PLS estimate for the direct effect γ_{61} in Model 1) between the two variates is maximized. As a result, the estimated weights no longer reflect the extent to which the different formative indicators contribute to the overall satisfaction level independently from antecedent variables like price importance.

The above discrepancies between CSA and PLS serve to emphasize that incorrect modeling of endogenously-positioned FMCs may lead to very different conclusions depending on the estimation method used. What is even more important, however, is that *neither* the CSA *nor* the PLS results for Model 1 accurately depict the true influence of price importance on satisfaction. Only Model 2 can unambiguously reveal this influence as shown below.

4.2 Estimation results – Model 2

In Model 2, price importance is supposed to impact satisfaction both indirectly, that is, through the observed formative indicators (which are now specified as endogenous pseudo-latent variables represented by η_1 - η_5 in Figure 4) and directly (in order to capture a possible impact via unobserved formative indicators). Since we presume that price importance would not completely account for the observed formative indicators' intercorrelations, the corresponding error terms (i.e., ζ_1 - ζ_5 in Figure 4) were allowed to covary in the CSA model. In the corresponding PLS model, satisfaction was measured by the two reflective items, that is, Mode A has been chosen for the outer model.

CSA estimation of Model 2 leads to the same overall fit as for Model 1. Likewise, the direct effect of price importance as well as the formative indicator weights are identical to those in Model 1 (see Table 2). However, the results now show that price importance impacts cafeteria satisfaction indirectly through significant positive effects mediated by taste ($p < 0.05$) as well as cleanliness ($p < 0.05$) and through a significant negative effect via prices ($p < 0.05$). These significant but opposing indirect effects ultimately result in a non-significant total effect of 0.13. The latter, however, should *not* be interpreted as implying that price importance does not affect satisfaction but rather that it has countervailing influences (some positive and some negative) channeled through different formative indicators. In fact, the finding that the *same* antecedent

construct (here price importance) can have significant but directionally opposing effects on different indicators of a FMC (here, satisfaction) corroborates the arguments made in Section 3.3 against the aggregation of formative indicators prior to analysis. Moreover, the non-significant direct path from price importance to satisfaction in Model 2 ($\gamma_{\text{direct}} = \gamma_{61} = 0.03, p > 0.10$) indicates that, at least for the explanatory variable price importance, the satisfaction construct's content domain seems to be adequately captured by the five formative indicators shown in Figure 4. Note that the results can now be used to provide *specific* managerial insights into how satisfaction can be improved. For example, since students that place high importance on price are more satisfied with taste and cleanliness but at the same time are less content with the prices charged, communicating a “best deal” or “value for money” image for the cafeteria may help increase students' satisfaction with the latter.

Unlike with Model 1, PLS estimation of Model 2 largely produces very similar parameter estimates as the CSA analysis (see Table 2; the total effect of 0.12 is non-significant as well) and thus leads to the same substantive conclusions. Thus the correct specification for modeling endogenous FMCs seems to lead to consistent results irrespective of the method of estimation whereas the incorrect specification does not.

5. Guidelines for Researchers

Based on our analysis, the following guidelines can be derived regarding the modeling of FMCs in endogenous positions. First, we recommend that researchers avoid aggregation of formative indicators of the endogenous FMC prior to estimation. Instead, a disaggregated approach should be adopted whereby each formative indicator is modeled as a separate endogenous variable and linked to the relevant antecedent construct(s) as in Figure 2.

Second, we recommend that the influence of antecedent constructs on an FMC should always be modeled by specifying direct effects on the corresponding formative indicators (like the paths γ_{11} and γ_{21} in Figure 2) instead of direct effects on the FMC only. If the measurement model for the FMC is correctly specified, this should suffice to completely capture the antecedent variables' impact on the focal FMC since all antecedent variables' effects on the FMC will be fully mediated by the formative indicators (as was the case in our illustrative example).

Third, we recommend that an *additional* direct effect (like the path γ_{31} in Figure 2) is introduced in order to capture any effects of the antecedent variables which are conveyed by unobserved components (i.e., omitted indicators) of the FMC. Testing this effect not only ensures that the total effect of the antecedent variable on the FMC will be correctly estimated but helps scrutinize the validity of the formative measurement model. Since a direct effect of an antecedent variable on an FMC captures its impact over and above that through the formative indicators, a significant direct effect implies that there are other (unobserved) indicators through which the antecedent variable operates. Especially if the direct effect of an antecedent construct on the FMC exceeds (in absolute terms) the corresponding indirect effects via the formative indicators, doubt would inevitably be cast on whether a sufficiently comprehensive set of indicators has been used to operationalize the FMC. In this case, it may be wise to revisit the specification of the formative indicators in light of the construct definition.

