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Moderated Mediation Analysis Using SmartPLS: A Tutorial for Business Researchers

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ABSTRACT

In regression models and structural equation modeling applications in business and management studies, conditional process analyses such as moderated mediation have become widely used methods in business research. They allow scholars to examine not only the mechanisms through which effects occur but also the conditions under which these mechanisms vary. Despite their increasing popularity, many researchers continue to struggle with the appropriate specification, estimation, and reporting of moderated mediation models. This editorial provides a step-by-step tutorial on conducting moderated mediation analysis using SmartPLS. We explain the conceptual logic underlying each model type and demonstrate how to specify and estimate them. We also clarify how conditional indirect effects should be examined and interpreted. In addition, we propose practical reporting guidelines covering model specification, measurement model evaluation, structural model assessment, and the interpretation of conditional indirect effects. This tutorial serves as a practical resource for business researchers seeking to conduct and report moderated mediation and conditional process analyses within linear regression and structural equation modeling frameworks.

Keywords: *Conditional process analysis, Mediator, Moderated mediation, Moderator, Regression analysis, Structural equation modeling, Quantitative methods*

INTRODUCTION

Relationships among phenomena in management and business research models are rarely linear or context-free. The same leadership behavior may inspire one team yet discourage another; the same organizational policy may succeed under one climate and fail under another. Understanding such contingencies requires analytical approaches that capture how and when theoretical mechanisms operate. Conditional process analysis, also referred to as conditional analysis, provides a comprehensive framework that integrates mediation with moderation. The objective is to explain the mediating mechanism through which an effect operates and to identify through moderation the conditions under which that effect changes in strength or direction (Hayes et al., 2017; Hayes, 2022). Within both regression and structural equation modeling traditions, this framework enables researchers to examine complex contingencies that conventional linear models may overlook (Sarstedt et al., 2020a). By combining moderation and mediation, conditional process analysis allows scholars to move beyond testing whether an effect exists to determining for whom, under what conditions, and through which pathways it unfolds (Sardeshmukh & Vandenberg, 2017; Igartua & Hayes, 2021; Hayes, 2022; Hair et al., 2026b). The increasing use of this approach represents an important step toward developing more contextualized theories in business research.

Recent methodological developments in management and business research emphasize that conditional process analysis is more than a statistical refinement (Vasist & Krishnan, 2024; Hayes, 2022). It provides an analytical framework for examining how and under which conditions relationships unfold. Conditional process analysis combines mediation and moderation in one model. It tests whether an indirect effect varies across levels of a moderator, thereby estimating conditional indirect effects. Compared with standard linear models, this approach allows explicit tests of context dependence and improves model specification and inference about causal mechanisms in organizational and business data.

The widespread adoption of conditional process analysis has been facilitated by computational tools that make complex models accessible to applied researchers. For more than a decade, the PROCESS macro for IBM SPSS and SAS (Hayes, 2022), which enables bootstrapping in these programs, has been a key tool for estimating mediation, moderation, and conditional process models in business research. However, as a regression-based framework relying exclusively on observed variables, PROCESS cannot model constructs (i.e., latent variables) or account for measurement error (Hayes et al., 2017). This limitation is particularly relevant in management and business research, where constructs such as leadership, engagement, trust, and satisfaction are inherently latent. Ignoring measurement error can bias indirect effect estimates and weaken construct validity and theoretical precision (Sardeshmukh & Vandenberg, 2017; Memon et al., 2018; Sarstedt et al., 2020a). In addition, estimating conditional relationships through separate regression equations may ignore shared variance among mediators or moderators, potentially introducing statistical bias and conceptual inconsistency. More specifically, as Cortina et al. (2019) note, a recurring weakness in the moderation and interaction literature is the failure to estimate full latent variable models. Researchers frequently rely on observed composites or scale averages, thereby neglecting measurement error and attenuating interaction effects. This simplification reduces statistical power and theoretical precision and may contribute to the weak or inconsistent findings often reported in studies of moderation and conditional processes (Sarstedt et al., 2020a). In contrast, SmartPLS 4 (Ringle et al., 2024) allows interactions among constructs to be modeled directly, preserving construct validity and providing more reliable and interpretable estimates of conditional relationships. SmartPLS provides both regression (e.g., Margalina et al., 2026) and structural equation modeling modules (e.g., Cheah et al., 2024; Cheah et al., 2026; Hair et al., 2026a) that support moderated mediation and conditional process analyses (Cheah et al., 2021; Hair et al., 2026b). Its ease of use, automated bootstrapping, and standardized output have reduced technical barriers for researchers without the need for advanced programming expertise.

The relationship between PROCESS and structural equation modeling (SEM) has been discussed from two methodological perspectives. Hayes, Montoya, and Rockwood (2017) argue that PROCESS and SEM are conceptually aligned when applied within their respective scopes:

PROCESS estimates mediation and moderation models using observed variables, whereas SEM extends this logic to constructs by incorporating measurement models and accounting for error. In contrast, Sarstedt et al. (2020a) contend that combining PROCESS and SEM within the same dataset—referred to as tandem analysis—is methodologically inconsistent because the approaches are based on different paradigms. PROCESS relies on separate regression equations, whereas SEM estimates all specified paths simultaneously. From this perspective, mediation and moderation involving constructs should be analyzed within an SEM analysis, particularly variance-based PLS-SEM, which accounts for measurement error and models complex relationships within a single structural system (Hair et al., 2026b). Taken together, these views reflect methodological progression rather than contradiction. Hayes et al. (2017) delineate the conceptual scope of PROCESS. However, for SEM, Sarstedt et al. (2020a) highlight that component-based SEM for mediation and conditional process analyses (e.g., by using the bootstrapping options in software applications such as the R package SEMinR or SmartPLS) directly provides the appropriate results—researchers should not use composite-based SEM in tandem with PROCESS (see also Memon et al., 2018), as the subsequent PROCESS analysis would entail flawed outcomes.

This editorial aims to provide a step-by-step tutorial on conducting conditional process analyses using SmartPLS, with specific attention to Type A and Type B conditional process models (for an illustration, see also the case study in Hair et al., 2026b). We explain the conceptual logic underlying each model type, demonstrate how to specify and estimate them in SmartPLS, and clarify how conditional indirect effects should be assessed and interpreted. In addition, the editorial proposes reporting guidelines covering model specification, measurement model evaluation, structural model assessment, and the interpretation of conditional indirect effects. The tutorial is intended to support business researchers in conducting and reporting conditional process analyses using PLS-SEM with greater rigor, transparency, and consistency.

KEY ELEMENTS OF CONDITIONAL PROCESS ANALYSIS

Understanding how and why organizational relationships unfold has long been central to management and business research. Yet human and organizational behaviors rarely follow simple, linear patterns. The same human resource practice that enhances performance in one context may have no effect, or even a negative one, in another. To capture such contingencies, researchers rely on three related analytical concepts: moderation, mediation, and conditional process analysis, an umbrella term for any analysis that includes both moderation and mediation. These models enable scholars to examine not only whether an effect exists but also how, when, and why it occurs.

Mediation models have become almost mandatory in contemporary business research, as they are widely regarded as essential for theoretical advancement (Bullock, Green, & Ha, 2010; Mathieu & Taylor, 2006; Memon et al., 2018). Mediation explains how or why one variable influences another by identifying the mechanism through which the effect operates (Baron & Kenny, 1986; MacKinnon, 2008; Preacher & Hayes, 2004; Shrout & Bolger, 2002). Rather than assuming a direct causal link between two variables, mediation focuses on the underlying mechanism that accounts for the observed relationship. A mediator provides the explanatory pathway through which an independent variable affects an outcome. For example, HR practices may not improve performance directly; instead, they may enhance employees' engagement, which in turn leads to higher performance. In this case, engagement functions as the mediator because it explains how supportive HR practices translate into improved outcomes. Similarly, in marketing contexts, advertising exposure may not directly increase purchases but may first strengthen brand trust, which subsequently drives buying decisions. Here, brand trust serves as the mediator linking advertising to customer behavior. By identifying such mechanisms, mediation analysis allows researchers to move beyond establishing that relationships exist to explaining the processes through which they operate.

Figure 1 illustrates a simple mediation model, which we draw on to help distinguish between direct and indirect effects. Direct effects are depicted by single arrows connecting two constructs. In Figure 1, the path labeled *c* represents the direct relationship between X and Y. Indirect effects, by contrast, involve a sequence of relationships operating through an intervening variable and are therefore represented by multiple arrows forming a causal chain. Specifically, X influences M through the *a* path, and M subsequently affects Y through the *b* path. The product of these two paths ($a \times b$) constitutes the indirect effect of X on Y via M. Accordingly, the mediating role of M is captured by the $a \times b$ term, which reflects the mechanism through which X affects Y beyond the direct path *c*. For more information, Zhao et al. (2010), Memon et al. (2018), and Nitzl et al. (2016) explain in detail how to run a mediation analysis.

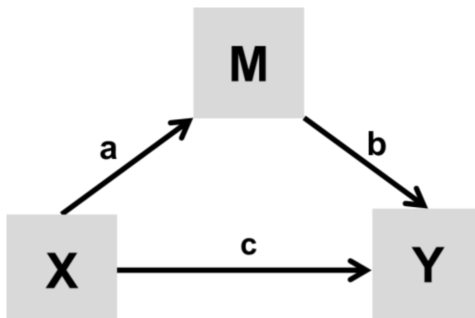

Figure 1: Mediation model

Moderation refers to the proposition that the strength or direction of the relationship between two variables depends on a third variable. In other words, a moderator indicates when an effect is stronger or weaker, or for whom it is more likely to occur (James & Brett, 1984; Baron & Kenny, 1986). By influencing the magnitude, or even the direction, of a relationship, a moderator helps explain why the same predictor can produce different outcomes under different conditions (Aguinis et al., 2017). As such, moderation is widely recognized as a key component of theory development in business and social science research, as it enhances the precision of scientific inquiry (Memon et al., 2019). For example, leadership support may strongly enhance employee engagement when employees perceive high levels of fairness, but it may have little effect when fairness perceptions are low. Similarly, in marketing contexts, a discount strategy may substantially increase sales among price-sensitive consumers while having minimal impact on those who prioritize exclusivity or premium experiences. In both cases, the moderator defines the contextual boundary within which the estimated relationship operates. By identifying such boundary conditions, moderation analysis enables researchers to clarify when and for whom a given effect holds, thereby providing a clearer understanding of organizational and behavioral phenomena.

