Marker Variables in SmartPLS: A Practical Guide to Common Method Variance

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Abstract: Common method variance (CMV) remains a persistent concern in survey-based structural equation modeling (SEM), yet practical guidance for implementing marker-variable procedures in partial least squares structural equation modeling (PLS-SEM) remains fragmented. Existing studies differ in how marker variables are selected, specified, and interpreted, creating inconsistent applications in SmartPLS, particularly for mediation, moderated mediation, and higher-order construct models. This paper consolidates existing methodological recommendations into a practical workflow covering marker selection, model specification, implementation, interpretation, and reporting. The proposed guidance clarifies the distinction between dependent-variable-only and broader measurement-level specifications, provides practical criteria for selecting and specifying marker variables, and demonstrates their implementation across direct-effect, mediation, moderated mediation, and hierarchical component models estimated using the repeated-indicators approach. Across the worked models, substantive relationships remained stable after marker inclusion, while marker paths were consistently unsupported. Particular attention is given to hierarchical component models, where marker paths are specified at the lower-order construct level at which the indicators are represented. The paper further provides practical decision rules for interpreting marker-variable results based on substantive path stability and marker-path behavior while emphasizing appropriate reporting practices and the limitations of marker-variable diagnostics. Rather than introducing a new statistical method, the paper provides an applied SmartPLS guide intended to improve the consistency, transparency, and rigor of marker-variable applications in PLS-SEM research.

Keywords: Common method variance, Marker variable, PLS-SEM, SmartPLS, Implementation framework

1. Introduction

Survey-based research remains one of the most widely used approaches in disciplines employing structural equation modeling (SEM), including management, marketing, information systems, psychology, and sustainability research. In many empirical studies, predictors, mediators, moderators, and outcomes are measured from the same respondents at a single point in time because longitudinal, multi-source, or archival data are often impractical or unavailable. Although this design is efficient and frequently unavoidable, it may introduce common method variance (CMV), that is, systematic variance attributable to the measurement method rather than to the constructs the measures are intended to represent (Baumgartner & Weijters, 2021; Chang, van Witteloostuijn, & Eden, 2010; Lindell & Whitney, 2001; Podsakoff et al., 2003, Podsakoff, MacKenzie, & Podsakoff, 2012). CMV is important because it may influence the interpretation of structural relationships. When respondents provide all measurements under the same survey conditions, part of the observed covariance may reflect shared response tendencies rather than the underlying theoretical constructs. Such tendencies may arise from common rater effects, social desirability, acquiescence, consistency motifs, item wording, or common scale formats (MacKenzie & Podsakoff, 2012; Podsakoff et al., 2024; Spector et al., 2019). However, the presence of CMV does not imply that every estimated relationship is substantially biased. Some method effects behave as random error, whereas others create systematic covariance that may inflate, attenuate, or redistribute structural relationships depending on the research context (Bozionelos & Simmering, 2022; Doty & Glick, 1998; Sturman et al., 2025). Nevertheless, because many SEM studies rely on relatively small direct, indirect, and interaction effects, even modest method-related distortion may influence statistical inference and theoretical conclusions.

To reduce CMV, researchers commonly combine procedural and statistical remedies (Podsakoff et al., 2003; Tehseen, Ramayah, & Sajilan, 2017). Procedural remedies include improving item clarity, reducing ambiguity,

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varying response formats, protecting respondent anonymity, and introducing psychological or temporal separation between measurements (Cooper et al., 2020; Podsakoff et al., 2024; Saxena et al., 2024). Although these approaches are recommended, they are not always feasible in field-based organizational research where data collection is constrained by time, access, and organizational realities (Min, Park, & Kim, 2016). Consequently, researchers frequently supplement procedural remedies with post hoc statistical diagnostics. However, the implementation of these diagnostics remains inconsistent. Many studies continue to rely on Harman's single-factor test despite longstanding evidence that it provides weak and often misleading evidence regarding CMV (Baumgartner, Weijters, & Pieters, 2021; Baumgartner & Weijters, 2021; Bozionelos & Simmering, 2022; Craighead et al., 2011). Other studies report statistical checks only briefly, making it difficult for reviewers and readers to evaluate whether CMV has been assessed rigorously (Tehseen, Ramayah, & Sajilan, 2017).

These limitations have contributed to increasing interest in marker-variable procedures as a more theoretically grounded approach to CMV assessment (Aguirre-Urreta & Hu, 2019). Rather than inferring method bias from a single-factor solution, the marker-variable approach introduces a construct that is theoretically unrelated to the substantive model but measured under the same survey conditions. When appropriately selected, the marker serves as a proxy for method-related response tendencies and provides additional evidence regarding whether the common measurement method may have influenced substantive relationships (Lindell & Whitney, 2001; Simmering et al., 2015; Williams, Hartman, & Cavazotte, 2010). Compared with broad factor-based diagnostics, marker-variable procedures allow researchers to evaluate method-related influence more directly within the structural model itself (Chin et al., 2013; Tehseen, Ramayah, & Sajilan, 2017).

Despite their growing use, existing applications reveal substantial inconsistencies. Researchers differ in how marker variables are selected, how they are incorporated into structural models, and how their results are interpreted (Leonard, Simmering, & Wall 2024; Sharma, Yetton, & Crawford, 2010; Williams, Hartman, & Cavazotte, 2010; Williams & McGonagle, 2016). Many empirical studies provide only limited justification for marker selection, report little information about marker measurement, or omit the rationale for the chosen specification. Simmering et al. (2015) further observed that published studies frequently provide insufficient reporting regarding marker characteristics and occasionally employ markers that are poorly justified conceptually. Consequently, the principal challenge is no longer the availability of marker-variable methodology, but rather its consistent operationalization in applied PLS-SEM research, particularly in relation to marker selection, model specification, interpretation, and reporting (Leonard, Simmering, & Wall 2024; Miller & Simmering, 2023; Saxena et al., 2024; Simmering et al., 2012).

Existing studies provide important foundations for addressing these issues, but their contributions are distributed across different aspects of marker-variable analysis. Rönkkö and Ylitalo (2011) provided early guidance on the use of marker variables in PLS analysis, Chin et al. (2013) developed a measured latent marker variable approach for PLS, and Simmering et al. (2015) provided detailed guidance on marker selection, implementation, and reporting. Collectively, these studies establish the methodological basis for marker-variable analysis, but practical guidance remains dispersed rather than organized around a complete SmartPLS implementation process. This becomes particularly relevant as structural models increase in complexity and researchers must determine how established marker-variable principles should be operationalized in mediation, moderated mediation, and hierarchical component models.

A particularly important implementation issue concerns how marker variables are incorporated into structural models. Some studies connect the marker only to the endogenous construct, implicitly assuming that CMV primarily inflates predictor-to-outcome relationships. Other studies adopt a broader measurement-level specification by allowing the marker to influence multiple constructs measured under the same survey conditions, reflecting the view that method effects arise from shared measurement processes rather than from a single dependent variable (Baumgartner, Weijters, & Pieters, 2021; Chin et al., 2013; Williams, Hartman, & Cavazotte, 2010; Williams & McGonagle, 2016). These alternative specifications represent different assumptions regarding how method effects operate, yet the literature provides limited practical guidance regarding when each specification is appropriate and how the resulting models should be interpreted. The implementation issue becomes especially important in hierarchical component models estimated through repeated indicators because the researcher must determine the level at which marker relationships should be specified. Since the indicators of the higher-order construct are represented through its lower-order dimensions, this paper argues that marker relationships should likewise be specified at the lower-order level rather than directly to the higher-order construct. More generally, SmartPLS applications involving mediation, moderated mediation, interaction terms, and hierarchical component models require clearer guidance regarding how marker-variable procedures

should be implemented and interpreted (Cheah et al., 2022; Ciavolino et al., 2024; Nitzl, Roldan, & Cepeda, 2016; Sarstedt & Moisescu, 2024).

Against this background, this paper does not propose a new statistical method for detecting CMV. Rather, it consolidates established methodological recommendations into a practical SmartPLS-oriented workflow for applying, interpreting, and reporting marker-variable procedures in PLS-SEM. Specifically, the paper addresses three practical questions that frequently arise in applied PLS-SEM research. 1) How should an appropriate marker variable be selected and justified. 2) How should marker variables be specified across increasingly complex PLS-SEM models, including direct-effect, mediation, moderated mediation, and higher-order construct models. 3) How should marker-variable results be interpreted and reported without overstating what the procedure can demonstrate.

The paper makes two related contributions. First, it brings together existing methodological recommendations into an applied workflow linking marker selection, model specification, baseline-to-marker comparison, interpretation, and reporting. In doing so, it clarifies the distinction between dependent-variable-only and broader measurement-level specifications and provides practical decision rules and a marker-selection checklist for applied SmartPLS research. Second, it extends this implementation guidance to increasingly complex PLS-SEM models, with particular attention to hierarchical component models estimated through the repeated-indicators approach. Specifically, the paper clarifies the rationale for specifying marker relationships at the lower-order construct level, where the indicators representing the hierarchical construct are located. The worked examples further demonstrate how substantive path stability and marker-path behavior can be evaluated jointly across direct-effect, mediation, and moderated mediation models. Thus, the contribution lies not in introducing a new marker-variable method, but in operationalizing established guidance and clarifying its application in more complex PLS-SEM settings.