Fourth, we recommend that researchers test for such (additional) direct effects after establishing that the *proportionality constraints* implied by formative measurement models (Bollen & Davis, 2009; Franke et al., 2008) hold for the FMCs in a study. Such constraints emerge because the effects of the formative indicators on downstream outcomes of a FMC (i.e., reflective indicators or dependent constructs) are assumed to be completely channeled through the FMC such that "there are no [additional] direct effects between the indicators and the

outcome variables in the model” (Diamantopoulos, 2011, p. 340). To illustrate, if a FMC’s influence on one outcome variable η_A is twice as strong as its effect on another outcome variable η_B , every formative indicator’s effect on η_A must likewise be twice as strong as its effect on η_B (hence the name ‘proportionality constraints’). If these proportionality constraints do not hold for a particular formative indicator (in CSA such violations can be revealed by inspecting the modification indices for direct effects between formative indicators and downstream outcome variables), this casts doubt on the latter’s validity (Bollen, 2007; Franke et al., 2008). Note that it is important to assess that proportionality constraints hold *before* testing for a direct effect of the antecedent variable on the FMC in order to ensure that the latter test is not distorted by inadequate formative indicators.

Fifth, we recommend that researchers opt for CSA rather than PLS when estimating models with endogenous FMCs. This is because (a) PLS requires at least one (additional) reflective indicator if an FMC is endogenous, (b) PLS does not allow the disturbance terms of endogenously-specified formative indicators to be correlated, and (c) PLS offers no diagnostics (such as modification indices) enabling the assessment of proportionality constraints. Taken together, these limitations suggest that CSA should be the method of choice when estimating models with endogenous FMCs.

By means of summarizing the above recommendations, Figure 5 provides a flowchart that marketing researchers can use for guidance when placing a FMC in an endogenous position in a structural equation model.

INSERT FIGURE 5 ABOUT HERE

Extant literature on formative measurement has so far lacked clear and detailed guidelines regarding the proper modeling of endogenously positioned FMCs in structural equations models. Hopefully, the procedures outlined in this paper, go some way towards filling this gap.

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Table 1

Endogenously-positioned FMCs in empirical marketing studies (2006-2012).

Prior aggregation of formative indicators/ components	Estimation method		
	CSA	PLS	Linear and non-linear regression, seemingly-unrelated regressions, ANOVA etc.
No		Ahearne/MacKenzie/Podsakoff/Mathieu/Lam (2010)	
		Ahearne/Rapp/Huges/Jindal (2010)	
		Antioco/Moenart/Feinberg/Wetzels (2008)	
		Antioco/Moenart/Lindgreen/Wetzels (2008)	
		Davis/Golicic (2010)	
		Ernst/Hoyer/Krafft/Krieger (2011)	
		Grégoire/Laufer/Tripp (2010)	
		Henning-Thurau/Henning/Sattler (2007)	
		Köhler/Rohm/de Ruyter/Wetzels (2011)	
		McFarland/Bloodgood/Payan (2008)	
		Miao/Evans (2012)	
		Rapp/Ahearne/Mathieu/Rapp (2010)	
		Storey/Kahn (2010)	
		Sundaram/Schwarz/Jones/Chin (2007)	
Yes			<i>Melancon/Noble/Noble (2011)^a</i>
			<i>Roggeveen/Tsiros/Grewal (2012)^a</i>
			<i>Seiders/Voss/Godfrey/Grewal (2007)^b</i>
			Becker/Greve/Albers (2009)
			Bell/Mengüç/Widing (2010)
			Fang/Palmatier/Scheer/Li (2008)
			Homburg/Fürst/Koschate (2010)
			Kim/Hsieh (2006)
			Lee/Johanson/Grewal (2008)
			Lo/Ghosh/Lafontaine (2011)
			Menguc/Auh (2006)
			Menguc/Auh (2008)
			Mooi/Gosh (2010)
			Noordhoff/Kyriakopoulos/Moorman/Pauwels/Dellaert (2011)
			Plouffe/Hulland/Wachner (2009)
			<i>Roggeveen/Tsiros/Grewal (2012)^a</i>
			Sarin/Challagalla/Kohli (2012)
			<i>Seiders/Voss/Godfrey/Grewal (2007)^b</i>
			Sethi/Iqbal (2008)
			Sethi/Iqbal/Sethi (2012)
		Stahl/Heitmann/Lehmann/Neslin (2012)	
		Verhoef/Leeflang (2009)	
		Vosgerau/Anderson/Ross (2008)	
	Ahearne/Hughes/Schillewaert (2007)		
	Bello/Katsikeas/Robson (2010)		
	Büttgen/Schumann/Ates (2012)		
	Camarero/Garrido (2012)		
	Gruen/Osmonbekov/Czaplewski (2007)		
	Homburg/Artz/Wieseke (2012)		
	<i>Melancon/Noble/Noble (2011)^a</i>		
	<i>Roggeveen/Tsiros/Grewal (2012)^a</i>		
	Yang/Smith (2009)		
	Yang/Su/Fam (2012)		
		Nakata/Zhu/Izberk-Bilgin (2011)	
		Wilken/Cornelißen/Backhaus/Schmitz (2010)	