In Figure 2, the path from X to Y represents the effect of X on Y when the moderator W is at its reference value (often the mean; for standardized and mean-centered variables, 0). Moderation occurs when the strength or direction of the effect from X on Y depends on the level of W, which is often represented by the interaction term X × W. Specifically, X influences Y through a path that is conditional on W, meaning that the effect of X on Y changes as W varies. The moderating role of W is captured by this interaction, reflecting the conditions under which X most strongly (or weakly) affects Y.

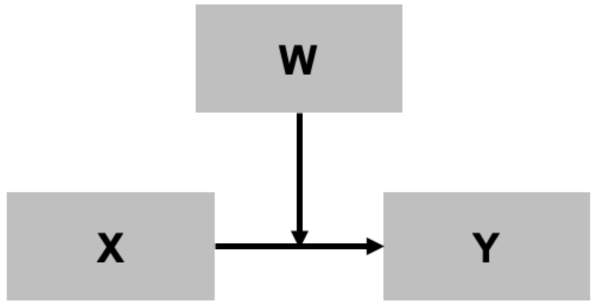

Figure 2: Moderation model

Conditional process analysis integrates mediation and moderation within a single analytical framework (Hayes, 2022). It encompasses models that simultaneously incorporate mediators and moderators. Conditional process analyses are particularly appropriate when theory suggests that the mechanisms through which one variable influences another, typically via one or more mediators, depend on the level of a moderating variable (Igartua & Hayes, 2021; Hayes, 2022). Whereas mediation explains how an effect occurs, moderation clarifies when or under what conditions that effect becomes stronger or weaker. Conditional process analysis combines these perspectives by examining whether and how a mediating process operates differently across levels of a moderator. In essence, it addresses the "when of the how," identifying the circumstances under which a mediating mechanism is more or less likely to function (Igartua & Hayes, 2021, p. 10). Accordingly, conditional process analysis encompasses a range of integrated models, including different forms of moderated mediation (e.g., Types A and B) as well as other configurations in which mediation and moderation processes operate simultaneously.

MODERATED MEDIATION

Type A

Because organizational behaviors are complex, mediating mechanisms often depend on contextual conditions. The same underlying process may not operate uniformly across individuals, groups, or situations, giving rise to moderated mediation analyses, which fall under the umbrella term conditional process analysis (Muller et al., 2005; Preacher et al., 2007). Moderated mediation Type A, also referred to as first-stage moderated mediation (Hair et al., 2026b) or conditional mediation Model A (Cheah et al., 2021), describes situations in which the indirect effect of an independent variable on an outcome through a mediator varies as a function of a moderator. Methodologically, moderated mediation Type A shifts attention from examining individual paths in isolation to evaluating the entire indirect effect and assessing how its magnitude changes across levels of the moderator (Hayes, 2022; Cheah et al., 2021; Hair et al., 2026b). This approach provides a finer-grained understanding of theoretical processes by demonstrating that mediating mechanisms are not universally applicable but instead differ across individuals, contexts, or boundary conditions. Figure 3 illustrates a graphical representation of a moderated mediation Type A model.

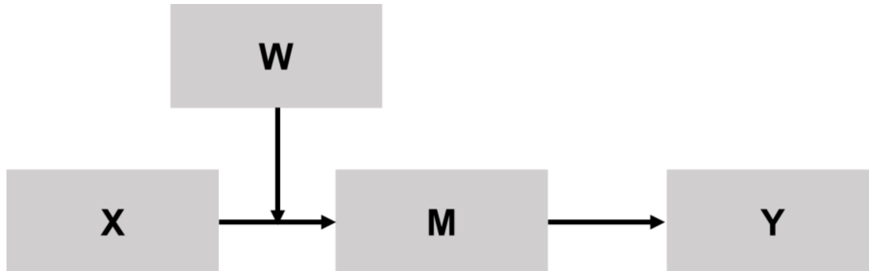

Figure 3: Moderated mediation Type A (example)

Suppose a firm introduces a training program intended to improve job performance by increasing employees' motivation to learn. In this model, training (X) fosters learning motivation (M), which in turn improves job performance (Y). However, this indirect effect does not operate uniformly across contexts. Rather, it depends on the level of supervisory support (W). When supervisory support is high, training is more likely to strengthen employees' motivation to learn, thereby translating into improved performance. In contrast, when supervisory support is low, training may fail to meaningfully enhance learning motivation, rendering the indirect effect on performance weak or negligible. This example illustrates moderated mediation Type A: the *how* of the effect (through learning motivation) depends on the *when* and *for whom* it operates—namely, the level of supervisory support.

A parallel example can be found in marketing: a brand uses emotional storytelling in its advertising to stimulate repeat purchases by cultivating consumers' emotional attachment. In this model, advertising (X) strengthens emotional attachment (M), which in turn promotes repeat purchase behavior (Y). However, this indirect effect does not operate uniformly across consumers. It is stronger among highly active social media users (W), who frequently engage with brand content, and weaker among those with limited online interaction. In this case, consumers' level of digital engagement moderates the indirect effect of advertising on repeat purchasing by influencing the strength of the relationship between advertising and emotional attachment. This example also illustrates moderated mediation Type A: the *how* of advertising effectiveness (via emotional attachment) depends on *when* and *for whom* it occurs, namely, the level of digital engagement. Overall, moderated mediation Type A underscores that identifying a mechanism is not sufficient on its own; the functioning of that mechanism often depends on contextual conditions. Even when the *how* of an effect is well established, it may not operate uniformly across individuals, groups, or settings. Recognizing this conditionality allows researchers to develop more robust and practically useful conclusions.

Type B

A conceptually distinct conditional process model is moderated mediation Type B, also referred to as conditional mediation Type B (Cheah et al., 2021) or second-stage moderated mediation (Hair et al., 2026b). Moderated mediation Type B arises when X influences M, but the effect of M on Y depends on a moderator (W). In other words, the M–Y relationship of the mediation process is moderated. Hayes (2022) describes this configuration as a situation in which the indirect effect of X on Y through M is contingent on the moderator's influence on the mediator–outcome relationship. Thus, the pathway through which X affects Y varies depending on the level of W, because W shapes the strength of the M–Y association. Figure 4 presents a graphical representation of a moderated mediation Type B model.

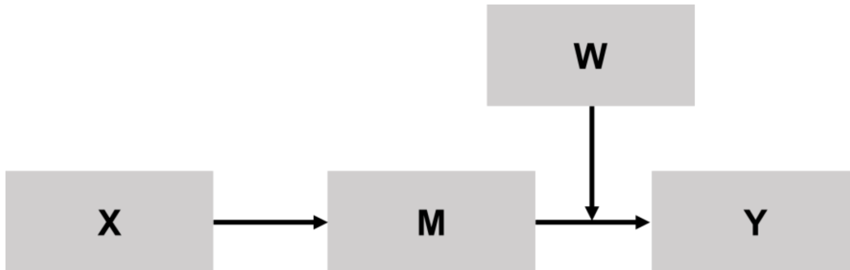

Figure 4: Moderated mediation Type B (example)

For example, training (X) may enhance employees' psychological empowerment (M), which in turn improves job performance (Y). However, the effect of empowerment on performance may be stronger when managerial trust (W) is high. In this case, managerial trust moderates the relationship between empowerment and performance—that is, the M–Y relationship of the mediation process. This example illustrates how contextual conditions shape the effectiveness of an underlying mechanism and, consequently, influence the overall relationship between training (X) and job performance (Y).

Many scholars question whether moderated mediation Type B offers meaningful advantages over Type A. In practice, both models often yield similar statistical information, suggesting that Type B rarely provides additional insight into when or how relationships operate (Cheah et al., 2021). Hayes (2022) likewise notes that this form of modeling can complicate interpretation by introducing an additional layer of complexity without necessarily enhancing theoretical clarity. More specifically, Hayes (2022) argues that the interaction term in moderated mediation Type B "has no substantive grounding in the measurement or manipulation process," and that the resulting indirect product term is substantively meaningless when the interaction itself lacks clear conceptual justification. Consequently, establishing a strong theoretical rationale for moderated mediation Type B is often challenging, making the model difficult to defend conceptually (Cheah et al., 2021). Accordingly, Hayes and Preacher (2013) and Hayes (2022) note that moderated mediation Type B may require strong theoretical justification, and they recommend conceptualizing conditional mechanisms within the broader and typically more interpretable framework of moderated mediation Type A. Type B models can still be useful, but researchers should demonstrate that they add explanatory value beyond what Type A provides.

In this illustration, we focus on moderated mediation Type A and Type B. However, moderation can, in principle, occur at multiple points of a mediation model simultaneously (e.g., see Hair et al., 2026b). A moderator may influence path *a* (the relationship between X and M), path *b* (the relationship between M and Y), or both in combination. Moreover, these moderated paths may be considered alongside moderation of the direct effect (c') between X and Y within the same conceptual framework. Extending moderated mediation models in these directions requires careful and thorough theoretical conceptualization to ensure clarity and interpretability. At the same time, such integrative approaches offer promising opportunities for advancing theory and represent a productive direction for future work. The same logic applies when incorporating multiple mediators, whether specified in individual, parallel, or serial mediation models, and when including multiple moderators and multi-way interaction effects among them (see Hair et al., 2026a, for further details).

Even though this editorial focuses on moderated mediation, it is important to distinguish between mediated moderation and moderated mediation, as they are often conflated despite being conceptually distinct. The conceptual difference lies in the research question. Moderated mediation asks whether a mediation process depends on a moderator—that is, whether the indirect effect of X on Y through M changes across levels of W. In contrast, mediated moderation asks why a moderation effect exists—that is, whether the interaction between X and W influences Y because it first changes M. In short, moderated mediation is about the conditionality of a mechanism, whereas mediated moderation is about the mechanism of a conditional effect (Hayes, 2022).