The remainder of the paper is organized as follows. Section 2 reviews the conceptual foundations of CMV and marker-variable procedures and clarifies what these procedures can and cannot demonstrate. Section 3 provides practical guidance for marker selection and specification, including hierarchical component models. Section 4 demonstrates the implementation procedure in SmartPLS across progressively complex structural models. Section 5 discusses the interpretation and reporting of marker-variable results, and Section 6 concludes with the main methodological implications, limitations, and directions for future research.

2. Common Method Variance and the Logic of Marker Variables

2.1 What CMV is and why it Matters

Common method variance (CMV) refers to variance attributable to the measurement method rather than to the constructs that the measures are intended to represent (Podsakoff et al., 2003). In survey-based research, multiple constructs are frequently measured using the same questionnaire, response format, respondents, and data collection occasion (Memon et al., 2023; Ramayah et al., 2017). Under such conditions, part of the observed covariance among constructs may reflect shared measurement processes rather than the substantive relationships specified in the theoretical model (Baumgartner, Weijters, & Pieters, 2021; MacKenzie & Podsakoff, 2012).

CMV is particularly relevant in structural equation modeling because both measurement evaluation and structural estimation rely on the relationships among observed indicators and latent constructs (Chin et al., 2013; Rönkkö & Ylitalo, 2011). When shared response tendencies influence several constructs simultaneously, structural coefficients, indirect effects, interaction effects, and standard errors may be either inflated or attenuated depending on how method effects align with the substantive constructs (Kock, 2015; Min, Park, & Kim, 2016; Podsakoff et al., 2024). However, the presence of CMV should not automatically be interpreted as evidence that all structural relationships are substantially biased. Method effects may behave as random measurement error, systematic shared variance, or a combination of both, and their influence varies across research settings (Bozionelos & Simmering, 2022; Doty & Glick, 1998; Sturman et al., 2025). The relevant methodological question is therefore not simply whether CMV exists, but whether method-related variance is sufficient to alter the substantive inferences drawn from the model.

Researchers have long been encouraged to minimize CMV through procedural remedies implemented during research design, including temporal separation of measurements, multiple data sources, improved questionnaire design, respondent anonymity, and reduced evaluation apprehension (Podsakoff et al., 2003). Although these practices remain the preferred first line of defense, they are not always feasible in organizational and field-based research because of practical constraints such as limited access to multiple respondents,

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organizational restrictions, and survey administration requirements (Cooper et al., 2020; Saxena et al., 2024; Sturman et al., 2025). Consequently, statistical diagnostics continue to play an important complementary role after data collection.

Several statistical approaches are available for assessing potential method-related influence, and they differ in their assumptions and analytical purposes. Harman's single-factor test remains widely reported despite substantial evidence questioning its diagnostic ability (Baumgartner, Weijters, & Pieters, 2021; Podsakoff et al., 2003, Podsakoff, MacKenzie, & Podsakoff, 2012). More developed approaches include full-collinearity assessment in PLS-SEM (Kock, 2015), latent method-factor techniques, and marker-variable procedures (Williams, Hartman, & Cavazotte, 2010). These approaches should not be regarded as interchangeable or as forming a simple hierarchy of superior and inferior tests. Rather, each relies on different assumptions about how method-related variance is represented. The present paper focuses specifically on marker-variable procedures because they permit a theoretically selected marker to be incorporated into the model and its relationship with substantive constructs to be examined directly.

2.2 Where CMV Operates in SEM Models

The way researchers conceptualize CMV determines how marker-variable diagnostics are implemented. A common practice in empirical research is to treat CMV primarily as a source of bias affecting the dependent variable. Under this perspective, the marker variable is introduced only as an additional predictor of the endogenous construct, and changes in the substantive structural paths are interpreted as evidence of possible method-related influence. Although this approach provides a useful robustness check, it implicitly assumes that method effects are concentrated in the outcome variable.

A broader conceptual perspective treats CMV as a consequence of shared measurement conditions rather than as contamination of a single construct (Aguirre-Urreta & Hu, 2019; Baumgartner, Weijters, & Pieters, 2021; Baumgartner & Weijters, 2021). Because multiple constructs are measured using the same respondents, questionnaire, and response format, method-related response tendencies may influence exogenous constructs, endogenous constructs, mediators, moderators, and the structural relationships among them simultaneously. This broader perspective becomes particularly important in mediation and moderation models, where substantive conclusions often depend on relatively small changes in indirect or interaction effects (Cheah et al., 2022; Ramayah et al., 2017; Sarstedt & Moisescu, 2024). Restricting marker-variable diagnostics to the dependent variable alone may therefore overlook method-related influence elsewhere in the structural model.

These different assumptions explain why existing studies vary considerably in marker-variable specification. Some studies connect the marker only to endogenous constructs, whereas others specify marker paths to multiple constructs measured under the same survey conditions (Chin et al., 2013; Simmering et al., 2012, 2015). Although both approaches appear in the literature, practical guidance regarding when each specification is appropriate remains fragmented. Accordingly, marker specification should follow an explicit assumption about where method-related influence may enter the model rather than being treated as a purely technical modeling decision.

The issue becomes particularly important in SmartPLS applications involving hierarchical component models. When higher-order constructs are estimated using the repeated-indicators approach, the measurement structure is represented through the lower-order components and their associated indicators (Sarstedt et al., 2019). Because CMV arises through the measurement process, this structure raises an important implementation question: should the marker be linked directly to the higher-order construct or to the lower-order dimensions through which the indicators are represented? Building on the measurement-level logic of marker-variable procedures, this paper adopts the latter specification. Marker paths are therefore directed to the lower-order dimensions rather than directly to the higher-order construct. This preserves the hierarchical structure while locating the diagnostic relationships at the level where the measured indicators enter the model. The practical implementation of this specification is developed further in Sections 3 and 4.

2.3 Marker-variable Approaches in PLS-SEM

Marker-variable procedures are based on a simple conceptual principle. Researchers introduce an additional construct that is theoretically unrelated to the substantive model but measured under the same survey conditions as the focal constructs (Rönkkö & Ylitalo, 2011). The underlying assumption is that if respondents exhibit common response tendencies, those tendencies may influence both the marker and the substantive measures despite the absence of any theoretical relationship between them (Chin et al., 2013; Simmering et al., 2012). Earlier marker-variable approaches primarily relied on correlational adjustments in which correlations

between the marker and substantive variables were used to estimate method-related variance. Although straightforward to implement, these approaches require relatively strong assumptions and provide limited transparency regarding how method effects are represented within the structural model (Miller & Simmering, 2023; Simmering et al., 2015).

In PLS-SEM, the Measured Latent Marker Variable (MLMV) approach extends this logic by modeling the marker as a latent construct and incorporating it directly into the structural model as a potential source of method-related influence (Chin et al., 2013). This approach is particularly attractive for SmartPLS users because it can be implemented using standard modeling procedures and evaluated through bootstrapped confidence intervals consistent with established PLS-SEM reporting practices. Rönkkö and Ylitalo (2011) similarly demonstrated the use of marker variables for diagnosing and controlling method variance in PLS models, while Simmering et al. (2015) highlighted the importance of marker choice, reporting, and interpretation. Thus, the methodological foundations of marker-variable analysis are already well established. The remaining challenge addressed in this paper is primarily one of implementation: how these principles can be applied consistently as PLS-SEM models become more complex, particularly when mediation, moderation, and hierarchical component structures are involved. Accordingly, the purpose of the present guide is not to position marker-variable analysis as superior to other CMV diagnostics or to modify the underlying MLMV estimator. Instead, it focuses on the practical decisions that researchers must make when translating established marker-variable principles into SmartPLS model specifications and interpreting the resulting evidence.

2.4 What Marker Variables can and Cannot Demonstrate

Although marker-variable procedures provide useful evidence regarding potential method-related influence, they should not be interpreted as definitive tests of CMV. Three limitations deserve particular attention. First, a marker-variable analysis cannot demonstrate the complete absence of common method variance. A non-significant marker effect may indicate that the selected marker does not adequately capture the relevant response tendencies rather than confirming that no method effects exist (Miller & Simmering, 2023). Consequently, researchers should avoid statements such as “CMV is absent” or “CMV is not a concern” based solely on marker-variable results. Second, marker-variable procedures do not guarantee unbiased parameter estimates. Method effects may differ across constructs, indicators, and measurement contexts, and different marker specifications may produce different levels of adjustment (Baumgartner, Weijters, & Pieters, 2021; Simmering et al., 2015). Marker-variable diagnostics should therefore be interpreted as evidence supporting the robustness of substantive conclusions rather than as proof that all method-related variance has been eliminated. Third, the validity of the procedure depends fundamentally on the quality of the selected marker variable. A marker chosen after examining sample correlations or selected solely because it appears weakly related to the substantive constructs undermines the conceptual assumptions of the approach and may produce misleading conclusions (Sharma, Yetton, & Crawford, 2010; Simmering et al., 2012). Marker selection should therefore be treated as a research design decision supported by theoretical justification rather than a post hoc statistical exercise.

