Type II mediated moderation model

Authors: Wang Yang, Wen Zhonglin, Wang Huihui, Guan Fang, Wen Zhonglin

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Abstract

Psychological research frequently utilizes mediated moderation models to uncover phenomena wherein moderation effects are indirectly achieved via mediator variables. This study introduces the concept and advantages of the second-type mediated moderation model (meMO-II); distinguishes meMO-II from other mixed mediation-moderation models; provides the modeling approach and analytical procedure for meMO-II, illustrated with an empirical example; and presents analytical methods for latent variable-based meMO-II, recent advances in meMO-II modeling methods, and variations of meMO-II. The research contributes to the advancement of moderation mechanism research.

Full Text

The Second Type of Mediated Moderation Model

Yang Wang[1], Zhonglin Wen[2], Huihui Wang[3], Fang Guan[4]

[1]School of Public Administration, Guangdong University of Finance, Guangzhou 510521, China
[2]School of Psychology/Center for Studies of Psychological Application, South China Normal University, Guangzhou 510631, China
[3]School of Education, Ningxia University, Yinchuan 750021, China
[4]Department of Psychology, Tsinghua University, Beijing 100083, China

Abstract: Mediated moderation models are commonly used in psychological research to reveal phenomena where a moderating effect is indirectly realized through mediating variables. This paper introduces the concept and advantages of the second type of mediated moderation model (meMO-II), distinguishes meMO-II from other mixed mediation-moderation models, presents the modeling approach and analysis procedure for meMO-II with a demonstration using a real example, and discusses latent variable-based meMO-II analysis methods, recent advances in meMO-II modeling approaches, and variations of meMO-II. This work contributes to advancing research on moderating mechanisms.

Keywords: the second type of mediated moderation, moderating mechanisms, two-level mediated moderation, variable system, latent variables

Complex variable relationships in social science research often cannot be fully revealed through simple mediation or moderation models (Liu et al., 2021). Consequently, an increasing number of researchers have constructed mixed mediation-moderation models, one of which is the mediated moderation model (meMO). This refers to a situation where a moderator W moderates the relationship between independent variable X and dependent variable Y, and this moderating effect is realized at least partially through a mediator M (Wen et al., 2021; Wen & Liu, 2020). The classic model (also referred to in some literature as the first type of mediated moderation, meMO-I; Liu et al., 2018) is shown in Figure 1 [Figure 1: see original paper].

Although the concept of meMO has been widely disseminated and applied since Baron and Kenny (1986) proposed it decades ago, and although there are classic methodological literatures guiding researchers in using this model (Wen et al., 2006; Ye & Wen, 2013; Edwards & Lambert, 2007), traditional meMO (i.e., meMO-I) has faced considerable criticism in recent years due to its conceptual limitations and susceptibility to misuse in applications (Liu et al., 2021; Hayes, 2017; Kwan & Chan, 2018). Meanwhile, the second type of meMO (meMO-II) has gradually attracted researchers' attention (Fang & Wen, in press; Liu et al., 2018; Liu et al., 2021; Wen et al., in press; Cortina et al., 2022; Kwan & Chan, 2018). It facilitates a more intuitive and clear definition of meMO and can answer questions about moderating mechanisms that meMO-I cannot address, such as "Through what indirect path does moderator W moderate the relationship between X and Y?" However, current research on meMO-II remains scarce. Key questions remain inadequately answered: What are the main differences between meMO-II and meMO-I or other mixed mediation-moderation models? What is the testing procedure for meMO-II? What are the modeling approaches for meMO-II? What are the variations of meMO-II? This paper begins by discussing the limitations of meMO-I to illustrate the concept and advantages of meMO-II and to distinguish it from related models. We then present the modeling approach and analysis procedure for meMO-II, demonstrate it with an example, and introduce latent variable-based meMO-II analysis methods, new developments in meMO-II modeling approaches, and variations of meMO-II.

2. Limitations of meMO-I and Introduction of meMO-II

2.1 Limitations of meMO-I

First, meMO-I is not easily interpretable. In meMO-I, the statistical indicator representing mediated moderation is the product of two path coefficients, XW→M and M→Y (Ye & Wen, 2013). Thus, the statistical meaning of meMO-I is actually that the interaction term XW indirectly affects Y through M (Edwards & Lambert, 2007). Consequently, some researchers refer to meMO-I as a mediated interaction model (Liu et al., 2018). Although X (e.g., weight) and W (e.g., intelligence) have practical meaning, their product XW does not measure any construct with real-world significance (Liu et al., 2021; Hayes, 2017; Kwan & Chan, 2018), such as the product of weight and intelligence. This makes interpreting meMO-I quite challenging. It should not be described like a typical mediation model as an interaction term (a variable without natural meaning) indirectly affecting Y through M (Hayes, 2017; Kwan & Chan, 2018). Nor can one say that the moderating effect affects Y through M, because a moderating effect is a constant rather than a variable. The only appropriate interpretation, as suggested in existing methodological literature, is the subtle phrasing that the moderating effect operates through the mediator (Ye & Wen, 2013). This difficulty in interpretation is why the popular SPSS plugin PROCESS does not include a function for analyzing meMO (Hayes, 2017).