GUIDELINES

Based on the steps presented in Table 1, we highlight key reporting guidelines for the conditional process analysis, which involves moderated mediation models Type A and Type B. Researchers should begin by describing the *hypothesized conditional process model* before presenting the empirical results. Following Holland et al. (2017), we recommend that researchers explicitly include a diagram of their hypothesized model when integrating mediation and moderation. A visual representation clarifies the structural logic of the conditional process, makes the locus of moderation transparent, and minimizes the risk of conceptual misclassification.

Researchers also need to identify the predictor (X), mediator (M), outcome (Y), and moderator (W), and explain how these constructs relate to one another theoretically. In mediation terminology, the *a*-path captures the effect of X on M (X → M), whereas the *b*-path represents the effect of M on Y (M → Y). In a moderated mediation framework, the moderator conditions one or more points of this mediation process by influencing the *a*-path, the *b*-path, or both. Authors should explicitly specify where moderation occurs and clarify that their primary objective is to examine whether the indirect effect of X on Y through M varies across levels of W, using the zero level of W as the reference point, whereby zero represents the average outcome of W when working with mean-centered or standardized data.

In this context, researchers may include a simple slope analysis graph to illustrate how the relationship changes across different levels of the moderator (e.g., Holland et al., 2017; Hair et al., 2024). Importantly, once a moderator enters the model, the originally specified direct effect becomes a conditional effect that depends on the level of the moderator. Researchers are therefore encouraged to interpret and explain the results in a manner that accurately reflects the conditional nature of the estimated relationships (e.g., Hair et al., 2024; Hair et al., 2026a; Hair et al., 2026b). As a result, the conditional process model is theory-driven rather than merely derived from statistical output. For example, in a Type A model, researchers may argue that Satisfaction (X) influences Continuance Intention (Y) indirectly through Usage (M), and that this indirect effect depends on Need for Human Interaction (W), which moderates the relationship between X and M. In a Type B model, researchers may propose that Enjoyment (X) influences Usage (Y) through Satisfaction (M), and that Habit (W) moderates the relationship between M and Y, thereby conditioning the indirect effect.

After evaluating the reflective and formative measurement models in accordance with established guidelines and criteria, researchers should then assess the structural model. They can conduct this evaluation systematically by following the procedures outlined by Hair et al. (2026a), Hair et al. (2019), and Sarstedt et al. (2025). In contemporary PLS-SEM practice, predictive model assessment has become a central component of structural model evaluation (e.g., Sharma et al., 2023). Furthermore, researchers should perform robustness checks, as recommended by Sarstedt et al. (2020b) and Vaithilingam et al. (2024), to strengthen the credibility and validity of their findings and conclusions.

Table 1. Stepwise Procedure for Conditional Process Analysis

Preparation	Basic understanding and preparation	1. Develop both conceptual and statistical frameworks consistent with the hypothesized conditional process model 2. Establish sample size adequacy for analysis
Step 1	Specify the PLS path model	Ensure that the structural paths reflect the theoretically established model and that indicators are correctly assigned to their respective constructs in accordance with the a priori conceptualized type of measurement model.
Step 2	Model estimation and results assessment	Compute the results and apply the standard procedures for the assessment of the measurement models and the structural model in PLS-SEM
Step 3	Conditional process analysis (moderated mediation)	1. Assess the index of moderated mediation (ω)* 2. Assess the conditional indirect effect *Note.* *1. Researchers should conduct the structural analysis in accordance with their hypothesized conditional process model. While individual structural paths (e.g., direct, mediation, and moderation effects) may be examined separately, conclusions regarding moderated mediation should be based primarily on the index of moderated mediation.* *2. *For moderated mediation Type B, the index of moderated mediation (ω) may not be directly produced by the software and therefore requires manual estimation (e.g., using the product of relevant bootstrapped path coefficients and their sampling distribution).*

Next, researchers conduct the conditional process analysis. Notably, they do not need an additional PROCESS macro or a separate two-stage estimation procedure when using SmartPLS. SmartPLS estimates the specified conditional process model within the PLS-SEM framework (Hair et al., 2026b) and provides all relevant results directly in the bootstrapping output (Sarstedt et al., 2020a). In a Type A model, researchers assess whether the indirect effect of X on Y through M varies as a function of the moderator operating on the *a*-path. A significant index of moderated mediation (ω), supported by a confidence interval that excludes zero, indicates that the indirect effect systematically changes across levels of the moderator. Conclusions should be based on the index of moderated mediation (ω), rather than on individual interaction terms, as the index provides a direct test of the conditional indirect effect. Researchers should further examine the conditional indirect effects at low (−1 SD), mean, and high (+1 SD) levels of the moderator to interpret how the mediation mechanism strengthens or weakens across these levels.

In a Type B model, researchers evaluate whether the moderator conditions the *b*-path and thereby alters the indirect effect of X on Y through M. If the software does not directly report the index of moderated mediation (ω), researchers should compute it manually as the product of the relevant bootstrapped path coefficients. A statistically significant index (ω) with a confidence interval excluding zero provides evidence of a conditional indirect effect. Researchers should then analyze the conditional indirect effects at different levels of the moderator to determine whether the indirect effect becomes stronger or weaker as the moderator increases. Together, these steps ensure a theory-driven and methodologically sound presentation of moderated mediation results.

This editorial focuses on conditional process analysis through moderated mediation Type A and Type B within the PLS-SEM framework using SmartPLS. However, the guidelines and recommendations we offer extend beyond PLS-SEM. Researchers can apply the same conceptual logic and reporting principles to regression-based conditional process models, including those estimated with the PROCESS approach proposed by Hayes (2022). SmartPLS 4 supports these analyses in a regression context through its path modeling and PROCESS module, which offer bootstrapping procedures enabling researchers to estimate and test moderated mediation models with the same inferential logic (see also Margalina et al., 2026).

MODEL AND DATASET

In this editorial, we present two examples to illustrate how researchers can conduct moderated mediation analyses Type A and Type B in a step-by-step manner (for an illustration, see also the corporate reputation model case study presented in Hair et al., 2026b). The first example focuses on a moderated mediation Type A model (Figures 5a and 5b) and comprises four reflective constructs: (1) Need for Human Interaction (NHI), (2) Usage (USAGE), (3) Satisfaction (SAT), and (4) Continuance Intention (CONT). NHI is measured using four items, SAT with four items, and both USAGE and CONT with three items each.

The second example focuses on a moderated mediation Type B model (Figures 5c and 5d). This model comprises four variables: (1) Enjoyment (ENJOY) as the independent variable, (2) Satisfaction (SAT) as the mediator, (3) Usage as the dependent variable (USAGE), and (4) Habit (HABIT) as the moderating variable. ENJOY is measured using five items, SAT with four items, USAGE with three items, and HABIT with four items.

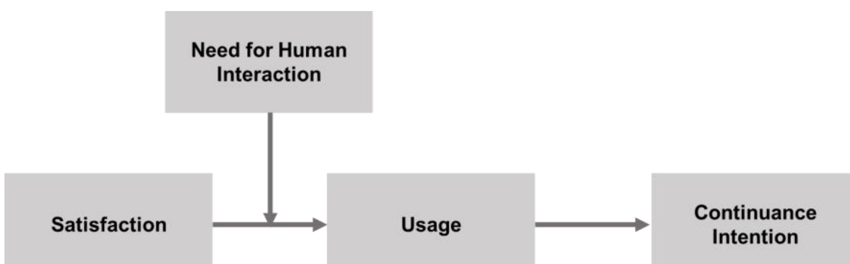

Figure 5(a): Moderated mediation Type A conceptual model

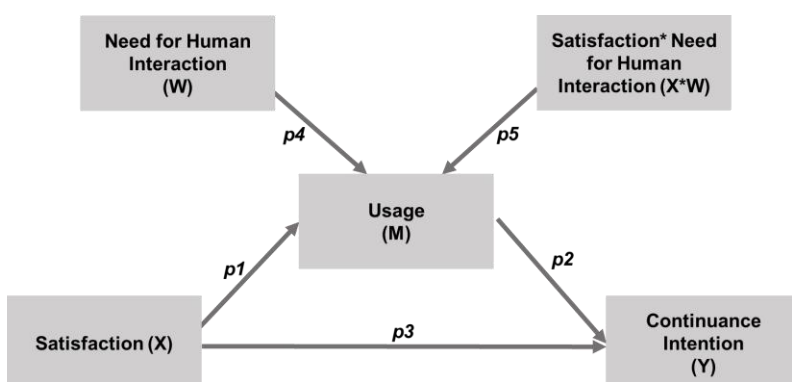

Figure 5(b): Moderated mediation Type A statistical model

Figure 5(c): Moderated mediation Type B conceptual model

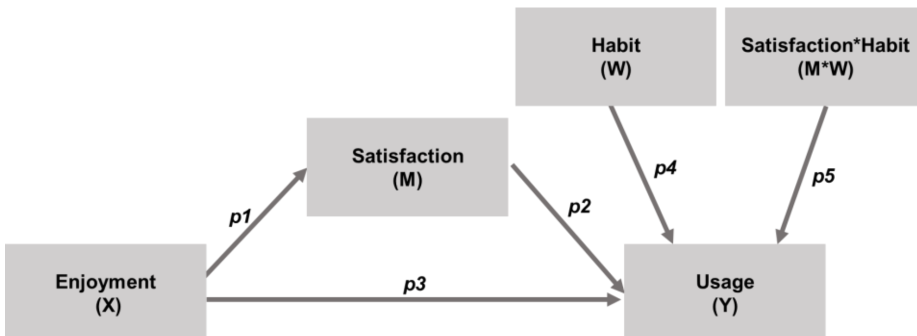

Figure 5(d): Moderated mediation Type B statistical model

Furthermore, we consider two analyses. The *first* analysis examines moderated mediation Type A. The key question is whether the indirect effect of Satisfaction on Continuance Intention transmitted through USAGE, varies as a function of the level of NHI. The focus is therefore on the conditional nature of the indirect effect rather than on any single direct path. In this example, we investigate whether the strength of the mediation process differs across individuals depending on their level of the moderator. The first analysis is guided by the focused hypothesis that captures the conditional mechanisms of a moderated mediation Type A analysis:

1. Hypothesis 1 for Moderated Mediation-Type A (Figures 5a & 5b): *The indirect effect of satisfaction on continuance intention through usage is conditional on need for human interaction, such that the indirect effect is weaker at higher levels of need for human interaction.*

The *second* analysis illustrates moderated mediation Type B. In this model, the causal sequence begins with ENJOY, which influences SAT, and SAT subsequently predicts USAGE. HABIT moderates the relationship between SAT and USAGE—that is, the M–Y relationship of the mediation process. The objective is to assess whether this moderating effect conditions the indirect pathway originating from Enjoyment, such that the strength of the mediated effect varies across levels of Habit. Similar to the first analysis, this analysis is also guided by a focused hypothesis, which captures the conditional mechanisms of a moderated mediation Type B:

2. Hypothesis 2 for Moderated Mediation-Type B (Figures 5c & 5d): *The indirect effect of enjoyment on usage through satisfaction is conditional on habit, such that the indirect effect is stronger at higher levels of habit.*

These hypotheses enable us to demonstrate, in a practical and intuitive manner, how moderated mediation (Types A and B) can be estimated, interpreted, and reported using simple models that researchers commonly encounter in empirical research.