^a Studies use several aggregation levels and estimation methods; ^b study uses several aggregation levels; studies in italics are those that estimate individual effects of antecedent variables on each formative indicator. We searched all issues in *IJRM*, *JAMS*, *JM*, *JMR*, *JCR* and *MS* published during 2006-2012 for articles including at least one of the following terms: 'formative', 'causal', or 'composite'. Next, each article identified in the first step was screened to determine whether it contained at least one endogenously-positioned FMC. Note that we only selected articles where the focal construct(s) were explicitly conceptualized as being formative by the authors (thus, for example, composites build from conventional second-order factor models were excluded).

Table 2

Unstandardized parameter estimates for illustrative model.

Parameter (from → to)	Model 1		Model 2	
	Only direct effect on FMC		Both indirect and direct effects on FMC	
	<i>CSA</i>	<i>PLS</i>	<i>CSA</i>	<i>PLS</i>
Price importance → Satisfaction (γ_{61})	0.03 (0.06)	0.31*** (0.08)	0.03 (0.06)	0.04 (0.05)
Taste → Satisfaction (β_{61})	0.53*** (0.08)	0.74** (0.33)	0.53*** (0.08)	0.35*** (0.06)
Healthiness → Satisfaction (β_{62})	0.22*** (0.05)	0.00 (0.23)	0.22*** (0.05)	0.20*** (0.05)
Variety → Satisfaction (β_{63})	0.28*** (0.05)	-0.01 (0.23)	0.28*** (0.05)	0.25*** (0.05)
Cleanliness → Satisfaction (β_{64})	0.28*** (0.08)	0.56 (0.38)	0.28*** (0.08)	0.21*** (0.06)
Prices → Satisfaction (β_{65})	0.22*** (0.06)	-0.93*** (0.19)	0.22*** (0.06)	0.19*** (0.05)
Price importance → Taste (γ_{11})	—	—	0.14** (0.07)	0.15* (0.08)
Price importance → Healthiness (γ_{21})	—	—	0.09 (0.09)	0.09 (0.08)
Price importance → Variety (γ_{31})	—	—	0.02 (0.09)	0.04 (0.08)
Price importance → Cleanliness (γ_{41})	—	—	0.13** (0.06)	0.16* (0.09)
Price importance → Prices (γ_{51})	—	—	-0.19** (0.08)	-0.19*** (0.07)

Notes: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (two-sided tests).