Second, meMO-I is prone to misuse by researchers. Although theoretical clarification can distinguish meMO-I from models where the front path of mediation is moderated (i.e., X affects Y through M, and this mediation path is moderated at the front stage, with the modeling focus on mediation), the two are statistically equivalent (Ye & Wen, 2013), leading many researchers to confuse mediated moderation with moderated mediation (Kwan & Chan, 2018). Compounding this problem, the former is more difficult to interpret than the latter, resulting in far more studies on moderated mediation than on mediated moderation in practical applications. Moreover, among studies on mediated moderation, erroneous applications are common. We searched CNKI for literature published in the past five years (July 25, 2017 to July 25, 2021) in *Acta Psychologica Sinica*, *Psychological Science*, and *Psychological Development and Education*, using "mediation" and "moderation" as keywords in titles, abstracts, and keywords, and found 130 articles involving mixed mediation-moderation models. Of these, 119 established moderated mediation models (including front- and back-path moderated mediation), while only 11 established mediated moderation models, with 9 of these 11 using meMO-I. Analysis of these 9 articles revealed that 3 described their research purpose in abstracts or main text as examining the mechanism of the independent variable on the dependent variable (rather than how it is moderated); 4 discussed mediation first (primary) and moderation second (secondary) in theoretical exposition, which does not conform to the logical sequence of meMO-I modeling; 4 tested mediation before moderation in model testing, which violates the testing procedure for meMO-I (Ye & Wen, 2013); and 3 contained inappropriate descriptions such as "the moderating effect affects the dependent variable through the mediator." Only 2 articles (18%) had no obvious problems in model construction, analysis, and presentation. Furthermore, 59 of the 130 articles had models like that shown in Figure 1, which could be viewed as either mediated moderation or front-path moderated mediation. The result was that 50 authors chose to frame their studies as moderated mediation, while only 9 chose meMO-I.

2.2 Concept of meMO-II

Given the limitations of meMO-I, some researchers advocate completely abandoning the concept of mediated moderation and reinterpreting all meMO-I models as front-path moderated mediation (Hayes, 2017), while others have turned to other forms of mediated moderation models, namely meMO-II (Liu et al., 2018; Liu et al., 2021; Kwan & Chan, 2018).

This model is illustrated in Figure 2 [Figure 2: see original paper]. Its meaning is that W first affects M, which then moderates the relationship between X and Y. Thus, W exerts an indirect moderating effect, leading some researchers to call meMO-II an indirect moderation model (van Kollenburg & Croon, 2017). In addition to this main path, the model in Figure 2 also allows W to have additional direct moderating effects on X and Y, and both W and M can affect Y. Since there are actually two moderators in the model, to distinguish them, W can be called the initial moderator, while M, because it moderates X and Y and separates W from the path X→Y, making W' s moderating effect indirect (similar to the role of a mediator, though not meeting the traditional definition of a mediator), can be called a mediator-moderator.

2.3 Theoretical Value of meMO-II

If mediation models examine the mediating mechanism from X to Y, or how X affects Y, then the theoretical value of meMO-II lies in its examination of the moderating mechanism of moderator W on X and Y—that is, through what path W moderates the relationship between X and Y. This is an interesting yet often overlooked question. Without investigating the specific mechanism of moderation, potentially biased conclusions may be drawn. For example, one study found that for adolescents and young adults, age moderated the relationship between envy and well-being (Ng et al., 2019). If the research had stopped there, the conclusion would have been that for older individuals, the negative effect of envy on well-being is always stronger. However, by constructing meMO-II, the researchers further discovered that the moderating effect of age was realized through self-esteem; that is, older individuals had higher self-esteem. Compared to low self-esteem individuals, the negative effect of envy on well-being was stronger among high self-esteem individuals. After removing this indirect moderating path, the remaining direct moderating effect of age was non-significant with a small effect size (Ng et al., 2019). In other words, age' s moderating effect on envy and well-being existed only among individuals whose self-esteem was related to age; for those whose self-esteem did not change with age, their age could not moderate the envy-well-being relationship.

This example illustrates that the moderating effect of W on X and Y typically obtained in research is actually the total moderating effect, which is the sum of numerous indirect and direct moderating paths. Investigating the true mechanism of moderation helps understand the deeper reasons why moderators exert their effects, a question rarely addressed in previous moderation research.

2.4 Comparison Between meMO-II and Other Mixed Mediation-Moderation Models

2.4.1 meMO-II and meMO-I The core difference between meMO-II and meMO-I lies in how the model represents mediated moderation. For meMO-II, mediated moderation can be intuitively explained as the initial moderator W indirectly moderating X and Y through the mediator-moderator M, with the interpretive focus on "what path the moderation takes." For meMO-I, as previously discussed, because the antecedent variable XM in the mediation model is not a variable with practical meaning, the mediation path is difficult to interpret intuitively. A better explanation for mediated moderation might be that W moderates the mediated part (rather than the direct part) of the relationship between X and Y, thereby moderating the overall X-Y relationship. The focus is not on what route the moderator takes but on "what part is being moderated." This interpretation also conveniently includes cases where the back path of mediation is moderated as a type of meMO-I.

Thus, meMO-II and meMO-I are not mutually exclusive competing models; they have different foci and are actually not comparable. Researchers should choose the appropriate meMO based on their theoretical hypotheses rather than categorically denying the value of one model. meMO-I still has clear theoretical meaning if interpreted as directly moderating the mediated path and thereby indirectly moderating the overall X-Y relationship (rather than as the interaction term affecting Y through M). Other differences between meMO-II and meMO-I are summarized in Table 1 .