For both examples, we draw on an artificial dataset comprising 384 observations. We generated data to resemble typical survey responses, exhibiting plausible correlations, acceptable reliability levels, and stable measurement properties. Because the dataset is simulated, it does not contain missing values or irregular response patterns. This allows us to concentrate directly on explaining the logic, estimation, and interpretation of moderated mediation analysis.

Before examining the moderated mediation Type A and Type B analyses, researchers should address two important considerations. *First*, they must follow the standard analytical sequence prior to conducting moderated mediation analysis. This includes establishing the adequacy of the measurement model by assessing internal consistency reliability, convergent validity, and discriminant validity (Hair et al., 2026a; Ramayah et al., 2018). These steps ensure that the constructs measured are reliable and valid so that any conditional effects observed at later stages are not artifacts of measurement errors. *Second*, hypotheses development and testing should be aligned with established practices in the literature. A common approach is to propose and test the main effects, the mediation pathway, and the moderation effect separately, followed by a formal assessment of the moderated mediation (Triana et al., 2024). This stepwise procedure creates a transparent analytical sequence and helps readers understand how the conditional effect emerges within the model. At the same time, we do not discourage researchers from formulating and testing moderated mediation (Type A or Type B) as a single overarching hypothesis when the prior research has already established the constituent relationships and the primary focus of the study lies in the conditional mechanism itself.

MODERATED MEDIATION TYPE A ANALYSIS

We illustrate the analysis of moderated mediation Type A using SmartPLS 4 (Ringle et al., 2024; see also Cheah et al., 2024) in a systematic, step-by-step tutorial. The assessment of the measurement and structural models in PLS-SEM follows state-of-the-art methodological guidelines, drawing on contemporary contributions by Guenther et al. (2025), Gudergan et al. (2025), Sarstedt et al., (2022), Sarstedt et al. (2023), Sarstedt et al. (2025), and Sharma et al. (2024).

Note that we focus on continuous moderators in this illustration. The reported result represents the conditional effect when the moderator equals zero, which typically corresponds to the average level of the moderator after standardization or mean centering. Thus, the conditional effect is interpreted relative to an average level of the moderator. The same logic, principles, and guidelines presented in this editorial also apply to binary moderators. However, standardization or mean centering is generally not appropriate for binary variables because their mean usually does not constitute a meaningful reference point. Instead, one category of the binary variable should be coded as zero and used as the reference category for interpreting the conditional effect. Becker et al. (2023) provide a detailed explanation of how binary moderator variables with a zero-reference category can be statistically modeled in PLS-SEM. SmartPLS automatically implements the necessary adjustments for binary moderators.

Step 1: Specify the PLS-SEM path model

Open SmartPLS 4 and create a new PLS-SEM project with an appropriate name. The first step is to specify the PLS-SEM path model. In our example, the model includes the following reflective indicators: Satisfaction (SAT1–SAT4), Usage (USAGE1–USAGE3), Continuance Intention (CONT1–CONT3), and Need for Human Interaction (NHI1–NHI4). Figure 6 displays the resulting PLS path model for the present study.

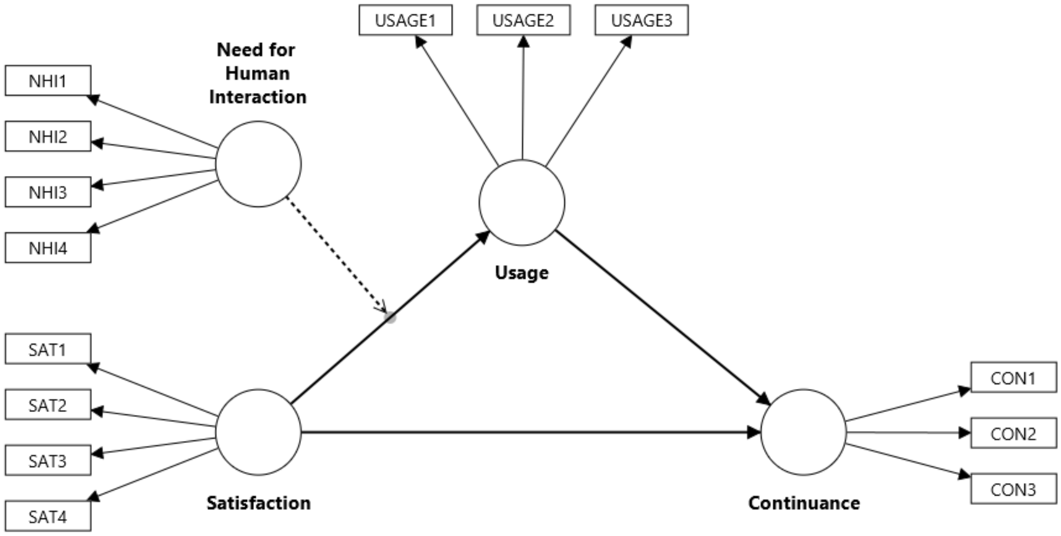

Figure 6: PLS-SEM path model

Step 2: Model estimation and results assessment

In Step 2, we estimate the model using the PLS-SEM algorithm (Wold, 1982) in the form introduced by Lohmöller (1989). This implementation represents the standard PLS model estimation procedure, which iteratively estimates the measurement and structural models by deriving latent variable scores as weighted aggregates of their indicators. The estimation is conducted using SmartPLS (Ringle et al., 2024), which applies this algorithm to obtain path coefficients, outer loadings, and construct scores. To assess the moderation effect, we apply the two-stage approach for modeling interaction terms in PLS-SEM (Becker et al., 2018), as operationalized in SmartPLS. In the first stage, the baseline model is estimated without the interaction term in order to obtain latent variable scores for the predictor (X) and moderator (W) constructs. In the second stage, these estimated latent scores are used to construct the interaction term by multiplying the predictor (X) and moderator (W) scores. The interaction construct is then included in the structural model and the model is re-estimated to assess the significance and strength of the moderation effect. This procedure reduces potential estimation bias and is particularly suitable when constructs are measured reflectively and when the research model contains complex interactions (Becker et al., 2018).

The results assessment begins with the evaluation of the measurement models, followed by the assessment of the structural model. Researchers can conduct this evaluation systematically by following the procedures outlined by Hair et al. (2026a), Hair et al. (2019), and Sarstedt et al. (2025). In particular, predictive model assessment has become an essential component of contemporary PLS-SEM evaluation (e.g., Sharma et al., 2023). In addition, researchers are encouraged to perform robustness checks, as recommended by Sarstedt et al. (2020b) and Vaithilingam et al. (2024), to further strengthen the validity of their findings and conclusions.

The SmartPLS project export (Type A) is available via the Google Drive link provided at the end of this editorial. After importing the project into SmartPLS, users can estimate the PLS-SEM results directly. The bootstrapping option in SmartPLS enables significance testing of the model estimates, while the $PLS_{predict}$/CVPAT module provides the necessary output for predictive model assessment. Although we do not report the detailed results here, they meet the relevant evaluation criteria and can therefore be considered satisfactory.

Step 3: Conditional process analysis (moderated mediation Type A)

The conditional process analysis for moderated mediation Type A in SmartPLS 4 (Ringle et al., 2024) follows the description provided by Hair et al. (2026a; see also Cheah et al., 2021; Sarstedt et al., 2020a). To assess the significance of the model estimates, bootstrapping is conducted in SmartPLS 4 by selecting *Calculate → Bootstrapping*. In the bootstrapping dialog box, the number of subsamples should be set to 5,000 or 10,000. A minimum of 5,000 subsamples is generally recommended to obtain stable estimates, whereas 10,000 subsamples may provide greater precision, particularly when examining indirect or weaker conditional effects (Figure 7). Under *Amount of Results*, select the *"Most important (faster)"* option to generate the required output. For hypothesis testing, the *one-tailed* test option is appropriate when the moderated mediation hypotheses specify a directional conditional effect. In contrast, a two-tailed test may be used for exploratory hypotheses without a specified direction. All other settings can remain at their default values. After clicking *Start calculation*, SmartPLS performs the bootstrapping procedure and generates the structural model results. Processing time depends on the model's complexity, the number of subsamples, the number of variables, and the available computing power.

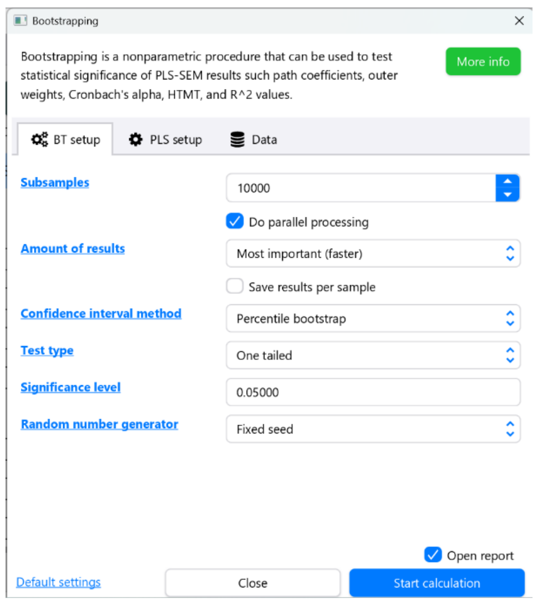

Figure 7: Bootstrapping parameter setting

Once the software generates the output, researchers can review and interpret the index of moderated mediation (ω). SmartPLS reports this value directly in the output under the *Specific indirect effects* section. The index of moderated mediation is computed as $\omega = p_2 \times p_5$ (see Figure 5b). The index indicates the linear change in the indirect effect associated with a one-unit increase in the moderator. The index can be located in the *Specific indirect effects* output (Figures 8a and 8b). A significant index ($p < 0.05$) indicates that the strength of the indirect effect varies depending on the level of the moderator. In contrast, a non-significant index ($p \geq 0.05$) suggests that the indirect effect remains constant across levels of the moderator.