Together, these limitations reinforce the diagnostic rather than confirmatory role of marker-variable procedures. Their value lies in examining whether substantive conclusions remain stable when a theoretically defensible marker is incorporated into the model and whether the marker itself shows meaningful relationships with the measured constructs. Marker-variable evidence should therefore complement procedural remedies and, where appropriate, other statistical diagnostics rather than be treated as proof that method-related variance has been eliminated. These considerations provide the foundation for the implementation framework developed in the following section. Section 3 presents practical guidance for selecting, specifying, and reporting marker variables in SmartPLS, including marker-selection criteria, recommendations for reflective specification, and reporting practices intended to improve the consistency, transparency, and interpretability of marker-variable applications in applied PLS-SEM research.

3. Selecting an Appropriate Marker Variable

The validity of any marker-variable procedure depends fundamentally on the quality of the selected marker construct. Regardless of how the marker is modeled statistically, the procedure can provide meaningful evidence only if the marker satisfies the conceptual assumptions underlying the approach. Consequently, the usefulness of a marker-variable analysis depends less on the estimation algorithm itself than on whether the marker has been selected and justified appropriately (Williams & O'Boyle, 2015). Marker variables do not measure common method variance directly. Instead, they serve as proxies for method-related response tendencies that may arise

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from shared measurement conditions. Consequently, marker selection should be viewed as a research design decision established before model estimation rather than as a statistical adjustment introduced after inspecting the data. Existing reviews indicate that many published studies provide only limited justification for marker selection, report little information regarding marker specification, or rely on markers whose conceptual independence from the substantive model is unclear (Leonard, Simmering, & Wall 2024; Miller & Simmering, 2023; Sharma, Yetton, & Crawford, 2010; Simmering et al., 2015). Such practices weaken the interpretability of marker-variable diagnostics regardless of how carefully the subsequent statistical analysis is conducted.

Importantly, marker suitability should not be evaluated primarily on the basis of observed sample correlations. A weak empirical correlation does not necessarily demonstrate theoretical independence, just as a moderate correlation does not automatically invalidate an otherwise well-justified marker. The primary criterion is whether the marker is conceptually appropriate for representing method-related response tendencies while remaining outside the theoretical domain of the substantive model (Sharma, Yetton, & Crawford, 2010; Simmering et al., 2012, 2015). Accordingly, marker selection should be guided by conceptual independence, methodological relevance, contextual appropriateness, and pre-analysis justification.

3.1 Conceptual Selection Criteria

3.1.1 Criterion 1: The marker should be theoretically unrelated to the substantive model

The most important requirement is conceptual independence. The marker should have no plausible theoretical relationship with the predictors, mediators, moderators, or outcomes specified in the substantive model (Sturman et al., 2025; Williams & O'Boyle, 2015). This requirement is grounded in theory rather than sample statistics. Accordingly, researchers should explain why the selected marker lies outside the nomological network of the focal constructs instead of relying solely on weak empirical correlations as evidence of independence.

3.1.2 Criterion 2: The marker should capture potential method-related response tendencies

Although conceptually unrelated to the substantive model, the marker should still be measured under the same survey conditions and therefore be exposed to the same response tendencies that may influence the substantive measures. These tendencies may include social desirability, acquiescence, consistency motifs, or other systematic response styles (Simmering et al., 2015). A variable that is unrelated both conceptually and methodologically provides little information regarding potential method effects. Consequently, an appropriate marker should remain independent in content while sharing the same measurement environment.

3.1.3 Criterion 3: Marker suitability should be evaluated within the research context

Marker suitability is context dependent rather than universal. A construct that functions as an appropriate marker in one research domain may overlap conceptually with focal constructs in another. For example, environmental attitudes may be unsuitable as a marker in sustainability research despite appearing unrelated in other contexts. Researchers should therefore evaluate marker independence in relation to the theoretical framework, research setting, sample characteristics, and construct definitions used in the specific study (Williams & O'Boyle, 2015).

3.1.4 Criterion 4: Marker selection should be established before statistical analysis

Marker selection should be determined during research design rather than after examining empirical correlations. Choosing a marker solely because it exhibits the smallest observed relationship with the substantive constructs lacks theoretical justification and may produce unstable or sample-specific conclusions (Sharma, Yetton, & Crawford, 2010; Simmering et al., 2012). Statistical evidence may support marker selection, but it should not replace conceptual reasoning.

3.2 Reflective Versus Formative Specification

Once an appropriate marker has been identified, researchers must determine how it should be specified within the measurement model. In PLS-SEM, marker variables may be modeled either reflectively or formatively, although the two approaches differ substantially in their underlying assumptions.

3.2.1 Reflective specification

Reflective specification is appropriate when the marker indicators are treated as manifestations of a common underlying construct or response tendency. Under this specification, the indicators are expected to be interchangeable, internally consistent, and manifestations of the same latent construct. Reflective markers can

therefore be assessed using established reflective measurement-model criteria and implemented directly in SmartPLS (Tehseen, Ramayah, & Sajilan, 2017).

3.2.2 Formative or composite specification

A formative marker combines several indicators that collectively represent method-related influence rather than reflect a single latent tendency. Although this approach has been discussed within the PLS literature (Chin et al., 2013), it requires a different conceptual rationale because changes in individual indicators may alter the meaning of the composite, and the indicators need not be interchangeable. The specification should also be evaluated for multicollinearity. Consequently, formative marker specification should be used when there is a clear conceptual rationale for treating the indicators as defining rather than reflecting the marker construct.

Practical recommendation. The marker's measurement specification should follow its conceptual measurement logic rather than be selected solely for analytical convenience. When the indicators represent manifestations of a common marker construct, reflective specification provides a straightforward implementation; formative or composite specification requires explicit justification for treating the indicators as defining the construct.

3.3 Number of Marker Items

The quality of a marker-variable analysis also depends on the quality of the marker measurement itself. Single-item markers provide limited representation of the marker construct and may be particularly sensitive to measurement error (Simmering et al., 2015). Multi-item markers can provide broader construct representation and permit assessment of measurement quality while remaining practical for survey administration.

There is, however, no universally appropriate number of marker items. The number should reflect the conceptual breadth of the marker, the quality of its indicators, and practical considerations such as questionnaire length and respondent burden. Rather than selecting items to meet a fixed numerical threshold, researchers should use a sufficiently representative multi-item measure and establish its measurement quality before using it for CMV diagnosis. Where established marker scales are available, their validated measurement structure should guide item selection and adaptation (Chin et al., 2013; Simmering et al., 2012, 2015).

3.4 Marker Selection Checklist

Before incorporating a marker into the structural model, researchers should document four questions:

- *Is the marker conceptually independent?* It should lie outside the nomological network of the focal constructs and remain independent within the particular research context.
- *Does the marker share the relevant measurement environment?* It should be administered under conditions that expose it to the response tendencies potentially affecting the substantive measures.
- *Is the marker adequately measured?* Its measurement specification should follow its conceptual nature, and its measurement quality should be established before structural analysis.
- *Was the marker selected independently of the observed results?* The theoretical rationale, measurement, and intended diagnostic role should be established and reported rather than determined from post hoc correlations.

Table 1 translates these considerations into a concise decision framework for applied PLS-SEM research.

3.5 Marker Variables in Higher-order Models

Hierarchical component models require additional consideration because conceptual independence must be evaluated across the hierarchical measurement structure. A marker that appears unrelated to the higher-order construct may nevertheless overlap conceptually with one or more lower-order dimensions. Consequently, marker suitability should be assessed against the complete hierarchical measurement structure rather than only the higher-order construct label (Rönkkö & Ylitalo, 2011; Simmering et al., 2015; Williams & O'Boyle, 2015). This means that theoretical independence should first be established between the marker and each lower-order component before the marker is introduced into the model.

A separate issue concerns where marker paths should be specified when the higher-order construct is estimated using the repeated-indicators approach. Under this approach, the indicators used to represent the higher-order construct are associated with its lower-order components, making the lower-order level the relevant measurement level at which potential shared response tendencies are represented. Consistent with the measurement-level logic developed in Section 2, the marker paths are therefore specified to the lower-order components rather than directly to the higher-order construct. This specification allows potential method-

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related relationships to be examined at the level where the measured indicators enter the hierarchical structure while preserving the substantive relationship between the lower- and higher-order components.

This distinction is important because linking the marker only to the higher-order construct may obscure method-related relationships associated with individual lower-order dimensions. Conversely, specifying marker paths at the lower-order level makes it possible to examine whether the marker relates differently to particular dimensions of the hierarchical construct. The procedure should therefore be interpreted as an implementation of the measurement-level logic of marker-variable analysis within a repeated-indicators hierarchical model, rather than as a new marker-variable estimator. Section 4 demonstrates this specification in SmartPLS.