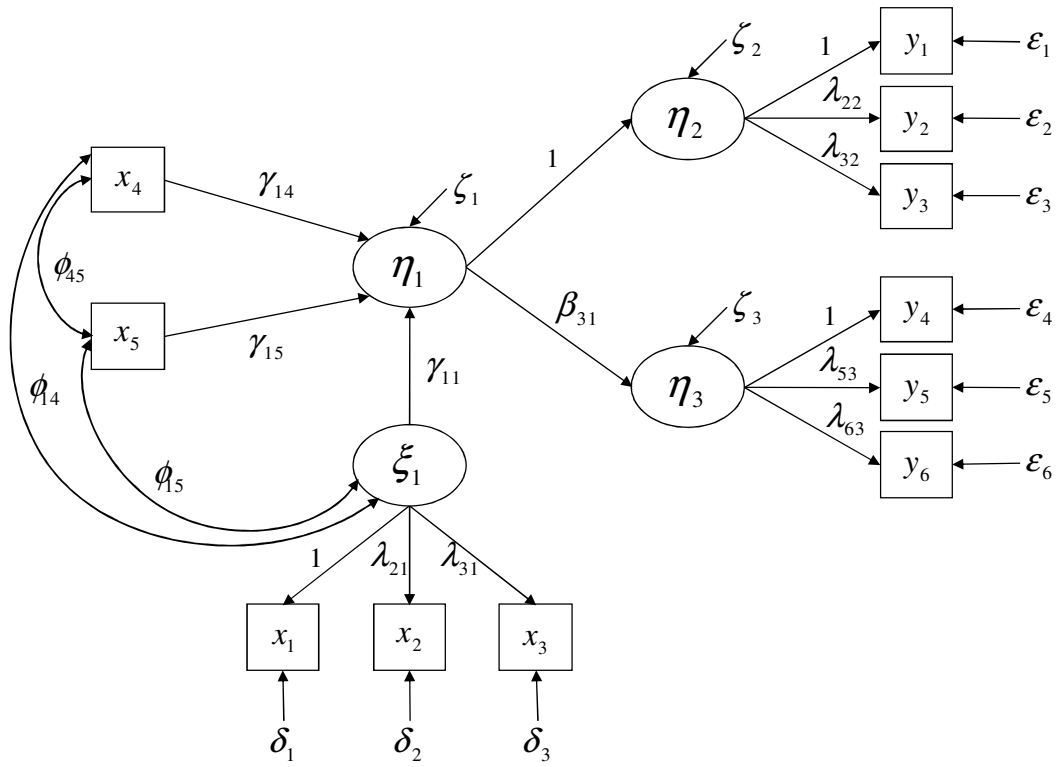
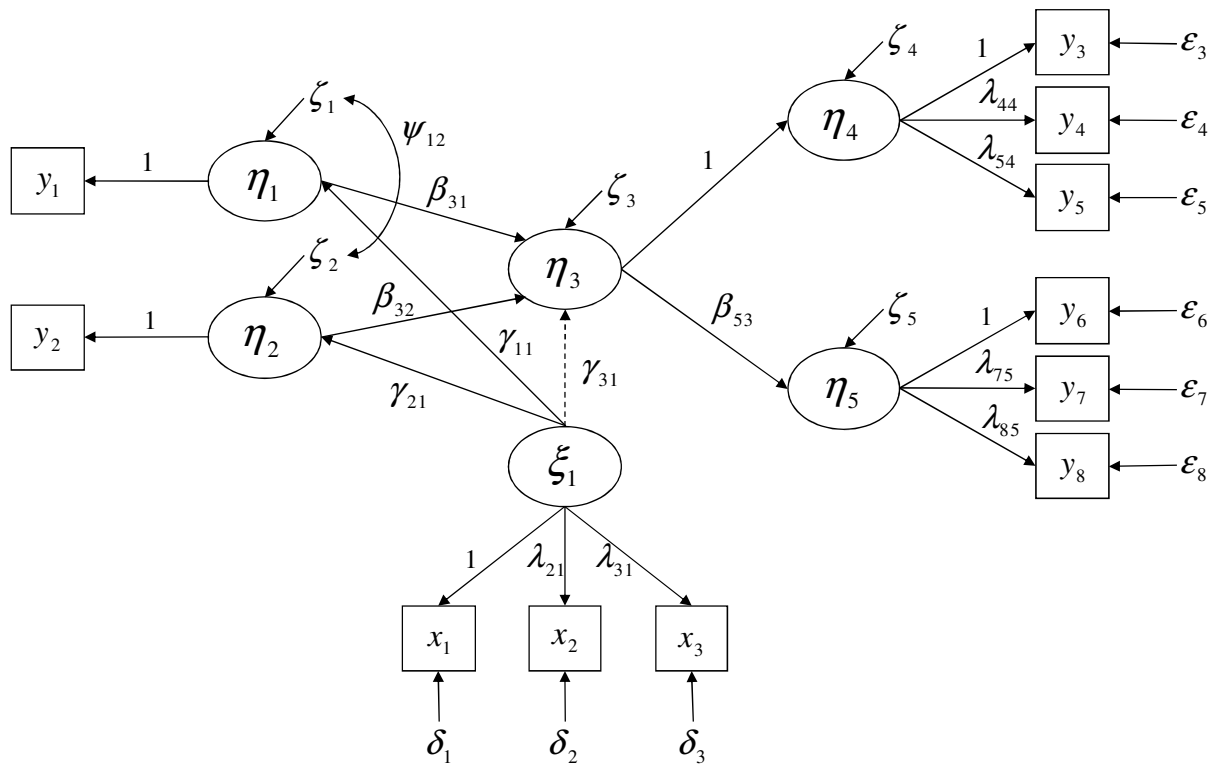