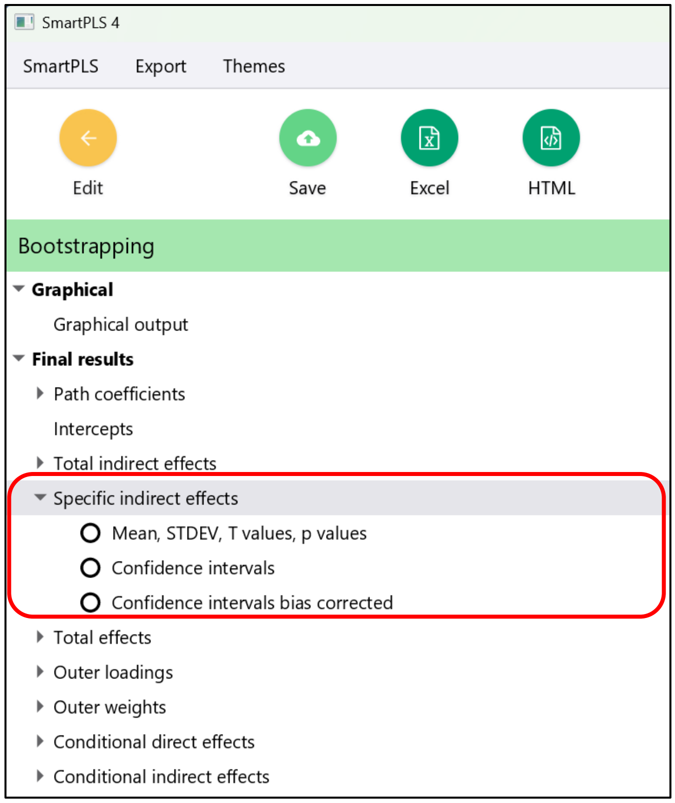

Figure 8(a): Location of specific indirect effect results in SmartPLS

Specific indirect effects - Mean, STDEV, T values, p values

	Original sample (O)
Need for Human Interaction x Satisfaction -> Usage -> Continuance	-0.042
Need for Human Interaction -> Usage -> Continuance	0.044
Satisfaction -> Usage -> Continuance	0.301

Figure 8(b): Index of moderated mediation (Type A)

To enhance robustness and transparency, we encourage researchers to report confidence intervals alongside the significance test. In this tutorial, we report the bootstrap confidence intervals of the percentile approach (i.e., using 10,000 bootstrap subsamples). As an alternative, researchers can report bias-corrected confidence intervals of the percentile approach, which adjust the bootstrap percentile cutoffs to account for discrepancies between the bootstrap distribution and the true parameter, producing more accurate interval estimates. As illustrated in Figures 8c and 8d, the results of the present study reveal a significant index ($p < 0.05$), with a confidence interval that excludes zero. This finding indicates that the moderator meaningfully influences the strength of the indirect effect. Substantively, individuals' levels of Need for Human Interaction significantly shape how Satisfaction translates into Continuance Intention through Usage.

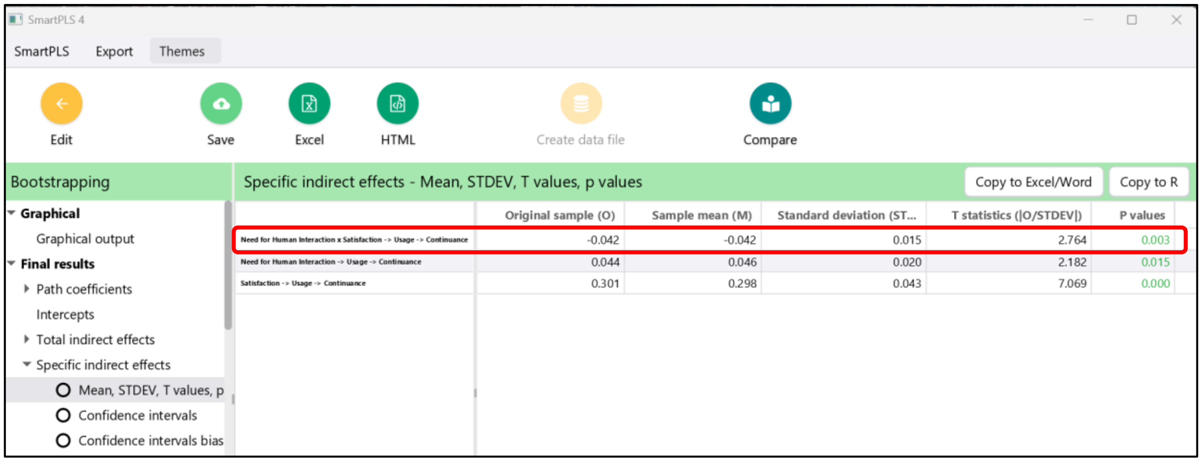

Figure 8(c): The specific indirect effect of the moderated mediation Type A

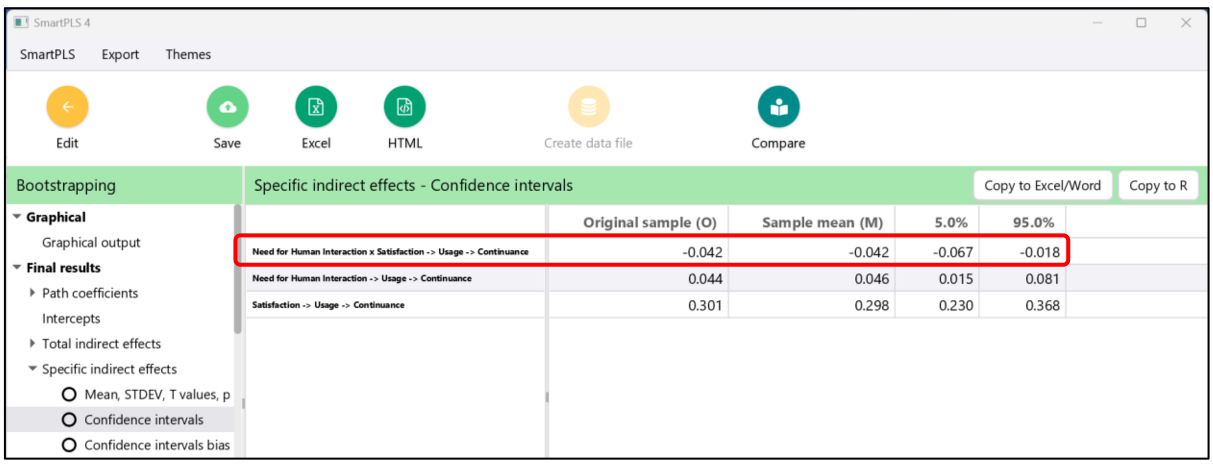

Figure 8(d): Estimate and interpret the confidence intervals

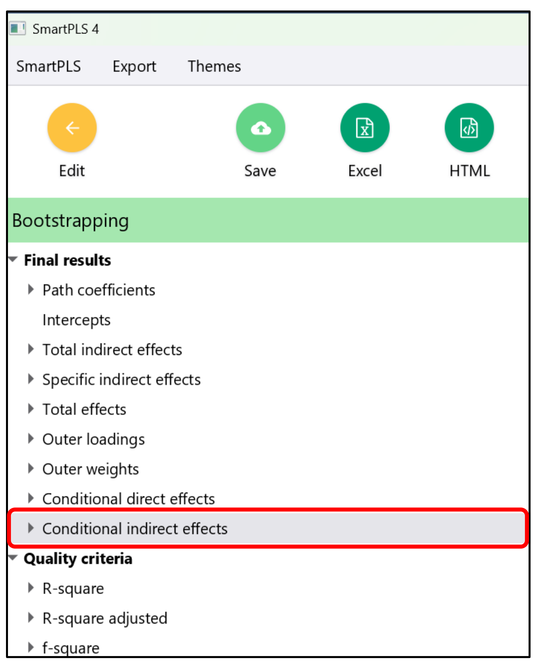

Figure 9(a): Conditional indirect effects in SmartPLS

The next step involves examining the conditional indirect effects. The conditional indirect effect at a given level of W is computed as $p_1 \times p_2 + p_2 \times p_5 \times W$ (see Figure 5b). The analysis of the conditional indirect effect is crucial because it reveals how the magnitude of the indirect effect changes across different levels of the moderator, which clarifies whether the mediation process operates consistently or varies across subgroups. In other words, it clarifies how and for whom the mediated relationship unfolds. SmartPLS conveniently reports these results by default. Researchers can locate them under the *Conditional indirect effects* section in the *Final results* output (Figure 9a). This procedure is commonly referred to as spotlight analysis (Spiller et al., 2013).

SmartPLS presents the conditional indirect effects at three levels of the moderator: −1 standard deviation (SD), the mean, and +1 SD (Figures 9b and 9c). These values correspond to substantively distinct groups within the data. The −1 SD value represents respondents with relatively low levels of the moderator, the mean reflects individuals with average levels, and the +1 SD value captures respondents with relatively high levels of the moderator. Evaluating the indirect effect at these three points allows researchers to determine whether the mediation mechanism remains stable across the full range of the moderator or whether its strength systematically increases or decreases as the moderator varies.

As illustrated in Figures 9(b) and 9(c), the conditional indirect effect decreases in magnitude when the moderator NHI is one SD above the mean ($\beta = 0.259$) compared to one SD below the mean ($\beta = 0.343$). This pattern indicates that the mediating role of Usage is stronger among individuals with a lower need for human interaction. Moreover, the conditional indirect effects at low (−1 SD), moderate (mean), and high (+1 SD) levels of the moderator are all statistically significant, as their confidence intervals lie entirely above zero at each level. This finding suggests that although the strength of the indirect effect varies, it remains statistically meaningful across the full range of the moderator. Taken together, these results provide evidence for the presence of a conditional mediation effect. The next step is to report these findings in a structured manner.