Table 1: Decision Framework for Selecting Marker Variables in PLS-SEM

Criterion	Why it matters	Recommended practice
Theoretical independence	A marker must lie outside the nomological network of the substantive model; otherwise, observed relationships may reflect genuine theoretical associations rather than method effects.	Select a construct with no plausible theoretical relationship to the predictors, mediators, moderators, or outcomes. Justify independence theoretically rather than solely through sample correlations.
Methodological relevance	The marker should experience the same measurement conditions as the substantive constructs so that it can capture potential response tendencies.	Measure the marker using the same respondents and survey conditions. It should be unrelated in content while being exposed to the same measurement environment.
Contextual independence	Marker suitability depends on the research context; a suitable marker in one domain may overlap conceptually in another.	Evaluate the marker against the study context and definitions of the focal constructs before data analysis.
Pre-analysis selection	Selecting a marker after examining correlations increases the risk of data-driven justification.	Identify and justify the marker during research design. Use empirical correlations only as supporting evidence.
Measurement quality	The diagnostic value of the marker depends on adequate representation and measurement of the marker construct.	Prefer an appropriately validated multi-item measure and evaluate its measurement quality rather than relying on a fixed item-count rule.
Measurement specification	The measurement model should reflect the conceptual nature of the marker construct.	Specify the marker reflectively when its indicators are manifestations of a common construct; use formative or composite specification only when theoretically justified.
Hierarchical model specification	In repeated-indicator hierarchical models, potential method-related relationships should be examined at the level where the measured indicators are represented.	Assess marker independence against each lower-order component and specify marker paths at the lower-order level.
Transparent reporting	Readers should be able to evaluate the appropriateness of the marker and reproduce the procedure.	Report the marker construct, theoretical justification, measurement specification, intended purpose, and interpretation of the resulting marker evidence.

Source: Developed by the authors based on Chin et al. (2013), Sharma, Yetton, and Crawford (2010), Simmering et al. (2015), Williams and O'Boyle (2015), and related literature.

Having established how an appropriate marker should be selected and specified, the next section translates these principles into SmartPLS implementation. The worked examples show how the marker is incorporated into direct-effect, mediation, and moderated mediation models and, importantly, how marker paths are specified when the model contains a higher-order construct estimated using repeated indicators.

4. Implementation of Marker-variable Diagnostics in SmartPLS

4.1 Purpose, Model Progression, and Worked-example Setup

Building on the marker-selection and specification principles outlined in Section 3, this section shows how these principles are operationalized in SmartPLS. It presents a practical workflow for applying marker-variable procedures to diagnose potential common method variance (CMV) in PLS-SEM models of increasing complexity. The worked examples translate the preceding guidance into model specification, estimation, and interpretation. The same dataset, constructs, and general estimation settings are used throughout so that comparisons remain consistent across models. The substantive analysis proceeds in three stages.

First, a direct-effect model is estimated to examine the relationship between Environmental Transformational Leadership (ETL) and Employee Green Behavior (EGB). Second, the model is extended to a mediation structure in which ETL predicts Employee Belief (EB), which in turn predicts EGB. Third, the analysis moves to a first-stage moderated mediation model in which the interaction term ETL × ET predicts EB, which then predicts EGB.

ETL is specified as a reflective higher-order construct represented by four reflective lower-order dimensions: Idealized Influence (II), Inspirational Motivation (IM), Intellectual Stimulation (IS), and Individualized Consideration (IC). Each lower-order dimension is measured with three indicators, and the higher-order construct is modeled using the repeated-indicators approach. EGB, EB, and ET are modeled as reflective constructs. The marker construct**,** M (price consciousness)**,** is also modeled reflectively and measured with four items. Consistent with marker-variable logic, M is treated as theoretically unrelated to the substantive constructs in the model. All models are estimated in SmartPLS using bootstrapping with 5,000 subsamples. For the moderated mediation model, the interaction term is estimated using the product-indicator approach.

4.2 Baseline Measurement Model Assessment

Before comparing the baseline and marker-adjusted structural models, it is necessary to confirm that the measurement model demonstrates acceptable quality. This step is important because marker-variable diagnostics are more meaningful when the substantive constructs themselves are measured reliably and validly. However, because the purpose of this paper is to demonstrate the logic and implementation of marker-variable procedures rather than to re-establish measurement properties, the substantive constructs and their measurement scales were adopted from previously validated studies where their psychometric properties had already been established.

Following standard PLS-SEM practice, the baseline model was assessed in terms of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Indicator loadings were examined to confirm that each item adequately represented its intended construct. Internal consistency reliability and convergent validity were evaluated using Cronbach's alpha, rho_A, composite reliability (ρc), and average variance extracted (AVE). The results showed that Cronbach's alpha and composite reliability values exceeded commonly accepted thresholds, while all AVE values remained above 0.50, supporting convergent validity (Hadi, Abdullah, & Sentosa, 2016; Hair, 2014; Hair et al., 2019).

Discriminant validity was further assessed using the heterotrait-monotrait ratio (HTMT) and the Fornell-Larcker criterion. HTMT values remained within conservative acceptable limits, and the square root of the AVE for each construct exceeded its correlations with other constructs, supporting adequate discriminant validity (Fornell & Larcker, 1981; Henseler, Ringle, & Sarstedt, 2015). These results indicate that the measurement model was satisfactory and that the analysis could proceed to structural comparisons between the baseline and marker-adjusted models. Since the primary objective of this study is methodological illustration rather than measurement validation, detailed measurement tables are not reproduced here, allowing greater focus on the implementation and interpretation of marker-variable CMV diagnostics in SmartPLS.

4.3 Decision Rules for Marker-variable CMV Diagnosis

The reliability, convergent validity, and discriminant validity assessments indicate that the measurement model is adequate for further analysis. The next step is therefore the structural stage, where marker-variable diagnostics are used to compare baseline and marker-adjusted models. In this guide, the assessment of common method variance (CMV) is based on two central questions: (1) Do the focal substantive paths remain stable after the marker variable is introduced? and (2) Do the marker paths themselves provide meaningful evidence of method-related influence? These two questions form the basis of interpretation across all models.

To ensure consistency and avoid overinterpretation, the practical comparison in this section follows four decision rules (see Table 2). These rules help researchers move beyond mechanical significance testing and focus instead on whether the substantive conclusions remain robust after the theoretically unrelated marker is incorporated into the model.

4.3.1 Rule 1: Compare the focal substantive paths across baseline and marker-adjusted models

The first step is to compare the key substantive relationships before and after the marker variable is added. The primary concern is whether the focal paths remain stable in direction, magnitude, and inferential support. If the key structural relationships remain similar after introducing the marker, this suggests that the marker does not capture meaningful method-related influence on the substantive conclusions. By contrast, if the estimates change substantially in size, reverse direction, or lose statistical support after the marker is introduced, the

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possibility of method-related distortion deserves closer attention. This rule is particularly important in mediation and moderation models, where conclusions often depend on relatively small differences across paths. In such cases, even modest shifts in coefficients may meaningfully alter interpretation.

4.3.2 Rule 2: Use bootstrapped confidence intervals as the primary basis for inference

Because SmartPLS relies on nonparametric bootstrapping, confidence intervals should be treated as the primary basis for inference. Although *p* values may still be reported, the main interpretation should depend on whether the bootstrapped confidence interval includes zero. If the confidence interval excludes zero, the path is considered statistically supported. If the interval includes zero, the relationship should be interpreted cautiously, even when the *p* value appears close to a conventional significance threshold. This rule becomes especially important in moderated mediation models, where interaction effects are often sensitive to sampling variation and where borderline findings can easily be overinterpreted if too much emphasis is placed on *p* values alone.

4.3.3 Rule 3: Examine the marker paths directly

Marker-variable procedures should not be interpreted only through changes in the substantive paths. The marker paths themselves must also be examined. If the marker paths are weak and their confidence intervals include zero, this suggests that the marker does not provide strong evidence of method-related influence in the model. If one or more marker paths are statistically supported and substantively meaningful, this indicates that the marker may be capturing variance associated with the common measurement method. However, marker effects should not be overstated. A significant marker path does not prove that all substantive relationships are biased, just as a non-significant marker path does not prove that CMV is absent. The marker serves only as a diagnostic indicator of whether the selected proxy suggests method-related influence under the specified model.

4.3.4 Rule 4: Draw cautious conclusions

Marker-variable diagnostics support cautious inference rather than absolute claims. The purpose of the procedure is to evaluate whether the substantive conclusions remain robust after introducing a theoretically unrelated marker. It does not prove that CMV has been fully removed, nor does it establish that the model is entirely free from method effects. Accordingly, conclusions should be framed in measured and defensible terms. For example, it is more appropriate to state that the marker-variable results do not indicate material CMV influence on the focal conclusions than to claim that CMV is not a concern. Such careful interpretation improves methodological rigor and avoids overstating what the procedure can actually demonstrate.