Fig. 1. Endogenously-positioned FMC: Misspecified model.



Notes: The formative indicators y_1 and y_2 are identical to x_4 and x_5 in the misspecified model in Figure 1. Their notation necessarily changes as a result of making the formative indicators endogenous. Further note that y_1 and y_2 are linked to the pseudo-latent variables η_1 and η_2 by means of the following conventional factor-analytic equations: $y_1 = \lambda_{11}\eta_1 + \epsilon_1$ and $y_2 = \lambda_{22}\eta_2 + \epsilon_2$, where λ_{11} and λ_{22} are measurement loadings and ϵ_1 and ϵ_2 are measurement errors. Setting the loadings to unity and the measurement errors to zero makes the formative indicators identical to the pseudo-latent variables. Finally, η_4 and η_5 in Figure 2 are identical to η_2 and η_3 in the misspecified model in Figure 1; again, the subscripts change as a result of making the formative indicators endogenous.

Fig. 2. Endogenously-positioned FMC: Correctly specified CSA model.

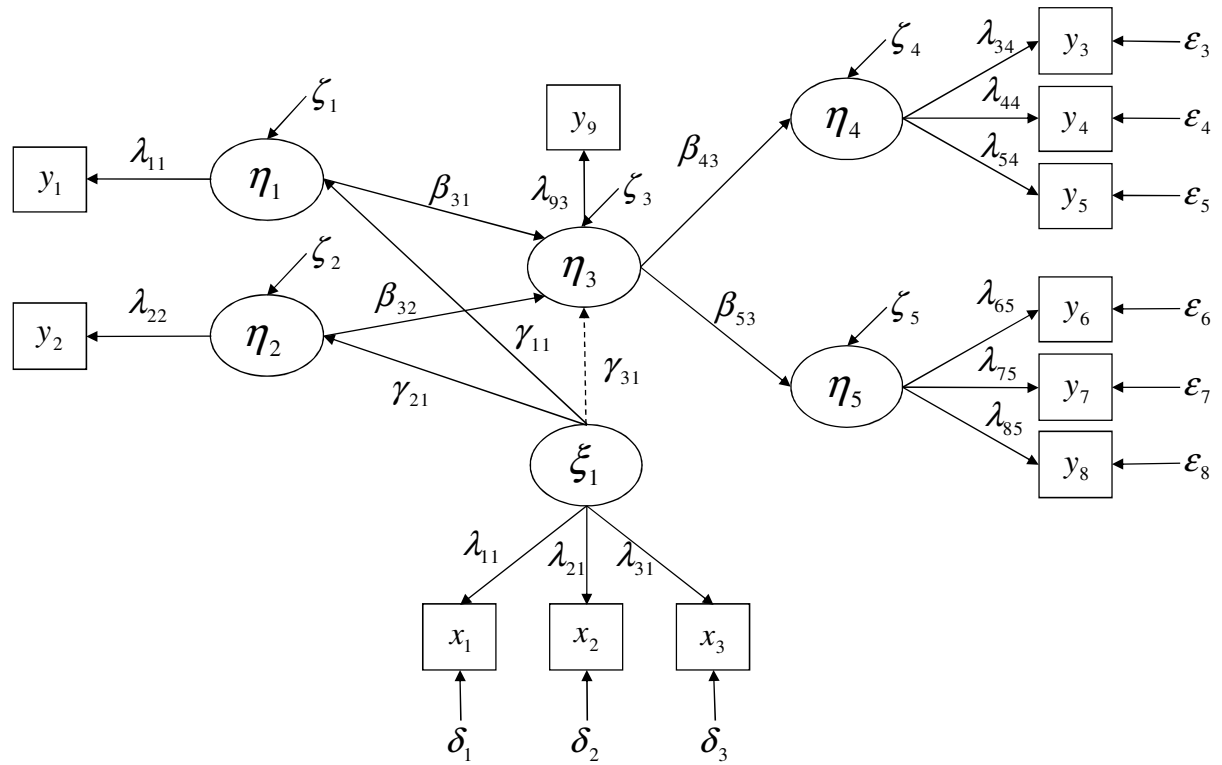


Fig. 3. Endogenously-positioned FMC: Correctly specified PLS model.

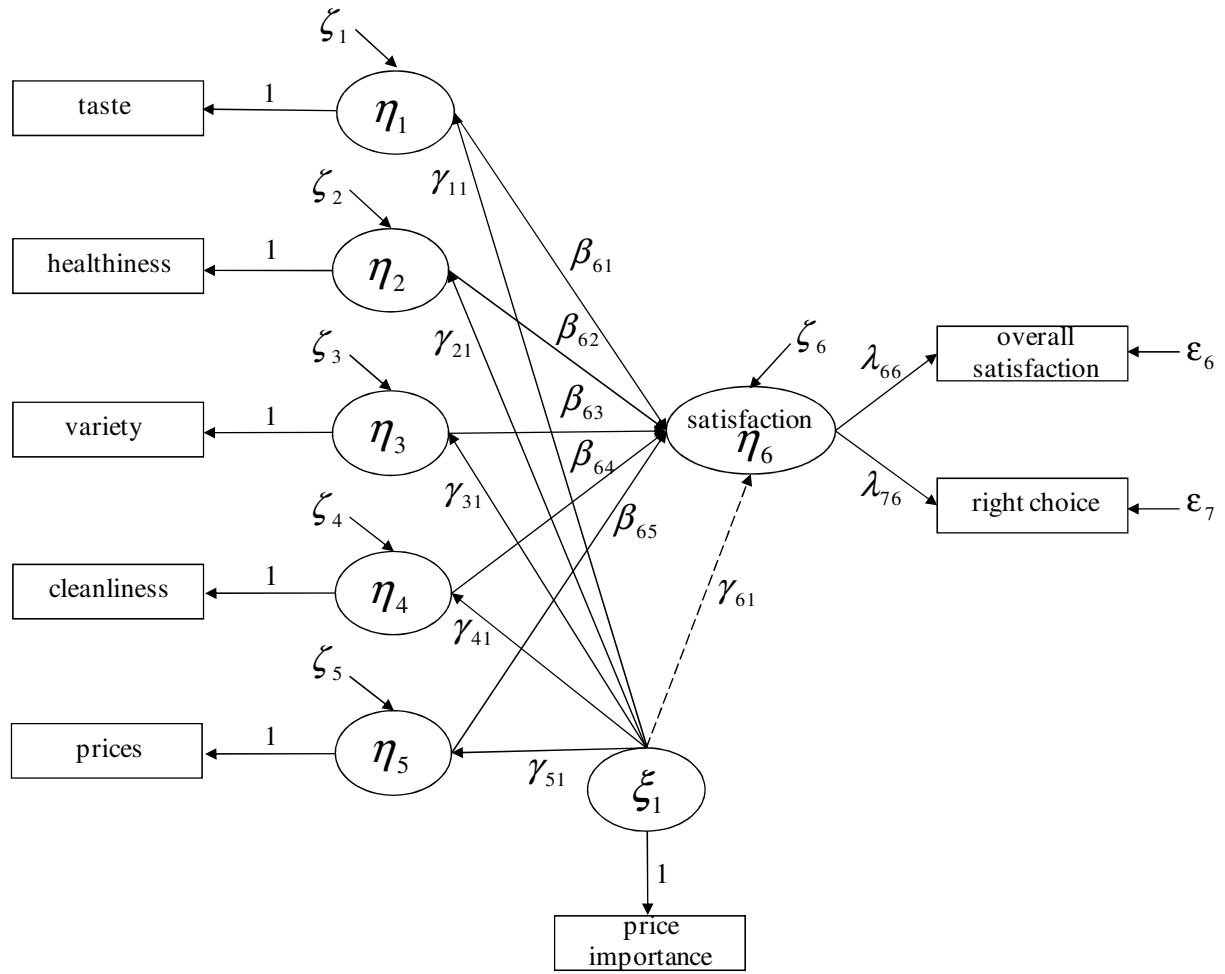


Fig. 4. Illustrative model.