2.4.2 meMO-II and Back-Path Moderated Mediation Models If we retain only the core part of meMO-II, as shown in Figure 3a [Figure 3: see original paper], and then rotate X, W, and M and their attached arrows 90 degrees counterclockwise around the intersection point of arrows emanating from X and M—treating X as the moderator and W and M as predictors of Y—meMO-II becomes formally identical (see Figure 3b) to the back-path moderated mediation model (see Figure 3c), making them difficult to distinguish (although they can still be differentiated from the perspective that the theoretical roles of independent and moderator variables are not interchangeable). Recognizing this issue, researchers have designed special model transformations (i.e., from conceptual to statistical models) and statistical methods specifically for meMO-II to avoid model confusion (Liu et al., 2021; Kwan & Chan, 2018).

3. Analysis Procedure for meMO-II

Currently, relatively few studies on mediated moderation domestically and internationally use meMO-II modeling. For example, among the Chinese psychological literature summarized earlier, only one article used meMO-II (Zhu et al., 2019). The lack of dedicated introductory literature may be an important reason, especially the absence of guiding literature on the complete analysis procedure for this model. Reviewing existing methodological literature reveals that procedural descriptions for meMO-II all suffer from missing steps or incorrect sequencing. For instance, the testing procedure proposed by Liu et al. (2018) suggests that testing the total moderating effect is unnecessary, yet this step has theoretical significance. The procedure proposed by van Kollenburg and Croon (2017) tests (1) W' s total moderating effect, (2) M' s moderating effect, (3) whether W no longer has a moderating effect after including M, and (4) whether W affects M, placing the front path of mediation as the final step, which violates the logical sequence of mediation path testing. Additionally, existing testing procedures all neglect steps after establishing the existence of moderation effects, namely simple slope analysis (Finsaas & Goldstein, 2021).

We propose a new meMO-II analysis procedure by referencing existing research on meMO-II and general mediation and moderation analysis steps (e.g., Liu et al., 2018; Ye & Wen, 2013; van Kollenburg & Croon, 2017). Based on the meMO-II model diagram (Figure 2), the relevant equations for this model are listed below:

eWcXc XWcWcXc XWcWcXc XMbMb

Equation 4 combines X' s coefficients to yield Equation 5:

eMbWcXMbWc

Substituting Equation 3 into Equation 4 yields Equation 6:

Step 1: Test whether W' s total moderating effect on X and Y exists. Using Y as the dependent variable, conduct hierarchical regression: in the first step, enter independent variable X and moderator W (Equation 1); in the second step, enter the interaction term XW (Equation 2). If the regression coefficient of XW, 3c , is statistically significant and ΔR^2 is sufficiently large (e.g., $ $0.02, or even 0.03; Wen & Ye, 2014a; Gardner et al., 2017; Marsh et al., 2004; O' Boyle et al., 2015), then the total moderating effect exists. From a statistical perspective, this step is not strictly necessary because indirect moderating effects can exist regardless of whether the total moderating effect exists. However, this step primarily serves to determine the direction of the theoretical argument and has theoretical significance. If the total moderating effect exists, a meaningful research question is what mechanism W uses to moderate the X-Y relationship. If the total moderating effect does not exist, although indirect moderating effects may still exist, discussing how W moderates the X-Y relationship becomes meaningless; a better research question would be why W fails to moderate the X-Y relationship. This can be discussed from the perspective that direct and indirect moderating effects are opposite and thus cancel each other out, similar to what the literature calls suppression effects/inconsistent mediation effects (Liu et al., 2021; Wen & Liu, 2020; Wen & Ye, 2014b).

Step 2: Test whether the indirect moderating effect exists. First, consider using a causal steps approach similar to mediation analysis by sequentially testing coefficients 2b (see Equations 3 and 4). If both are significant, the indirect moderating effect exists. If at least one coefficient is non-significant, use the more powerful bootstrap method to directly test the product of coefficients 21ba in Equation 6. If the 95% bootstrap confidence interval for 21ba does not contain zero, the indirect moderating effect is statistically significant. If both the causal steps and product of coefficients tests are non-significant, the indirect moderating effect is not significant and analysis should stop. This hierarchical testing procedure balances the advantages of the causal steps approach (low Type I error rate, rich information because details about each segment of the mediation path are available, and more convincing significant results) and the product of coefficients method (high statistical power), yielding better results than using either method alone. Note that testing the product of coefficients can be implemented using the SPSS plugin PROCESS. Although PROCESS does not provide any mediated moderation analysis functions, by referring to Figure 3b, if you select the back-path moderated mediation template in PROCESS (e.g., Model 15) but place moderator W in the independent variable box and independent variable X in the moderator box, the Index output by PROCESS is the indirect moderating effect a1b2.

Step 3: Simple slope analysis. The previous steps test whether moderating effects exist, but beyond this, a complete moderation analysis should further reveal how X and Y change with W (Finsaas & Goldstein, 2021). This is simple slope analysis, which is often of greater interest to researchers in moderation analysis.

There are two popular approaches to simple slope analysis: the pick-a-point approach and the Johnson-Neyman (JN) method. The pick-a-point approach examines how the effect of X on Y differs when the moderator takes high versus low values. Based on the simple slope expression (see Equation 5) and the relationship between W and M (Equation 3), both the original moderator W and the mediator-moderator M can be fixed at specific levels simultaneously. For example, with all variables standardized, one can first select the point where W = 1 and M = a1 (assuming a1 here is the coefficient after variable standardization), then select the point where W = -1 and M = -a1, substituting these two WM value combinations into the simple slope expression to obtain simple slope values under both conditions (significance testing of simple slopes follows Fang et al., 2015). In this case, simple slopes are interpreted as: when W is high (low), M is high (low), and X positively (negatively) affects Y / the effect of X on Y is larger (smaller).