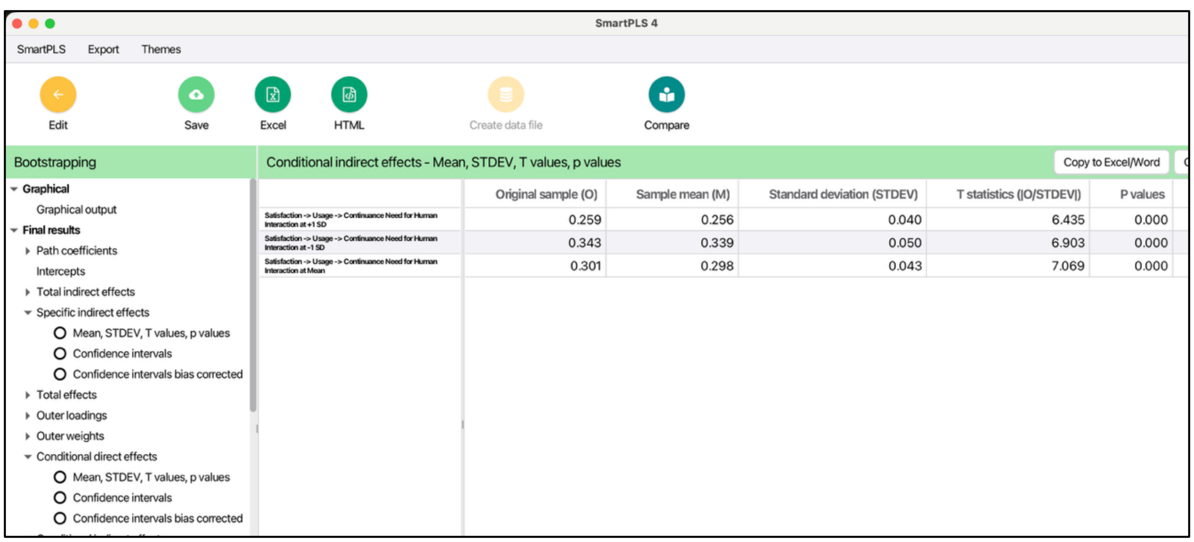

Figure 9(b): Estimate and interpret the different levels of moderated mediation Type A results

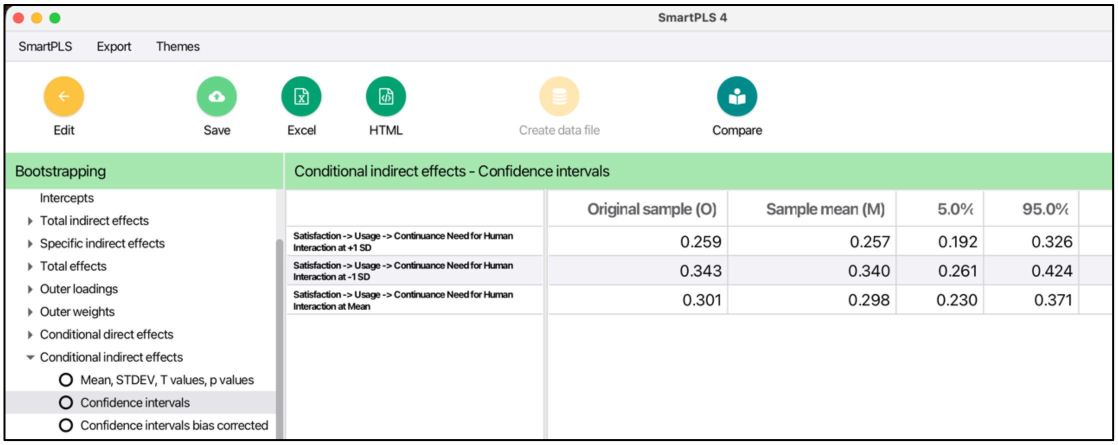

Figure 9(c): Estimate and interpret the confidence intervals

Preparing result tables

We recommend reporting two sets of result tables. First, present the index of moderated mediation. A statistically significant index indicates that the indirect effect systematically varies as a function of the moderator. Second, report the conditional indirect effects, which display the magnitude and significance of the indirect effect at different levels of the moderator (e.g., −1 SD, mean, +1 SD). Tables 2 and 3 provide illustrative examples of these reporting formats.

Table 2: Index of Moderated Mediation (Type A).

Relationship	Beta	STDEV	*t*	*p*	CI LL (5%)	CI UL (95%)
*Need for Human Interaction x Satisfaction → Usage → Continuance	-0.042	0.015	2.764	0.003	-0.067	-0.018

*Note: *A significant index indicates that the indirect effect varies systematically as a function of the moderator.*

Table 3: Conditional Indirect Effect

Levels	Beta	STDEV	*t*	*p*	CI LL (5%)	CI UL (95%)
Satisfaction → Usage → Continuance Need for Human Interaction at +1 SD	0.259	0.040	6.435	0.000	0.192	0.326
Satisfaction → Usage → Continuance Need for Human Interaction at Mean	0.301	0.043	7.069	0.000	0.230	0.371
Satisfaction → Usage → Continuance Need for Human Interaction at -1 SD	0.343	0.050	6.903	0.000	0.261	0.424

When space constraints exist, researchers may combine these results into a single table. However, we recommend reporting the index of moderated mediation and the conditional indirect effects separately to preserve conceptual clarity and enhance interpretability. We provide detailed systematic reporting guidelines at the end of this editorial.

MODERATED MEDIATION TYPE B ANALYSIS

As with moderated mediation Type A, we follow similar steps in SmartPLS to run the moderated mediation Type B model, except for assessing the index of moderated mediation and the conditional indirect effects. Both the index and the conditional indirect effects require manual calculation using an external worksheet that we will explain in detail. Please note again that we focus on continuous moderators in this step-by-step tutorial (see section Moderated Mediation Type A Analysis).

Step 1 and Step 2: Model specification, estimation and results assessment

First, set up the path model using indicators from enjoyment (ENJOY1 to ENJOY5), satisfaction (SAT1 to SAT4), usage (USAGE1 to USAGE3), and habit (HABIT1 to HABIT4). Figure 10 presents the PLS path model for the moderated mediation analysis Type B.

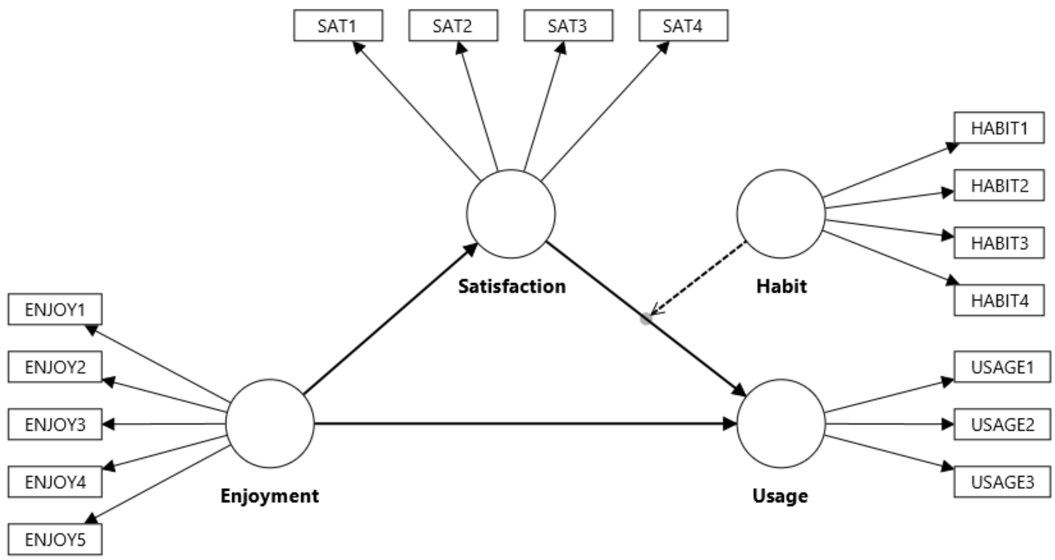

Figure 10: PLS path model

The SmartPLS project export (Type B) is available via the Google Drive link provided at the end of this editorial. After importing the project into SmartPLS, users can estimate the PLS path model directly. SmartPLS supports significance testing through its bootstrapping procedure and provides the required output for predictive model assessment via the $PLS_{predict}$/CVPAT module. Although we do not report the full set of results here, the estimates meet the relevant evaluation criteria and support the adequacy of both the measurement and structural model assessments.

Step 3: Conditional process analysis (moderated mediation Type B)

Again, the conditional process analysis for moderated mediation Type B in SmartPLS (Ringle et al., 2024) follows the description provided by Hair et al. (2026a; see also Cheah et al., 2021; Sarstedt et al., 2020a). To assess the significance of the effects, bootstrapping is conducted in SmartPLS by selecting *Calculate → Bootstrapping*. In the dialog box, set the number of subsamples to 5,000 or 10,000. We generally recommend at least 5,000 subsamples to obtain stable estimates, whereas 10,000 subsamples provide greater precision, particularly when testing indirect or weaker conditional effects (Figure 11). Under *Amount of results*, select *Most important (faster)* to generate the required output. In addition, check the option *Save results per sample*, as this setting is essential for the manual computation of the index of moderated mediation.

The *one-tailed* test option is appropriate when the moderated mediation hypotheses specify a clear directional conditional effect. By contrast, a two-tailed test may be used for exploratory hypotheses without a specified direction. All remaining settings can be left at their default values. After clicking *Start calculation*, SmartPLS performs the bootstrapping procedure and generates the structural model results. Processing time depends on the model's complexity, the number of subsamples, the number of variables, and the available computing power.