Table 2: Decision Framework for Marker-Variable CMV Diagnosis in PLS-SEM

Step	What to Evaluate	Interpretation Logic
Step 1	Compare focal substantive paths across baseline and marker-adjusted models	Stability in direction, magnitude, and inferential support suggests robustness against material CMV influence
Step 2	Examine bootstrapped confidence intervals	Confidence intervals excluding zero provide stronger inferential support than reliance on p values alone
Step 3	Assess marker paths directly	Statistically meaningful marker paths may indicate potential method-related influence, but should not be overinterpreted
Step 4	Draw cautious conclusions	Avoid claiming the absence of CMV; conclude only whether marker-variable results indicate material CMV influence

Source: Authors compilation

In the following subsections, these four decision rules are applied consistently across three models of increasing complexity: a direct-effect model, a mediation model, and a first-stage moderated mediation model. This progression allows researchers to see how marker-variable diagnostics can be implemented systematically across increasingly complex PLS-SEM designs.

4.4 Case A: Direct-effect Model

4.4.1 Step 1: Estimate the baseline model

After confirming acceptable measurement quality, the baseline structural model was estimated using bootstrapping with 5,000 subsamples. The model examined the direct relationship between Environmental Transformational Leadership (ETL) and Employee Green Behavior (EGB) without including the marker variable.

The baseline structural specification is illustrated in Figure 1, and the corresponding results are reported in Table 3. The baseline results indicate that ETL is positively associated with EGB (β = 0.280, t = 5.491, p < .001), and the bootstrapped confidence interval excludes zero **(**0.186 - 0.386), providing support for the hypothesized direct relationship. These baseline estimates serve as the reference point for evaluating whether the focal structural relationship remains stable after the marker variable is introduced.

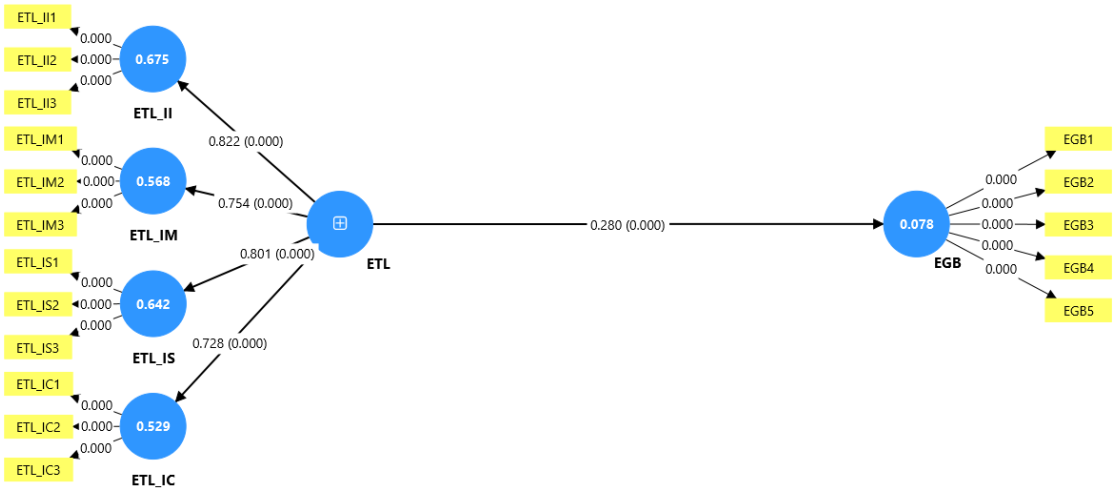


Figure 1: Baseline direct-effect model (without marker variable)

Because ETL was modeled as a higher-order construct using the repeated-indicators approach, its relationships with the four lower-order dimensions were also examined in the baseline model. These paths were strong and statistically significant, indicating that the higher-order representation was adequately supported before the marker variable was introduced.

4.4.2 Step 2: Add the marker construct and specify marker paths

The marker construct M (price consciousness) was then added to the model and estimated using the same bootstrapping settings. In this guide, marker-path specification follows the broader measurement-level logic discussed earlier. Because ETL is modeled as a higher-order construct using repeated indicators, the marker is linked to the lower-order dimensions rather than directly to the higher-order construct. Accordingly, the marker paths were specified as M → ETL_IC, M → ETL_II, M → ETL_IM, M → ETL_IS**,** and M → EGB. The marker-adjusted model is illustrated in Figure 2.

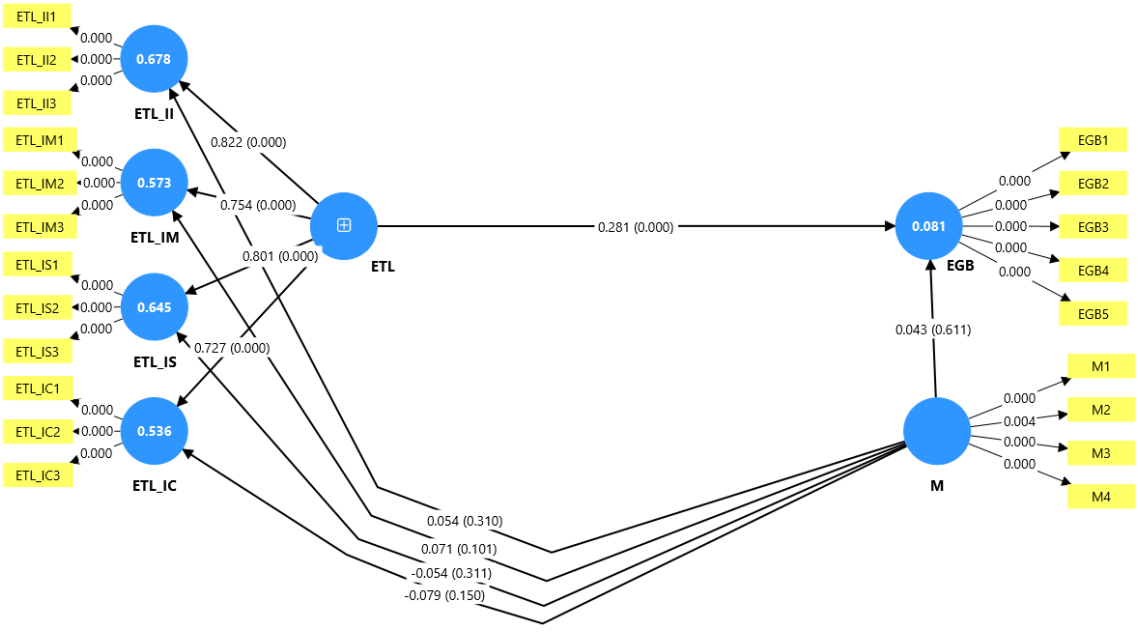


Figure 2: Marker-adjusted direct-effect model

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4.4.3 Step 3: Compare the baseline and marker-adjusted models

After the marker construct was introduced, the direct relationship between ETL and EGB remained positive and statistically supported **(**β = 0.281, t = 5.422, p < .001). As shown in Table 4**,** the estimated coefficient was virtually identical to the baseline model **(**β = 0.280), indicating strong stability of the focal direct effect after the marker adjustment.

The marker paths were then examined to assess potential method-related influence. The marker did not show a statistically meaningful relationship with EGB **(**β = 0.043, p = .611), and its confidence interval included zero (-0.175- 0.147). Likewise, the marker paths to the ETL lower-order dimensions were not supported, and their confidence intervals also crossed zero (Figure 2). This pattern indicates that the marker did not capture meaningful shared method variance in the substantive constructs.

Following the decision rules outlined in Section 4.3, two conclusions can be drawn. First, the substantive ETL → EGB relationship remained stable in direction, magnitude, and overall inference after the marker was introduced. Second, the marker paths themselves were not supported (Table 3). These findings suggest that common method variance is unlikely to materially influence the direct-effect results in this example. Accordingly, the positive relationship between ETL and EGB appears robust to the marker-variable CMV diagnostic applied here.

Table 3: Case A comparison of baseline and marker-adjusted direct-effect model

Path	Baseline β	Baseline 95% CI	Marker-adjusted β	Marker-adjusted 95% CI	Interpretation
ETL → EGB	0.280	[0.186, 0.386]	0.281	[0.181- 0.385]	Stable
M → EGB	-	-	0.043	[-0.175 - 0.147]	Not supported
M → ETL_IC	-	-	-0.079	[-0.158 - 0.061]	Not supported
M → ETL_II	-	-	0.054	[-0.093 - 0.113]	Not supported
M → ETL_IM	-	-	0.071	[-0.032 - 0.140]	Not supported
M → ETL_IS	-	-	-0.054	[-0.129 - 0.081]	Not supported

Source: Authors' compilation

4.5 Case B: Mediation Model

4.5.1 Step 1: Estimate the baseline mediation model

The direct-effect model was then extended to a mediation structure by introducing Environmental Belief (EB) as a mediator between Environmental Transformational Leadership (ETL) and Employee Green Behavior (EGB). The baseline mediation model estimated three substantive paths: ETL → EB**,** EB → EGB**,** and ETL → EGB. These baseline results provide the reference point for assessing whether the substantive conclusions remain stable after the marker variable is introduced. The baseline mediation model is illustrated in Figure 3.

As reported in Table 4, the baseline results showed that EB was positively associated with EGB (β = 0.323, p < .001), whereas ETL was not significantly related to EB (β = 0.045, p = .493). At the same time, ETL retained a positive direct relationship with EGB (β = 0.266, p < .001). These results suggest that the direct path from ETL to EGB remains important , whereas the indirect path through EB is not supported at this stage.