The JN method, by contrast, can examine how the significance and direction of X' s effect on Y differ across different intervals of the moderator' s actual values (technical details see Fang et al., 2015). Combining X' s coefficients in Equation 6 yields Equation 7:

XWbaWc

The simple slope is X's coefficient, namely . Using Mplus's model constraint and plot commands, one can easily solve for the range of W values where the simple slope is statistically significant and plot the simple slope graph (example syntax in Appendix). Although the JN method using W intervals better reveals the full picture of simple slopes than the pick-a-point approach, it is difficult to intuitively see M' s role in indirect moderation models. The pick-a-point approach can calculate M' s values based on W' s chosen points, simultaneously reflecting the roles of both W and M, which better fits the characteristics of indirect moderation. Therefore, for simple slope analysis in indirect moderation models, we recommend using both the pick-a-point and JN methods simultaneously.

The above procedure is relatively simple to implement but ignores some implicit parameter constraints in the meMO-II model (detailed later). Fortunately, in most cases this simplification does not cause obvious estimation bias, and the analysis results remain reliable.

4. Demonstration with an Application Example

We demonstrate the procedure described above with a real example examining the moderating effect of self-esteem on the relationship between envy and life satisfaction. The sample consisted of 744 high school students (38.4% male) with a mean age of 16.29 ± 0.91 years. For convenience in subsequent analyses, all variables were standardized beforehand, and an interaction term was created by multiplying self-esteem and envy. Life satisfaction was then regressed on envy and self-esteem as predictors in the first step, and the envy × self-esteem interaction term was added in the second step of a hierarchical regression model.

Results showed that the regression coefficient of the interaction term (the total moderating effect, 3c) was statistically significant ($\beta = 0.14$, $p < 0.001$), with $\Delta R^2 = 0.06$, indicating that self-esteem moderated the envy-life satisfaction relationship.

To further explain why self-esteem could moderate the envy-life satisfaction relationship, we introduced positive coping as a mediator-moderator to construct an indirect moderation model. Following the causal steps approach, we first regressed positive coping on self-esteem, finding a significant coefficient (a1) for self-esteem ($\beta = 0.25$, $p < 0.001$). Next, we regressed life satisfaction on envy, self-esteem, positive coping, the envy × self-esteem interaction, and the envy × positive coping interaction, finding a significant coefficient (b2) for the envy × positive coping interaction term ($\beta = 0.08$, $p < 0.05$). Thus, the indirect moderation model was established: higher self-esteem leads individuals to adopt more positive coping styles, which in turn positively moderate the envy-life satisfaction relationship. Additionally, the remaining direct moderating effect of self-esteem after removing the indirect effect was also statistically significant ($\beta = 0.12$, $p < 0.001$), indicating that the mediator-moderating effect of positive coping was partial, and other mediator-moderators may exist. The model with analysis results is shown in Figure 4 [Figure 4: see original paper].

Although not essential for the significance of indirect moderation, to obtain more specific information about the indirect moderation index, we used the product of coefficients method to obtain the point estimate and 95% bootstrap confidence interval for the indirect moderating effect. Selecting PROCESS plugin Model 15 and placing self-esteem (W) in the independent variable box and envy (X) in the moderator box (referring to Figure 3b), the Index in the output corresponds to coefficient a1b2. The result was a1b2 = 0.02, with a 95% bootstrap confidence interval of (0.005, 0.039).

To further illustrate how the envy–life satisfaction relationship changes along the indirect moderation path from self-esteem to positive coping, we conducted simple slope analysis. Using the pick-a-point approach, we selected the point where standardized self-esteem score = -1 (equivalent to mean minus 1 SD) and standardized positive coping score = -0.25 (because M = 0.25 × W = 0.25 × (-1) = -0.25) as the low W, low M point, and the point where standardized self-esteem score = 1 (mean plus 1 SD) and standardized positive coping score = 0.25 (because M = 0.25 × W = 0.25 × 1 = 0.25) as the high W, high M point. We then substituted the original variables with standardized self-esteem minus -1 and positive coping minus -0.25 in Equation 4 for regression analysis. For the low W, low M point, the regression coefficient for envy was β = -0.22, $p < 0.001$, indicating that when self-esteem was low, positive coping was also low, and envy decreased life satisfaction. Next, we substituted the original variables with standardized self-esteem minus 1 and positive coping minus 0.25 in Equation 4. For the high W, high M point, the regression coefficient for envy was $\beta = 0.06$, $p = 0.27$, indicating that when self-esteem was high, positive coping was also high, and the relationship between envy and life satisfaction was not statistically significant. The simple slope plot is shown in Figure 5 [Figure 5: see original paper].

The JN method can also be used to determine the interval where simple slopes are statistically significant. Results showed that when standardized self-esteem scores were between -3.20 and 0.03, envy always negatively affected life satisfaction; when self-esteem scores were between 1.74 and 7.55, envy always positively affected life satisfaction. All analyses except the JN method can be implemented using SPSS. The Appendix also provides Mplus and R programs for analyzing this example.

5. Latent Variable-Based meMO-II

The meMO-II analysis methods described above are based on observed variable analysis, which implicitly assumes that all variables are measured without error (i.e., reliability = 1). This may lead to underestimation of parameters (Fang & Wen, 2018), especially considering that interaction terms often have poor reliability (Ng & Chan, 2020). Latent variable modeling can effectively control for measurement error and improve estimation precision of indirect moderating effects. We recommend two latent variable-based methods: latent moderation structural equation and factor score approach.