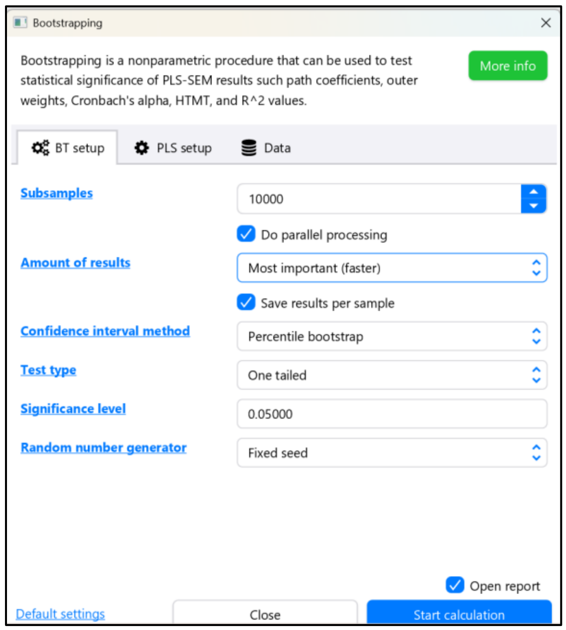

Figure 11: Bootstrapping parameter setting

After generating the bootstrapping output, researchers must calculate the index of moderated mediation (ω) for Type B. We compute this index as $\omega = p_1 \times p_5$, where p_1 represents the path from the independent variable (X) to the mediator (M), and p_5 represents the path from the interaction term (M × W) to the dependent variable (Y). Figure 5d visually depicts these relationships.

Unlike moderated mediation Type A, SmartPLS does not report the index of moderated mediation for Type B directly. The software provides only the individual path estimates (direct and indirect effects). Therefore, researchers must compute the Type B index manually using a spreadsheet. To do so, download the *Moderated mediation example* file from the SmartPLS website (i.e., https://www.pls-sem.net/downloads/additional-useful-downloads/). The file includes two worksheets; use the "Example 2" worksheet to perform the manual calculation of the Type B index. A simplified version of a comparable worksheet is also available via the referenced Google Drive link (see full URL at the end of this editorial).

After downloading the Excel file, researchers should copy the sample-level path coefficients (p_1 and p_5, Figure 5d) from SmartPLS and paste them into the corresponding fields in the worksheet. These sample-level estimates are available only if the *Save results per sample* option was selected in the bootstrapping dialog box (Figure 12), and they can be located in SmartPLS under *Bootstrapping Results* → *Algorithm* → *Samples* (Figure 13). To identify which coefficient corresponds to p_1 and which to p_5, researchers should refer to the structural model specification, as illustrated in Figure 5d. Once the correct values have been entered, the worksheet automatically computes the index of moderated mediation (ω) for Type B.

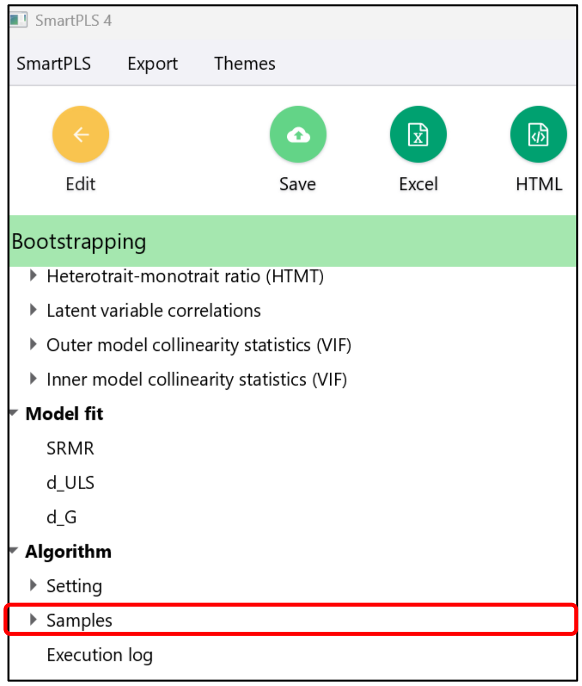

Figure 12: Location for sample-level path coefficients

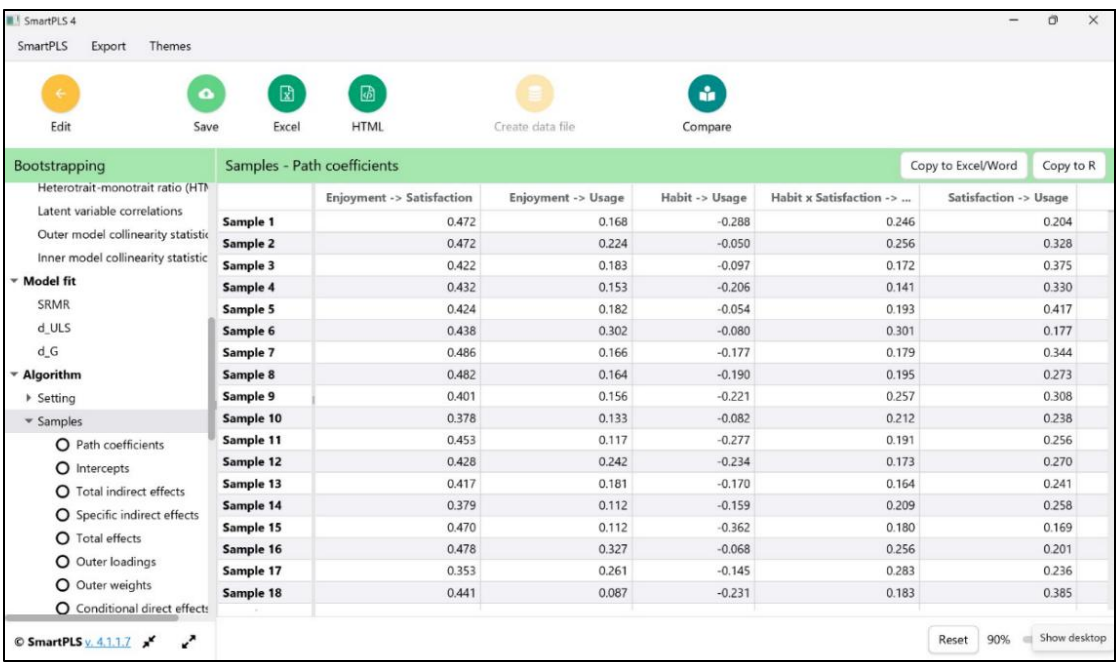

Figure 13: Extracting sample-level path coefficients from SmartPLS

As shown in Figure 14, the computed index of moderated mediation ($p_1 \times p_5$) is statistically significant ($\beta = 0.089$, $p = 0.001$), and the 95% confidence interval excludes zero (CI [0.045, 0.139]). This result provides evidence of a conditional indirect effect, indicating that the indirect effect of X on Y through M varies as a function of the moderator on the M–Y path of the mediation process.

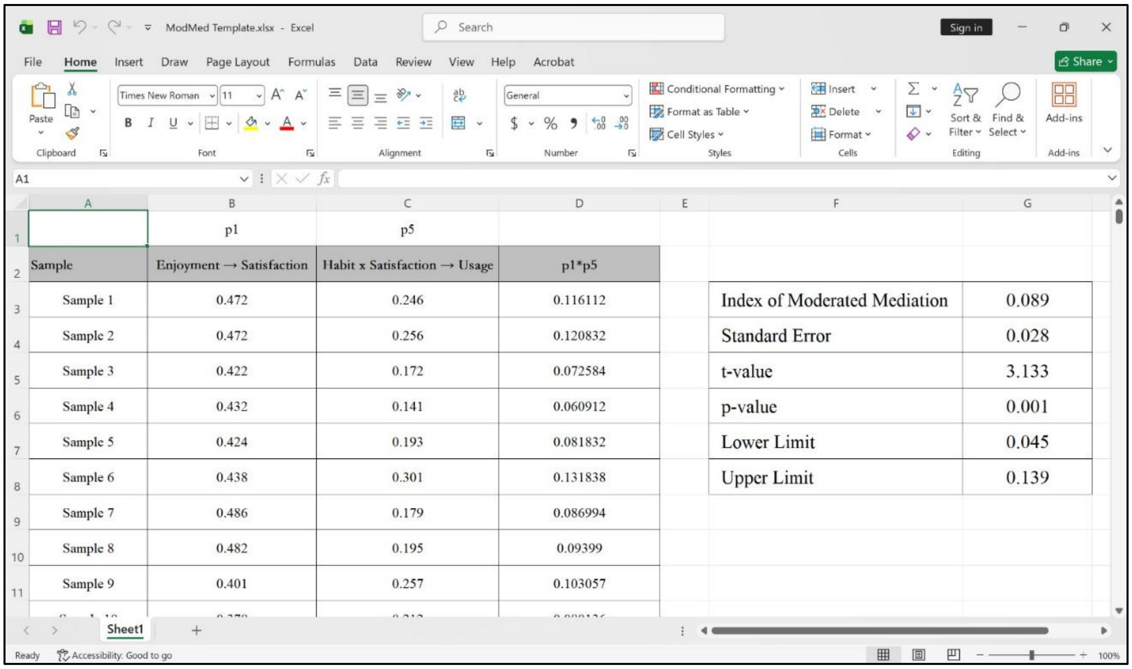

Figure 14: Index of moderated mediation Type B (manual estimation)

Next, we examine the effect of the mediator (M) on the outcome (Y) across different levels of the moderator. SmartPLS provides these results directly under the *Conditional indirect effects* section in the final output. Figures 15a and 15b show that the conditional indirect effect of Enjoyment on Usage through Satisfaction increases as Habit increases. Specifically, the indirect effect is strongest when Habit is one SD above the mean (β = 0.205) and remains significant at the mean level of Habit (β = 0.118). In contrast, the indirect effect is not significant when Habit is one SD below the mean (β = 0.030). These findings indicate that the indirect effect of Enjoyment on Usage via Satisfaction depends on Habit. As Habit increases, the indirect relationship between Satisfaction and Usage strengthens, which amplifies the overall indirect effect. This pattern provides empirical support for our a priori hypothesis.