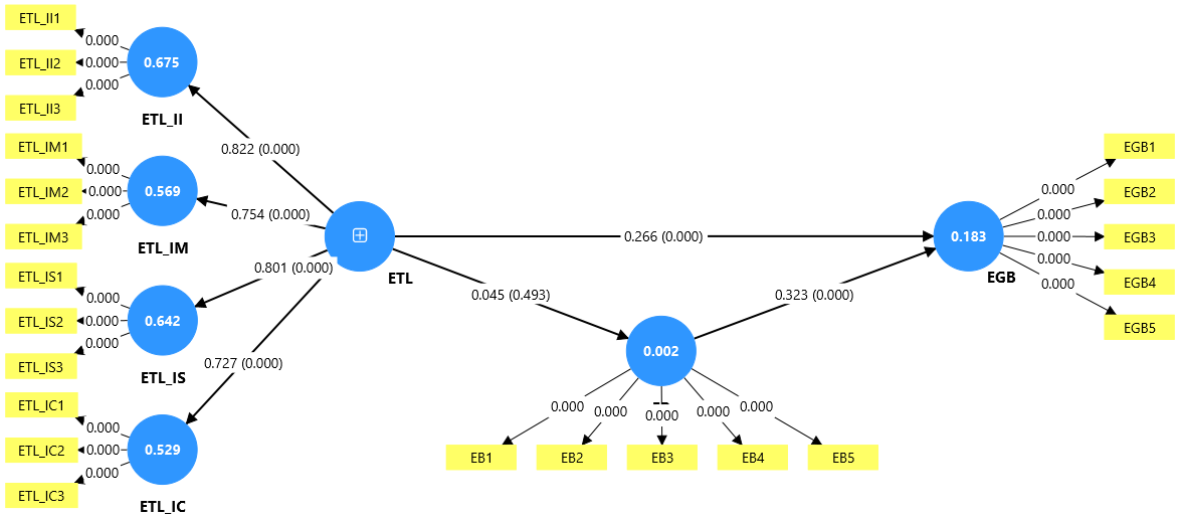


Figure 3: Baseline mediation model

4.5.2 Step 2: Add the marker construct and specify marker paths

The marker construct M (price consciousness) was then added to the mediation model using the same bootstrapping settings. Consistent with the broader measurement-level logic adopted in this guide, the marker was linked to the endogenous constructs in the model (M → EB and M → EGB) and to the lower-order dimensions of ETL rather than to the higher-order ETL construct itself. This specification reflects the assumption that method effects, if present, enter through measured dimensions and survey responses rather than through the higher-order construct as an abstract representation. The marker-adjusted mediation model is illustrated in Figure 4.

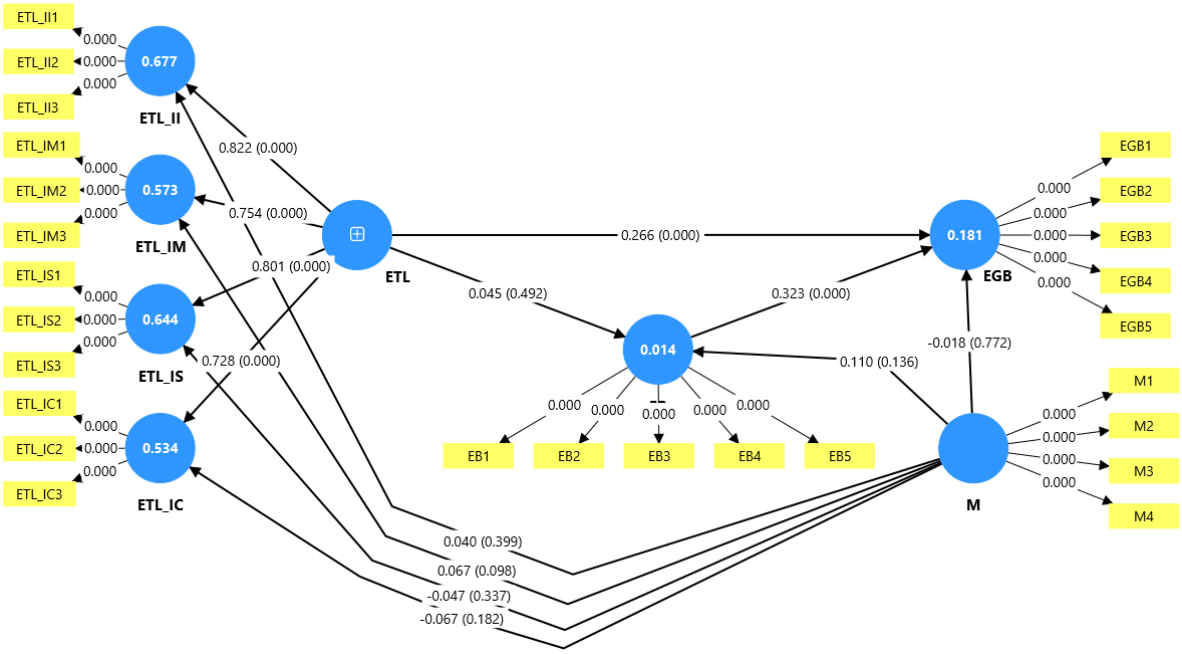


Figure 4: Marker-adjusted mediation model

4.5.3 Step 3: Compare the baseline and marker-adjusted mediation models

After introducing the marker construct, the substantive pattern of relationships remained unchanged. As shown in Table 6**,** the path from EB to EGB remained positive and statistically supported (β = 0.323; 95% CI [0.227 - 0.432]), while the path from ETL to EB remained unsupported (β = 0.045; 95% CI [−0.082 - 0.176]). Likewise, the direct path from ETL to EGB continued to be positive and statistically supported (β = 0.266; 95% CI [0.161 -

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0.365]). The similarity between the baseline and marker-adjusted estimates indicates that the substantive relationships were stable after the marker variable was introduced.

The marker paths also provided little evidence of method-related influence. The paths from M to EB (β = 0.110; 95% CI [-0.067 - 0.225]) and M to EGB β = -0.018; 95% CI [-0.160 - 0.090]) were not statistically supported, and their confidence intervals included zero. A similar pattern was observed for the marker links to the lower-order ETL dimensions, whose confidence intervals also crossed zero (M → IC: 95% CI [-0.156 - 0.040]; M → II: 95% CI [-0.075 - 0.112]; M → IM: 95% CI [-0.022 - 0.139]; M → IS: 95% CI [-0.127 - 0.061]) see Table 4.

Following the decision rules outlined in Section 4.3, two conclusions can be drawn. First, the focal structural relationships remained stable after the marker variable was introduced. Second, the marker paths themselves were not supported. These findings suggest that common method variance is unlikely to materially influence the results of the mediation model. Accordingly, the marker-adjusted model leads to the same substantive conclusion as the baseline model: EB is positively related to EGB, whereas the path from ETL to EB is not supported, and ETL retains a direct positive association with EGB.

Table 4: Case B comparison of baseline and marker-adjusted mediation model

Path	Baseline β	Baseline 95% CI	Marker-adjusted β	Marker-adjusted 95% CI	Interpretation
EB → EGB	0.323	[0.231, 0.431]	0.323	[0.227 - 0.432]	Stable
ETL → EB	0.045	[-0.082, 0.178]	0.045	[-0.082 - 0.176]	Not supported; unchanged
ETL → EGB	0.266	[0.163, 0.365]	0.266	[0.161 - 0.365]	Stable
M → EB	-	-	0.110	[-0.067 - 0.225]	Not supported
M → EGB	-	-	-0.018	[-0.160 - 0.090]	Not supported
M → ETL_IC	-	-	-0.067	[-0.156 - 0.040]	Not supported
M → ETL_II	-	-	0.040	[-0.075 - 0.112]	Not supported
M → ETL_IM	-	-	0.067	[-0.022 - 0.139]	Not supported
M → ETL_IS	-	-	-0.047	[-0.127 - 0.061]	Not supported

Source: Authors' compilation

4.6 Case C: Moderated Mediation Model

4.6.1 Step 1: Estimate the baseline moderated mediation model

The mediation model was next extended to a first-stage moderated mediation specification by introducing Environmental Training (ET) as a moderator of the ETL → EB relationship. The baseline model therefore included the main effects of ETL and ET on EB**,** the interaction effect (ETL × ET → EB), the mediator-to-outcome path (EB → EGB), and the direct effect of ETL → EGB. The baseline specification is shown in Figure 5, and the corresponding path estimates are reported in Table 5.

The baseline results showed that EB remained positively associated with EGB **(**β = 0.321, t = 6.129, p < .001; 95% CI [0.224 - 0.430]), and ETL retained a positive direct relationship with EGB **(**β = 0.266, t = 5.135, p < .001; 95% CI [0.163 - 0.366]). The interaction term (ETL × ET → EB) was also positive and supported in the baseline model (β = 0.287, t = 2.029, p = .042; 95% CI [0.242 - 0.411]), indicating that the effect of ETL on EB varies across levels of environmental training. By contrast, the main effect of ET on EB was not supported (β = −0.273, p = .132; 95% CI [−0.495 - 0.171]). The main effect of ETL on EB was positive (β = 0.267, p = .042; 95% CI [0.214 - 0.440]. Overall, the baseline model suggests that the conditional effect is more informative than the main effects alone. Full statistics are provided in Table 5.