5.1 Latent Moderation Structural Equation

The current popular method for latent variable moderation analysis is latent moderation structural equation (LMS). This method not only has the advantage of controlling measurement error in latent variable modeling but also estimates the regression coefficient of the latent interaction term (i.e., the moderating effect) using the joint distribution function of all measurement indicators of the latent moderation model, without requiring artificial construction of interaction terms (Fang & Wen, 2018), thus avoiding complex problems arising from this practice (such as non-normality issues of interaction terms and the impact of different interaction construction strategies on results; Liang et al., 2020). The specific principles of LMS can be found in Wen et al. (2013).

For applied researchers, using LMS is quite simple. In Mplus software, one only needs to define the latent interaction term variable name with a command like "kxiXW | kxiX XWITH kxiW;", where kxiX and kxiW refer to the latent variable forms of the independent and moderator variables, respectively. The Appendix provides Mplus syntax based on LMS corresponding to the previous example.

5.2 Factor Score Approach

When the moderation model is complex (e.g., many factors and measurement indicators) but sample size is relatively insufficient, LMS may not converge or may converge too slowly (Ng & Chan, 2020). For instance, using the original questionnaire items in our example requires 15 minutes to converge, and even with item parceling, it takes 5 minutes.

In such cases, consider using another latent variable-based method—the factor score approach (FS). This method splits the latent variable modeling process into two steps (Ng & Chan, 2020): The first step establishes measurement models for each variable to obtain parameter estimates such as factor variance-covariance, factor loadings, and error variance-covariance; these estimates are then used to calculate factor score matrices; subsequently, factor scores are obtained by multiplying the factor score matrix by individuals' raw scores on questionnaire items. The second step uses the factor scores from the first step for path analysis. FS simplifies the model through stepwise modeling, has lower sample size requirements, involves smaller computational loads, converges easily (Ng & Chan, 2020), and helps avoid the problem of measurement model misspecification contaminating structural model coefficients that can occur with simultaneous modeling methods like LMS. The Appendix provides Mplus syntax based on FS corresponding to the previous example.

6. New Developments in meMO-II Modeling Methods

The meMO-II modeling approach and analysis procedure proposed in this paper are organized according to the basic form of meMO-II and can be called basic meMO-II. Basic meMO-II is simple and easy to understand, can be mastered with basic knowledge of mediation and moderation, and can be analyzed using SPSS software. However, it is not without limitations. First, as a multiple regression-based model, meMO-II also needs to satisfy assumptions such as homogeneity of error variance. Some research indicates that models containing interaction terms can hardly guarantee completely equal error variances (Liu & Yuan, 2021), and violation of this assumption may increase Type II error rates and reduce the power of moderation effect tests (Liu et al., 2021). Second, variable M is endogenous (i.e., affected by other variables in the model), and the interaction term XM constructed from it should also be endogenous (Kwan & Chan, 2018), but basic meMO-II does not reflect this (because XM has no predictor variables), which may be a potential source of bias. Third, typical mediation paths are coherent, with the same intermediate variable connecting the front and back segments. However, as shown in Figure 2b, the front and back segments of basic meMO-II are W→M and XM→Y, respectively, which are not coherent. This may cause some difficulty for applied researchers in understanding basic meMO-II. Two meMO-II modeling approaches that have emerged in recent years—variable system and two-level mediated moderation—provide new ways to address these limitations.

6.1 Variable System

To avoid confusion between the statistical models of back-path moderated mediation and meMO-II, Kwan and Chan (2018) proposed the variable system (VS) modeling approach. meMO-II based on VS can be represented by Equation 3 plus the following equations:

XWaXa

where \$ \$0 and \$ \$00 are regression intercepts, and \$ \$1, \$ \$10, \$ \$01, \$ \$11, \$ \$02, and \$ 12areregressioncoefficients.Itisnotdifficulttoseethat,exceptfortheformofcoefficientexpress
II−relatedequationspresentedearlier.Equations9–11aresimplywritteninmultilevelmodelformat(butthisfor
II′sindirectmoderationindexcanbeexpressedastheproductofpathcoefficientsXW→XM→Y, a1 11.Thischa
(1)XMhaspredictorvariables, makingitsendogeneityexplicit; (2)theindirectmoderationpathbecomescoherent
IIandismoreeasilydistinguishedfromback−pathmoderatedmediationmodels.Thisisbecausetheinterceptterm
in Equation 8 (i.e., equal to a0 and a1, respectively). Thus, VS has two more degrees of freedom than basic meMO-II. Although basic meMO-II also implicitly includes paths from X to XM and from XW to XM, because the path coefficient a0b2 in Equation 6 can be viewed as X' s indirect effect on Y through XM, and a1b2 can be viewed as XW' s indirect effect on Y through XM, basic meMO-II does not utilize Equation 8 in modeling and statistical analysis, and therefore cannot constrain the aforementioned pairs of path coefficients to be equal.

Based on the VS modeling approach, Kwan and Chan (2018) developed the VS program. Researchers only need to input a simple conceptual model, and the program automatically builds a statistical model based on structural equations. This program can analyze various meMO-II variations. Download address: http://www.psy.cuhk.edu.hk/vs. However, regarding the estimation accuracy of indirect moderation effects and their standard errors, existing research shows little difference between VS and basic meMO-II (Kwan & Chan, 2018).

6.2 Two-Level Mediated Moderation

Drawing on the error decomposition approach in multilevel modeling, Liu et al. (2021) proposed two-level mediated moderation (2meMO; model diagram shown in Figure 6 [Figure 6: see original paper]), which essentially adds two random error terms 0 and 1 to Equations 10 and 11 of VS, becoming Equations 12 and 13:

where 0 cannot be distinguished from the Level 1 error term eY in parameter estimation and is relatively minor; 1 represents the individual differences in X' s effect on Y that cannot be explained by current moderators, reflecting the possible existence of other moderators. The presence of 1 also allows Y' s residual variance to vary with different values of X, i.e., it can violate the homogeneity of variance assumption. Simulation studies also show that when 1' s variance is heterogeneous, 2meMO' s parameter estimation accuracy and Type I error rate control are superior to VS (when homogeneity of variance is satisfied, both methods perform similarly; Liu et al., 2021).