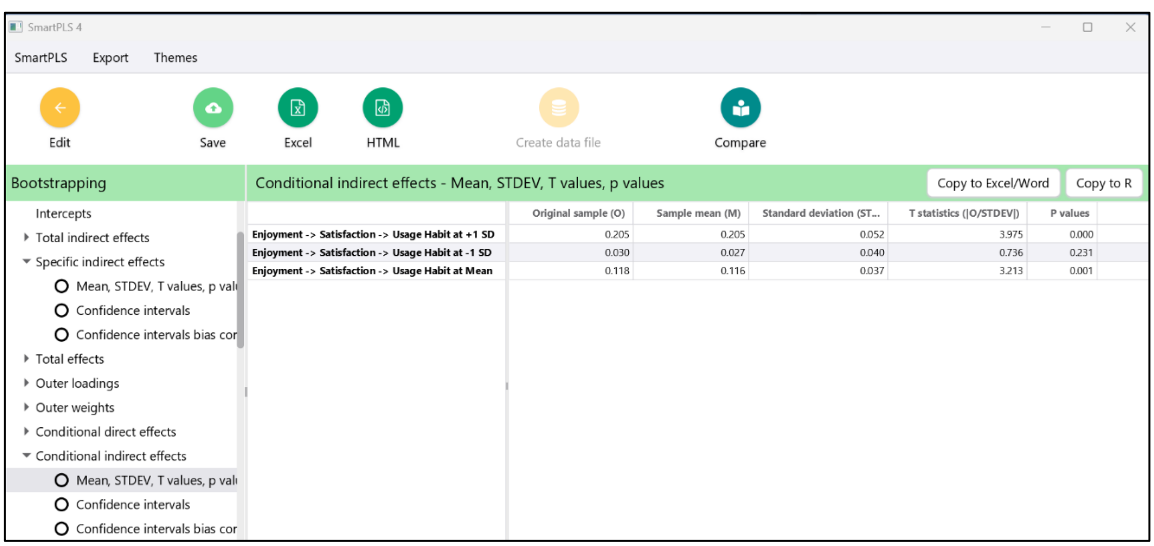

Figure 15(a): Estimating the significance of the conditional indirect effect at different levels of the moderator

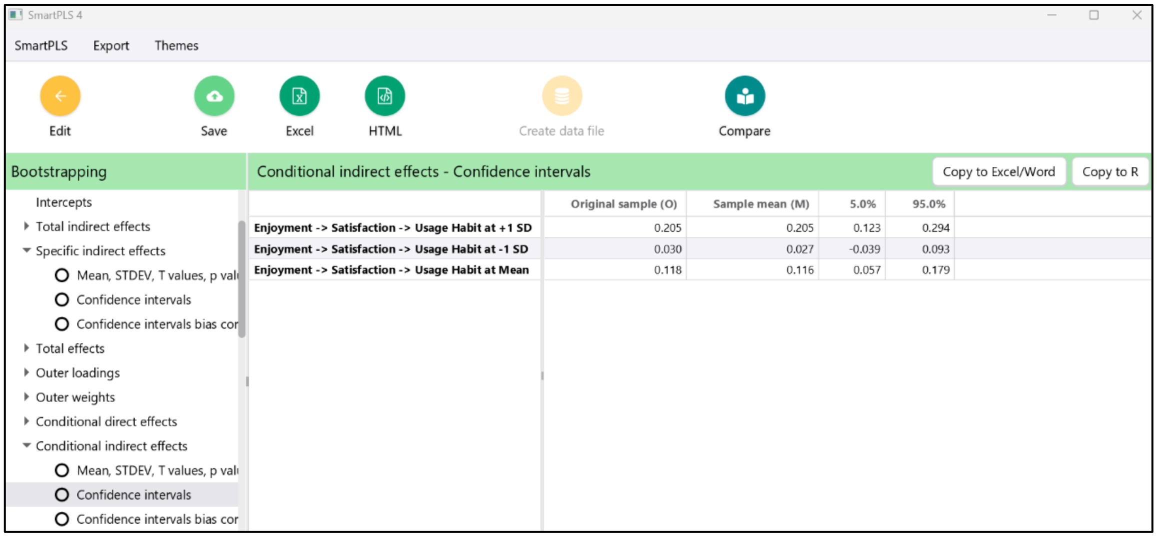

Figure 15(b): Examining confidence intervals at different levels of the moderator

Preparing result tables

As with moderated mediation Type A, reporting Type B results requires two sets of tables. First, researchers should report the index of moderated mediation, which they manually calculated using the Excel worksheet. A statistically significant index indicates that the indirect effect systematically varies as a function of the moderator. Second, researchers should present the conditional indirect effects at different levels of the moderator (e.g., −1 SD, mean, +1 SD). Tables 4 and 5 illustrate these recommended reporting formats. We advise reporting these results separately to maintain conceptual clarity, although authors may combine them into a single table when space constraints require.

Table 4: Index of Moderated Mediation Type B (Manually Estimated)

Relationship	Beta	STDEV	*t*	*p*	CI LL (5%)	CI UL (95%)
*Habit x Satisfaction → Usage	0.089	0.028	3.113	0.001	0.045	0.139

**Note: A significant index indicates that the indirect effect varies systematically as a function of the moderator.*

Table 5: Conditional Indirect Effect

Levels	Beta	STDEV	*t*	*p*	CI LL (5%)	CI UL (95%)
Enjoyment → Satisfaction → Usage Habit at +1 SD	0.205	0.052	3.975	0.000	0.123	0.294
Enjoyment → Satisfaction → Usage Habit at Mean	0.118	0.037	3.213	0.001	0.057	0.179
Enjoyment → Satisfaction → Usage Habit at -1 SD	0.030	0.040	0.736	0.231	-0.039	0.093

FINAL NOTE

Conditional process analysis, particularly through moderated mediation models, is now widely used in business and management research. This editorial provides a step-by-step tutorial for conducting moderated mediation analysis using SmartPLS. We explain the conceptual logic of Type A and Type B models, demonstrate how to specify and estimate them in SmartPLS, and show how to evaluate and interpret the results. Although we focus on Types A and B, moderation can occur at multiple points within a mediation model. A moderator may influence the *a* path (X → M), the *b* path (M → Y), or both simultaneously. Researchers may also examine these moderated paths alongside the moderation of the direct effect (c′) between X and Y.

We also propose reporting guidelines to improve the quality and reproducibility of PLS-SEM-based moderated mediation research, with attention to Type A and Type B models. Our guidelines cover model specification, measurement model evaluation, structural model assessment, and the interpretation and reporting of conditional indirect effects. In doing so, this tutorial aims to support business researchers in conducting and reporting moderated mediation analyses in PLS-SEM with greater methodological care.

A common misinterpretation of Type B models is the assumption that moving the moderator from the X → M path to the M → Y path automatically converts the model into mediated moderation. This is incorrect. Relocating the moderator does not change the fundamental nature of the conditional process. As long as the moderator conditions the indirect effect through one of its constituent paths, the model remains a form of moderated mediation rather than mediated moderation. Confusing Type B with mediated moderation reflects a misunderstanding of conditional process logic and leads to labeling and interpretation errors. We also acknowledge that many scholars do not generally recommend moderated mediation Type B because it often provides limited theoretical insight beyond what Type A models can already explain. We do not rule out Type B models, but researchers who use them should justify them with strong theoretical reasoning and articulate what explanatory value they add over a Type A specification.

We selected SmartPLS as the editorial platform because it provides an integrated and practical environment for exploratory quantitative analysis and for estimating moderated mediation models efficiently and robustly (Cheah et al., 2021; Hair et al., 2026b). This choice does not limit researchers' methodological options, and other software tools may be equally suitable. Applying analytical techniques without understanding their limitations can undermine empirical conclusions. Most importantly, strong analyses cannot compensate for weak theory. Whether researchers use Type A or Type B moderated mediation, they must ground their models in well-articulated theoretical reasoning, explain the relationships under investigation, and specify the expected conditional patterns. Beyond reporting statistical significance, researchers should demonstrate how their models advance knowledge and inform practice.

Developing competence in conditional process analysis requires ongoing reading of the methodological literature. Baron and Kenny (1986) provide a foundational framework for mediation and moderation, and Zhao et al. (2010) extend this perspective by clarifying common misconceptions about indirect effects. Researchers can deepen their understanding through the influential work of Hayes and Preacher (2013), Hayes (2015, 2022), Hayes et al. (2017), and Hayes and Rockwood (2020), as well as the accessible overview by Igartua and Hayes (2021). Scholars working with latent variables should consult Sarstedt et al. (2020a), who explain how to estimate conditional process models within composite-based SEM frameworks such as PLS-SEM. Applied methodological contributions by Becker et al. (2018), Rasoolimanesh et al. (2021), Cheah et al. (2021), Xu and Shiau (2026), and earlier editorials by Memon et al. (2018, 2019) further strengthen rigorous application and clarify recurring misunderstandings. A recent contribution by Hair et al. (2026b) provides detailed guidelines on moderated mediation and its various model specifications, offering a deeper and more contemporary understanding of conditional process analysis within PLS-SEM. The authors extend the discussion beyond models with continuous moderators and provide practical guidance for estimating and interpreting conditional process analysis with categorical moderators. Finally, although this editorial focused on PLS-SEM using SmartPLS, the guidelines apply to regression-based analyses following the PROCESS logic of Hayes (2022). SmartPLS supports this through its path analysis and PROCESS module, which uses bootstrapping-based inference.

SMARTPLS PROJECT EXPORT (TYPE A)

https://drive.google.com/file/d/1ykXZrD07-v7BwOBL7lwsoi616uRs-AYm/view?usp=drive_link

SMARTPLS PROJECT EXPORT (TYPE B)

https://drive.google.com/file/d/1KhGT-wX5zfWW0QhfBP0Wg0IZUIbIOmrd/view?usp=drive_link

SMARTPLS MODERATED MEDIATION TYPE B INDEX ESTIMATION SHEET

https://drive.google.com/drive/folders/1uldopCKrEZIxbQZYTr5lI8-dlxnLZdaf?usp=sharing

DECLARATION

This research uses the statistical software SmartPLS (https://www.smartpls.com). Christian M. Ringle is a co-founder and co-developer of SmartPLS and acknowledges a financial interest. The authors disclose that OpenAI's ChatGPT (January 2026 version) was used solely for language refinement, including improving clarity, grammar, and readability. The authors confirm that all content, analyses, and interpretations are their own and take full responsibility for the integrity of the manuscript.

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