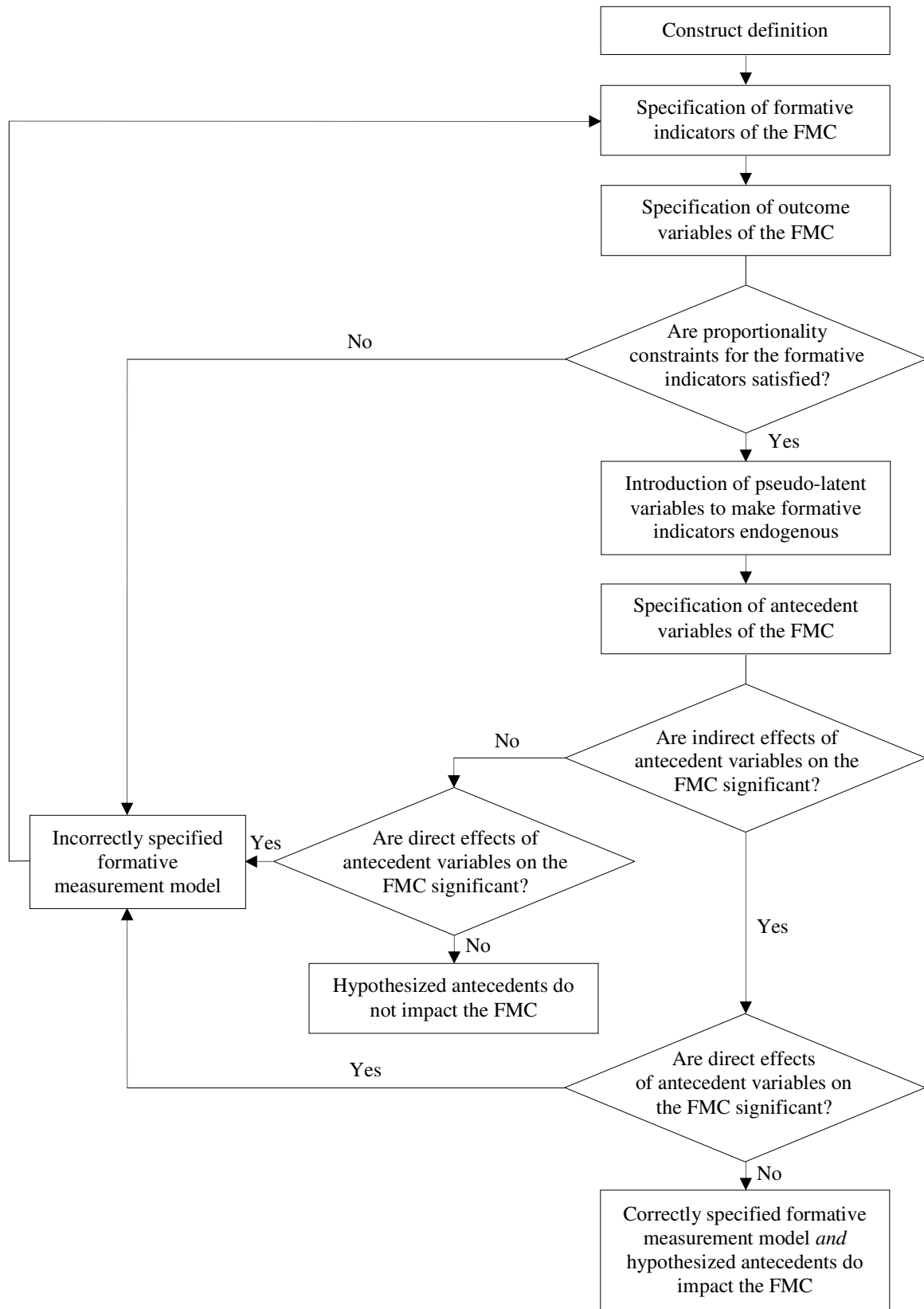


Fig. 5. Steps for specifying and assessing the influence of antecedent variables on a FMC.