Figure 6 [Figure 6: see original paper] shows the 2meMO statistical model diagram. Note: Adapted from Liu et al. (2021); solid dots indicate that the corresponding regression coefficient contains random effect 1; removing this dot yields the VS model diagram.

Furthermore, 2meMO does not obtain paths X→XM and XW→XM by multiplying Equation 3 by X. Instead, it directly uses these two paths implied by Equation 6 in statistical analysis and constrains them in Mplus programming to equal the intercept term of M regressed on W and the path coefficient from W to M, respectively. Thus, 2meMO also has all the aforementioned advantages of VS.

Although essentially the indirect moderation indices of 2meMO, VS, and basic meMO-II are identical, 2meMO' s statistical model specification is more reasonable, and its explanation of variation in the X-Y relationship is more realistic. Additionally, based on the decomposition of variation in the X-Y relationship, it helps define meaningful effect sizes for moderation (detailed below). Note that 2meMO only borrows the method of multilevel analysis; the data and models it handles are still single-level.

Using VS and 2meMO to analyze the example data (Mplus syntax templates in Appendix) yields results that differ little from basic meMO-II, especially in that the estimates of indirect moderation effects and their standard errors are identical to two decimal places. Detailed results are shown in Table 2 .

Based on the above analysis and previous research (Liu et al., 2021; Kwan &

Chan, 2018), 2meMO is currently the most effective method for meMO-II modeling, particularly when it cannot be determined whether 1 satisfies homogeneity of variance. One can also first test whether the variance of the residual 1 in the Level 2 slope equation (i.e., the between-level variance in 2meMO' s Mplus output) is zero. If it is non-significant or sufficiently small, using meMO-II and VS can simplify the model.

7. Effect Size for Indirect Moderation

Effect size is an indispensable component of statistical inference. The meMO-II modeling methods and procedures described above only involve significance testing and do not address effect size issues. By summarizing existing literature, we can identify several indicators for evaluating the magnitude of indirect moderation effects.

(1) **Ratio of indirect to total moderation effect.** This effect size indicator is similar to PM in mediation models (Wen et al., 2016), representing the proportion of indirect moderation effect relative to total moderation effect. Using our data as an example, the indirect moderation effect size c/ba = PM = 14.0/02.0). The advantages of PM are: easy to understand and calculate; indirect and direct moderation effects sum to total moderation effect; when indirect and direct moderation effects have the same sign, it possesses the essential properties of an effect size, being independent of measurement units, unaffected by sample size, monotonic, bounded, and normalized (i.e., values between 0 and 1; Wen et al., 2016). Disadvantages are: when indirect and direct moderation effects have opposite signs, PM is unbounded; PM is only a relative indicator that does not reflect absolute effect size and needs to be combined with the indirect moderation effect value or other effect size indicators; it lacks empirical cutoff values for evaluation and comparison.

(2) **.** is an R^2-type effect size previously used for simple mediation models, equal to the square of the product of the front and back path coefficients (Lachowicz et al., 2018). When applied to indirect moderation effect analysis in our example, ba . The advantages of this effect size indicator are: easy to calculate; possesses essential properties of an effect size; can borrow empirical cutoff values for R^2 (Lachowicz et al., 2018). The limitation is that it cannot be understood as proportion of variance explained; its meaning is not easily interpretable and may be less intuitive than using the absolute value of the coefficient product (Wen et al., 2016).

(3) **Effect size based on coefficient variation decomposition.** In moderation analysis, a commonly used effect size is the change in model R^2 after adding the interaction term. Liu and Yuan (2021) point out that such effect sizes only reflect how much variance in the dependent variable can be explained by the interaction term and cannot distinguish the roles of the moderator and independent variable, thus failing to answer the key

question in moderation analysis: how much of the variation in the relationship between independent and dependent variables is contributed by the moderator? They propose an effect size based on coefficient variation decomposition and extend it to mediated moderation models (Liu et al., 2021). Among them, MO_{ind} represents the proportion of variation in the total path coefficient from X to Y explained by W' s indirect moderation effect through M, and can measure the magnitude of indirect moderation effect. Its calculation formula is:

The Mplus program for calculating this effect size can be found in Liu et al. (2021). Using Equation 14, MO_{ind} in our example equals 0.003.

The advantages of coefficient variation decomposition-based effect sizes are: the effect size definition matches the conceptual model of meMO-II, making it easy to understand and interpret; it possesses essential properties of an effect size (Liu et al., 2021); and it applies to all aforementioned meMO-II modeling methods (for basic meMO-II and VS, simply exclude 1 variance from the denominator). Disadvantages are: such effect sizes only have relative meaning and need to be combined with the denominator of the formula, indirect moderation effect values, or other effect sizes to evaluate absolute magnitude; they lack empirical cutoff values; and indirect and direct moderation effects do not sum to total moderation effect (Liu et al., 2021).

Each of the above effect sizes has its own advantages and disadvantages and focuses on different perspectives. Based on previous recommendations for reporting mediation and moderation effect sizes (Liu et al., 2021; Wen et al., 2016; Lachowicz et al., 2018; Liu et al., 2021), reporting multiple effect size indicators simultaneously (including the standardized indirect moderation effect value) is a better choice.