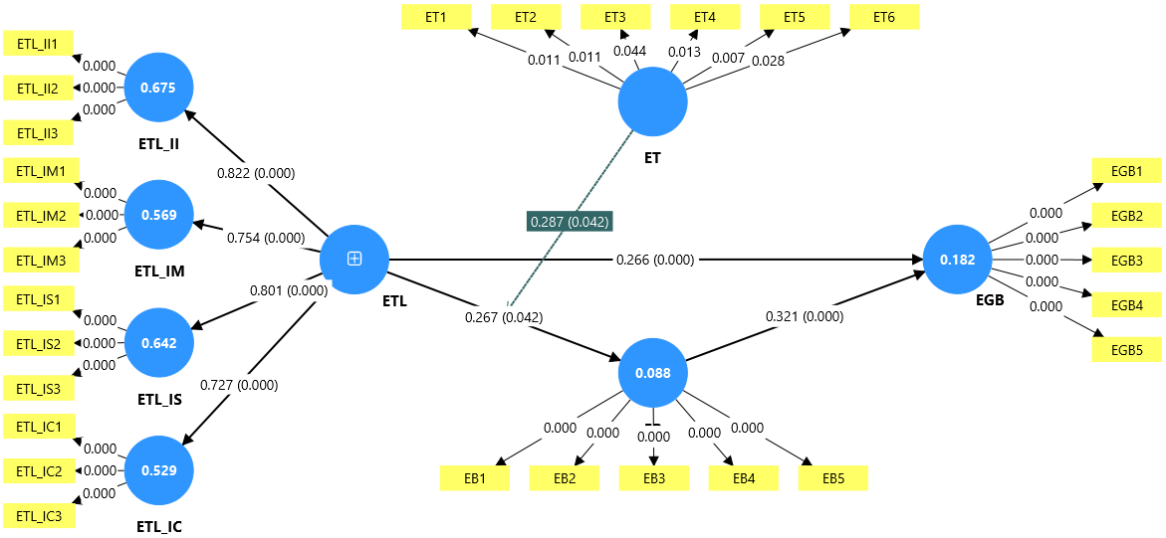


Figure 5: Baseline moderated mediation model (without marker variable)

Table 5: Baseline moderated mediation model

Path	β	SD	t - values	p - values	2.5%	97.5%
EB → EGB	0.321	0.052	6.129	0.000	0.224	0.430
ET → EB	-0.273	0.181	1.507	0.132	-0.495	0.171
ETL × ET → EB	0.287	0.141	2.029	0.042	0.242	0.411
ETL → EB	0.267	0.131	2.034	0.042	0.215	0.440
ETL → EGB	0.266	0.052	5.135	0.000	0.163	0.366

Source: Authors' compilation

Note. ETL is modeled as a second-order construct using repeated indicators with four reflective dimensions (IC, II, IM, IS). ETL × ET is the product-indicator interaction term. Bootstrapping used 5,000 subsamples.

4.6.2 Step 2: Add the marker construct and specify marker paths

The marker construct M (price consciousness) was then introduced to evaluate potential CMV in the moderated mediation model. In line with the measurement-level logic used throughout this guide, the marker was linked to the endogenous constructs **(**M → EB and M → EGB), to the moderator (M → ET), and to the lower-order dimensions of ETL rather than to the higher-order ETL construct itself. This marker-adjusted specification is shown in Figure 6, and the estimated results are reported in Table 6. This specification reflects the assumption that, if common method variance is present, it may influence not only the mediator and outcome but also the moderator and the lower-order dimensions through which the higher-order construct is formed.

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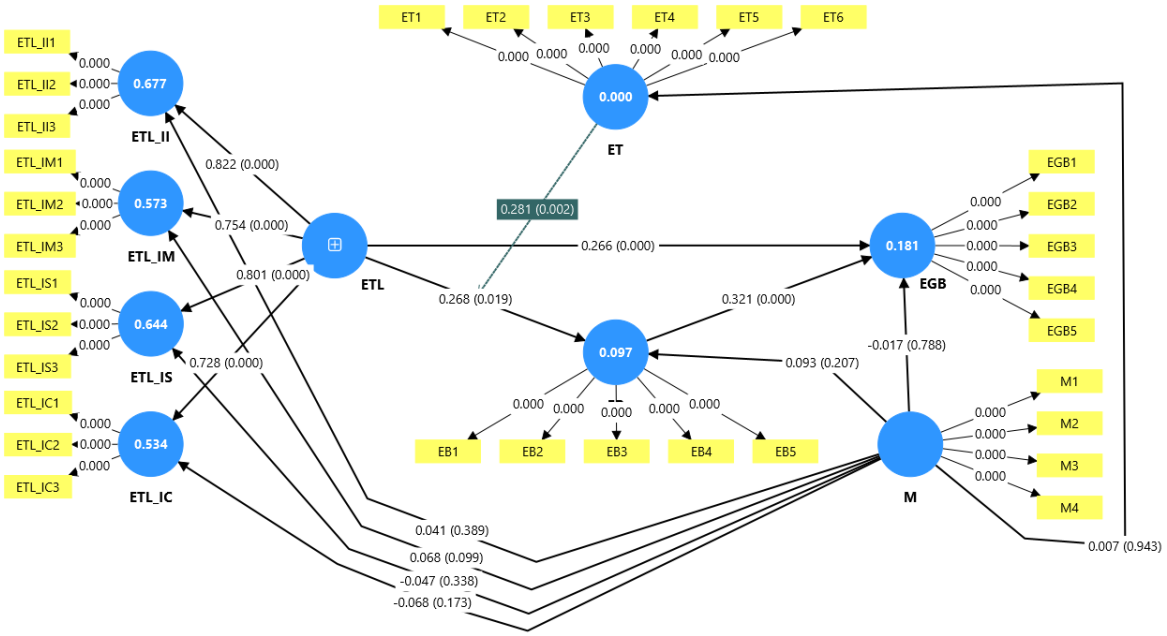


Figure 6: Marker-adjusted moderated mediation model

Table 6: Moderated mediation model with marker variable

Path	β	SD	t - values	p - values	2.5%	97.5%
EB → EGB	0.321	0.053	6.078	0.000	0.222	0.430
ET → EB	-0.272	0.150	1.821	0.069	-0.486	0.090
ETL × ET → EB	0.281	0.092	3.059	0.002	0.100	0.408
ETL → EB	0.268	0.114	2.348	0.019	0.242	0.444
ETL → EGB	0.266	0.052	5.127	0.000	0.161	0.366
M → EB	0.093	0.074	1.262	0.207	-0.082	0.210
M → EGB	-0.017	0.063	0.269	0.788	-0.159	0.089
M → ET	0.007	0.097	0.071	0.943	-0.172	0.159
M → ETL_IC	-0.068	0.050	1.362	0.173	-0.154	0.039
M → ETL_II	0.041	0.047	0.862	0.389	-0.077	0.111
M → ETL_IM	0.068	0.041	1.649	0.099	-0.022	0.138
M → ETL_IS	-0.047	0.049	0.958	0.338	-0.126	0.066

Source: Authors' compilation

4.6.3 Step 3: Compare the baseline and marker-adjusted models

The key substantive relationships remained stable after the marker was introduced. As shown in Table 7, the path from EB to EGB remained positive and statistically supported (β = 0.321; 95% CI [0.222 -, 0.430]), and the direct path from ETL to EGB also remained positive and supported (β = 0.266; 95% CI [0.161 - 0.366]). The estimates were nearly identical to those in the baseline model, indicating that the core substantive conclusions were unchanged after the marker adjustment.

The moderation results were likewise preserved. The interaction term ETL × ET → EB remained positive and supported, with a confidence interval that excluded zero in the marker-adjusted model (β = 0.281; 95% CI [0.100 - 0.408]). This indicates that the conditional effect of ETL on EB remained intact after the marker was added. By contrast, the main effect of ET on EB remained unsupported because its confidence interval included zero (β = -0.272; 95% CI [-0.486 - 0.090]). The main effect of ETL on EB also remained positive (β = .268, t = 2.348, p = 0.019; 95% CI [0.242, .444]).

The marker paths did not show meaningful evidence of method-related influence. The paths from M to EB**,** M to EGB**,** and M to ET were all non-significant, and their confidence intervals included zero. The same pattern was observed for the marker paths to the lower-order ETL dimensions. Thus, the marker did not explain meaningful variance in the substantive constructs. The comparison in Table 7 leads to two conclusions. First, the focal substantive paths remained stable in direction, size, and inference after the marker was introduced. Second, the marker paths themselves were not supported. Taken together, these findings suggest that CMV is unlikely to materially alter inference in this moderated mediation example.