8. Variations of meMO-II

Previous research (including the preceding sections) has mostly focused on the basic form of meMO-II. Below we introduce some variations of meMO-II that help enrich its forms and deepen researchers' understanding of indirect moderation.

(1) **Multiple indirect moderation.** Similar to multiple mediation, indirect moderation can have multiple paths, with the significance of revealing multiple potential reasons why W can moderate the relationship between X and Y. Returning to our example, self-esteem may moderate the envy-life satisfaction relationship not only through positive coping but also through positive affect as a mediator-moderator, because individuals with positive self-evaluations tend to generate more positive emotions, which help buffer the negative emotions produced by envy. This is parallel multiple indirect moderation. If self-esteem increases positive coping, which in turn generates more positive emotions that then moderate the envy-life satisfaction relationship, this would be chained multiple indirect moderation.

(2) **Suppression analysis in moderation.** Similar to suppression effects discussed in mediation models (Liu et al., 2021; Wen & Ye, 2014b), this belongs to inconsistent moderation. W' s total moderating effect on X and Y may also be suppressed by the presence of two indirect moderation effects with opposite directions and similar magnitudes. For example, on the one hand, self-esteem may positively moderate envy and life satisfaction through increased positive coping; on the other hand, excessively positive self-evaluation may cause narcissism, which may negatively moderate envy and life satisfaction. If the two indirect moderation paths cancel each other out, the overall moderating effect of self-esteem may appear non-significant. Suppression analysis in moderation helps explain why many theoretically plausible moderating effects fail to obtain significant results.

(3) **Multilevel indirect moderation.** This can handle situations where variables in indirect moderation models are at different levels. Common scenarios include W at Level 2 while M, X, and Y are all at Level 1, or W and M at Level 2 while X and Y are at Level 1 (Liu et al., 2018). For example, a nation' s collective self-esteem (Level 2) may moderate the envy–life satisfaction relationship by increasing each individual' s positive coping.

(4) **Indirect moderation based on categorical variables.** This can handle situations where categorical variables exist in indirect moderation models. W in indirect moderation research is often a categorical variable. When W is a between-subjects dichotomous variable, meMO-II can be analyzed following the procedure described earlier. If W is a between-subjects variable with more than three categories—for example, dividing participants into high, medium, and low self-esteem groups based on self-esteem scores to examine how self-esteem category moderates envy and life satisfaction through positive coping—one can convert self-esteem categories into two dummy variables and examine the indirect moderation effect of each dummy variable. This is relative indirect moderation analysis, similar to relative mediation effect analysis (Fang et al., 2017). Notably, this type of indirect moderation model can also be used in psychological experimental research to examine how experimental manipulations indirectly moderate the X-Y relationship.

(5) **Moderated indirect moderation model.** If there is a moderator on the indirect moderation path of a typical meMO-II, the model can be called a moderated indirect moderation model. This model can be used to explain boundary conditions of indirect moderation effects. For example, the front path of the indirect moderation of envy and life satisfaction by self-esteem through positive coping (i.e., self-esteem → positive coping) may be moderated by other variables (e.g., emotion regulation self-efficacy). For individuals with high emotion regulation self-efficacy, the association between self-esteem and positive coping may be stronger, and

the indirect moderation effect on envy and life satisfaction may also be larger; for those with low emotion regulation self-efficacy, the association may be weaker and the indirect moderation effect smaller.

(6) **Mediation model with indirect moderation.** If a typical meMO-II has antecedent variables before X or consequence variables after Y, the model can be called a mediation model with indirect moderation. In this case, the model is fundamentally still a mediation model, and the presence of indirect moderation not only informs us about boundary conditions of the mediation effect but also explains why the mediation model has such boundary conditions. For example, attachment anxiety may increase individuals' envy, which in turn reduces life satisfaction. The back path of this mediation model is moderated by self-esteem. So how does self-esteem moderate the back path of the mediation model? This may be because self-esteem first increases positive coping, which then buffers the negative effect of envy on life satisfaction.

This paper has introduced the concept, advantages, modeling methods, analysis procedure, latent variable-based analysis methods, and model variations of the second type of mediated moderation model (meMO-II). We hope this work will encourage more applied researchers to pay attention to the mechanism of moderating variables and to use meMO-II in their research. Beyond the topics covered here, more methodological work on meMO-II remains to be done in the future. For example, given that there are still too few comparative studies of basic meMO-II, VS, and 2meMO under different sample or assumption violation conditions, future simulation and empirical studies comparing the three are needed to provide more accurate and detailed recommendations for researchers selecting meMO-II modeling methods.

Finally, it must be emphasized that although much of this paper is devoted to introducing various statistical analysis methods and procedures for meMO-II, for any applied study, building an appropriate model based on theoretical meaning is the foundation, with corresponding statistical analysis methods considered afterward. Tools, models, and statistical analyses serve research needs; do not neglect theoretical significance for the sake of using complex statistical models.