Table 7: Comparison of baseline and marker-adjusted moderated mediation model

Path	Baseline β	Baseline 95% CI	Marker-adjusted β	Marker-adjusted 95% CI	Interpretation
EB → EGB	0.321	[0.224 - 0.430]	0.321	[0.222 - 0.430]	Stable
ETL × ET → EB	0.287	[0.242 - 0.411]	0.281	[0.100 - 0.408]	Stable; interaction retained
ETL → EGB	0.266	[0.163 - 0.366]	0.266	[0.161 - 0.366]	Stable
ET → EB	-0.273	[-0.495 - 0.171]	-0.272	[-0.486 - 0.090]	Not supported in either model
ETL → EB	0.267	[0.215 - 0.440]	0.268	[0.242 - 0.444]	Stable
M → EB	-	-	0.093	[-0.082 - 0.210]	Not supported
M → EGB	-	-	-0.017	[-0.159 - 0.089]	Not supported
M → ET	-	-	0.007	[-0.172 - 0.159]	Not supported

Source: Authors' compilation

5. Interpreting and Reporting Marker-variable Results in PLS-SEM

5.1 Interpreting Marker-variable Results

The implementation framework presented in Section 4 demonstrates that marker-variable diagnostics should be interpreted through two complementary questions: (1) Do the substantive relationships remain stable after the marker variable is introduced? and (2) Do the marker paths provide evidence of meaningful method-related influence? Rather than relying on a single statistical result, researchers should consider these two sources of evidence jointly when evaluating whether common method variance may have influenced the substantive conclusions of a PLS-SEM model.

The strongest indication of robustness occurs when substantive relationships remain stable following marker inclusion and the marker paths are unsupported. In this situation, the marker-variable analysis provides little evidence that the method-related variance captured by the selected marker materially influences the substantive conclusions. If marker paths are supported while substantive relationships remain stable, some method-related influence may be present, but it does not appear to alter the substantive interpretation. Conversely, substantial changes in the magnitude, direction, or inferential support of substantive relationships following marker inclusion warrant greater caution because the substantive conclusions may be sensitive to method-related variance.

These patterns should be evaluated primarily using bootstrapped confidence intervals alongside changes in the substantive path estimates. This joint interpretation is particularly important in mediation, moderation, and moderated mediation models, where relatively small changes in structural coefficients may alter the interpretation of indirect or interaction effects. Table 8 summarizes the principal empirical patterns and their corresponding interpretations.

5.2 Reporting Marker-variable Results

Transparent reporting is equally important. Because marker-variable analyses are often summarized in only a few sentences, reviewers may lack sufficient information to evaluate whether the procedure has been implemented appropriately. To improve transparency and reproducibility, researchers should report (1) the theoretical justification for selecting the marker variable, (2) the marker's measurement specification (reflective or formative), (3) how the marker was incorporated into the structural model, (4) comparisons between the

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baseline and marker-adjusted models, and (5) the interpretation of both the substantive and marker paths, including the corresponding bootstrapped confidence intervals.

Higher-order models require additional reporting considerations. When hierarchical constructs are estimated using the repeated-indicators approach, researchers should explicitly state that the marker variable was linked to the lower-order dimensions rather than directly to the higher-order construct. The rationale for this specification should also be reported so that readers can understand how the marker-variable procedure corresponds to the hierarchical measurement structure. Explicit reporting of this specification enables reviewers and readers to evaluate whether the marker-variable procedure has been implemented appropriately.

5.3 Boundary Conditions and Limitations

Marker-variable procedures should be interpreted as diagnostic evidence rather than definitive statistical tests of common method variance. A marker-variable analysis cannot demonstrate the complete absence of CMV, nor can it guarantee unbiased parameter estimates. A non-significant marker path may indicate that the selected marker does not adequately capture the relevant response tendencies, while different marker specifications may produce different levels of adjustment (Baumgartner, Weijters, & Pieters, 2021; Miller & Simmering, 2023; Simmering et al., 2015). The diagnostic value of the procedure therefore remains dependent on the conceptual relevance and measurement quality of the selected marker.

Marker-variable procedures also represent only one approach to evaluating potential method-related influence. They are best used alongside procedural remedies incorporated during research design and, where appropriate, complementary statistical diagnostics. The evidence generated by a marker analysis is therefore conditional on the selected marker and the specified model rather than a general demonstration that the data are free from method effects. Consequently, researchers should avoid statements such as *"CMV was eliminated," "CMV was ruled out,"* or *"CMV is no longer a concern."* A more defensible conclusion is that the marker-variable analysis did not provide evidence of material common method influence on the substantive findings under the specified model. Such wording better reflects the inferential role of the procedure and avoids overstating its diagnostic capability.

Overall, the value of marker-variable analysis lies not in establishing the absence of CMV, but in providing a transparent robustness assessment of whether substantive conclusions remain stable after a theoretically justified marker is incorporated into the model. When supported by appropriate marker selection, model specification, and reporting, the procedure can provide useful supplementary evidence regarding the robustness of findings in survey-based PLS-SEM research.

Table 8: Interpretation Framework for Marker-Variable Results in PLS-SEM

Empirical Pattern	Interpretation	Recommended Conclusion
Substantive paths stable; marker paths not supported	Little evidence of material method-related influence captured by the selected marker	Substantive conclusions appear robust under the specified marker-variable model.
Substantive paths stable; marker paths supported	Marker captures some method-related variance, but substantive conclusions remain unchanged	Substantive conclusions remain stable, but evidence of method-related influence should be acknowledged.
Substantive paths change after marker adjustment	Marker adjustment influences substantive inference	Interpret structural relationships cautiously and discuss possible method-related effects.
Marker selection is conceptually weak	Diagnostic validity is uncertain	Reconsider marker selection and avoid strong conclusions regarding CMV.

Source: Authors' compilation

6. Concluding Remarks

This paper provides a practical guide for implementing marker-variable procedures in PLS-SEM using SmartPLS. Rather than proposing a new statistical technique, it brings together existing methodological recommendations and translates them into a consistent workflow for marker selection, model specification, implementation, interpretation, and reporting. The central principle is that marker-variable evidence should not be interpreted from a single coefficient or significance test. Instead, researchers should consider whether substantive relationships remain stable after marker inclusion and whether the marker paths themselves indicate meaningful method-related influence. This provides a more transparent basis for evaluating the robustness of substantive conclusions.

The worked examples demonstrate how this logic can be applied consistently as model complexity increases. Across the direct-effect, mediation, and moderated mediation models, the substantive relationships remained largely stable following marker inclusion, while the marker paths were unsupported under the specified models. These results illustrate how baseline and marker-adjusted estimates can be compared without interpreting unsupported marker effects as proof that CMV is absent. Rather, the findings indicate that the substantive conclusions were robust to the particular marker-variable specifications examined in the illustrations.

An important practical implication concerns higher-order constructs estimated using the repeated-indicators approach. In such models, marker-variable implementation should reflect the hierarchical measurement structure. The guide therefore specifies marker paths at the lower-order construct level, where the indicators representing the hierarchical construct are located, rather than directly at the higher-order construct. This provides researchers with explicit guidance for an implementation issue that becomes increasingly relevant as marker-variable procedures are applied to more complex PLS-SEM models.

Marker-variable procedures nevertheless have important limitations. Their diagnostic value depends on the theoretical appropriateness and measurement quality of the selected marker, and unsupported marker paths cannot establish that data are free from common method variance. The illustrations in this paper are also based on a single dataset and are intended to demonstrate implementation rather than compare the statistical performance of alternative CMV procedures. Accordingly, the paper does not establish the relative superiority of marker-variable diagnostics over other approaches. Future research could use simulation studies and multiple empirical settings to examine the performance of alternative marker specifications under different levels and forms of method-related variance. Further work could also evaluate marker-variable implementation across alternative approaches to estimating hierarchical component models.

For applied researchers, the main recommendations are straightforward: select and justify the marker before analysis, ensure that it is conceptually independent but exposed to the relevant measurement environment, specify marker relationships consistently with the measurement structure of the model, compare substantive estimates before and after marker inclusion, examine marker paths directly, and report conclusions cautiously. Used in this way, marker-variable procedures provide a useful robustness diagnostic that complements sound research design and procedural remedies while improving the transparency of CMV assessment in survey-based PLS-SEM research.

Declaration on the Use of AI and Language-Editing Tools: The authors confirm that Grammarly was used solely for language editing, including improvements to grammar, clarity, readability, and linguistic expression. The research ideas, conceptual development, analysis and interpretation of all cases, arguments, conclusions, and overall intellectual contribution are entirely the authors' own work. No AI or language-editing tool was used to generate the study's ideas, conduct the analysis, and formulate the conclusions. The authors carefully reviewed and verified the final manuscript and take full responsibility for its accuracy, originality, integrity, and content.

Ethical Statement: This study draws on data previously collected in accordance with established ethical principles and guidelines for academic research. Participation in the original data collection was voluntary, and appropriate measures were taken to protect participants' confidentiality and anonymity. The present study uses the dataset to address a distinct research question and conceptual framework from another manuscript currently under review. The analysis, theoretical framing, interpretation, and conclusions presented in this study are specific to the current research objectives. The authors confirm that the data have been used responsibly and in accordance with applicable ethical standards.

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