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Appendix

Mplus Syntax Template for Basic meMO-II

```
DATA:FILE = meMOII example data.csv;
VARIABLE:NAME = L1-L5 T1-T12 E1-E10 EN1-EN8 LSM envyM seM PCM ID;
USEVARIABLES = LSM envyM seM PCM envy_{se} envy_{pc};
!LSM life satisfaction mean; envyM envy mean; seM self-esteem mean; PCM positive coping mean
DEFINE:standardize LSM envyM seM PCM; !standardize all variables
envy_{se} = envyM*seM;envy_{pc} = envyM*pcM; !create two interaction terms
ANALYSIS:BOOTSTRAP = 1000; !bootstrap 1000 replications
MODEL:
LSM ON envyM(c1pp) !direct effect of envy on life satisfaction
seM PCM
envy_{se} (c3pp) !direct moderation effect
envy_{pc}(b2); !back path of indirect moderation
PCM ON seM (a1); !front path of indirect moderation
[PCM] (a0);
!To convert to VS syntax, add the following statements at this location:
!envy_{pc} ON envy_{se} (a1); envy_{pc} ON envyM(a0); envy_{pc} WITH PCM;
!seM WITH envy_{se}; envy_{se} WITH envyM; envyM WITH seM;
MODEL CONSTRAINT:NEW(modtotal ind);
ind = a1*b2; !indirect moderation effect
modtotal = a1*b2+c3pp; !total moderation effect
loop (seM,-3, 7, 0.01); !parameters in parentheses are: original moderator self-esteem, lowe
plot (effect); !y-axis of simple slope plot represents effect
effect = c1pp+a0*b2+(c3pp+a1*b2)*seM; !simple slope named effect
plot: type = plot2;
!If JN method is not needed, omit commands from loop to this line
OUTPUT:CINTERVAL (BOOTSTRAP);
```

R Syntax Template for Basic meMO-II

```
install.packages ("lavaan") #install lavaan package
library (lavaan) #load lavaan package
meMOIIdata<-read.csv("C:/Users/user/Desktop/memoII example data R.csv", header = F) #import
#header = F means data file does not contain variable names
```

```
names (meMOIIdata)[1:5] <- c ("LSM", "envyM", "seM", "PCM", "ID") #variable naming
meMOIIdata$LSM<-scale(meMOIIdata$LSM) #variable standardization
meMOIIdata$envyM<-scale(meMOIIdata$envyM)
meMOIIdata$seM<-scale(meMOIIdata$seM)
meMOIIdata$PCM<-scale(meMOIIdata$PCM)
model <- '
LSM ~ c0pp*1 + c1pp*envyM + c2pp*seM + b1*PCM + c3pp*envyM:seM + b2*envyM:PCM
PCM ~ a0*1 + a1*seM
Ind := a1*b2
modtotal := c3pp + (a1*b2)
' #list equations involved in modeling and name it model; *right side is variable, left side
fit <- sem(model, data = meMOIIdata, se = "bootstrap")
summary(fit) #output analysis results
```

Mplus Syntax Template for meMO-II Based on Latent Moderation Structural Equation

```
DATA: FILE = meMOII example data.csv;
VARIABLE: NAME = L1-L5 T1-T12 E1-E10 EN1-EN8 LSM envyM seM PCM ID;
USEVARIABLES = L1-L5 T1-T12 E1-E10 EN1-EN8;
ANALYSIS: TYPE = random;algorithm = integration;
MODEL:
LS by L1-L5;PC by T1-T12;SE by E1-E10;envy by EN1-EN8;
envy_{se} | envy XWITH SE;envy_{pc} | envy XWITH pc; !define latent interaction term names
LS ON envy se PC envy_{se} (c3pp) envy_{pc}(b2);
PC ON se (a1);
MODEL CONSTRAINT: NEW(modtotal ind);
ind = a1*b2;
modtotal = a1*b2+c3pp;
```

Mplus Syntax Template for meMO-II Based on Factor Score Approach

Step 1 (Save factor scores):

```
DATA: FILE = memoII example data.csv;
VARIABLE: NAME = L1-L5 T1-T12 E1-E10 EN1-EN8 LSM envyM seM PCM ID;
USEVARIABLES = L1-L5 T1-T12 E1-E10 EN1-EN8;
MODEL:
LS by L1-L5;
PC by T1-T12;
SE by E1-E10;
envy by EN1-EN8;
OUTPUT: STANDARDIZED(STDYX) CINTERVAL;
save: save = fscores; !save factor scores
file = fs.txt; !factor scores stored in text file named fs; meaning of each column variable
```

Step 2 (Path analysis with factor scores):

```
DATA:FILE = fs.txt;
VARIABLE:NAME = L1-L5 T1-T12 E1-E10 EN1-EN8 LS LSSE pc pcSE se seSE envy envySE envy_{se} en
!LSSE pcSE seSE envySE are standard errors of each factor score
USEVARIABLES = LS pc se envy envy_{se} envy_{pc};
DEFINE:standardize LS envy se PC;
envy_{se} = envy*se; envy_{pc} = envy*pc;
ANALYSIS: BOOTSTRAP = 1000;
MODEL:
LS ON envy se PC envy_{se} (c3pp) envy_{pc}(b2);
PC ON se (a1);
MODEL CONSTRAINT: NEW(modtotal ind);
ind = a1*b2;
modtotal = a1*b2+c3pp;
OUTPUT:CINTERVAL (BOOTSTRAP);
```

Mplus Syntax Template for 2meMO

```
DATA: FILE = memoII example data.csv;
VARIABLE: NAME = L1-L5 T1-T12 E1-E10 EN1-EN8 LSM envyM seM PCM ID;
USEVARIABLES = LSM envyM seM PCM envy_{se} envy_{pc};
CLUSTER = ID;
WITHIN = LSM envyM seM PCM envy_{se} envy_{pc};
DEFINE: standardize LSM envyM seM PCM;
envy_{se} = envyM*seM; envy_{pc} = envyM*pcM;
ANALYSIS: TYPE IS TWOLEVEL RANDOM; ESTIMATOR IS BAYES;
MODEL:
%WITHIN%
c | LSM ON envyM;
LSM on PCM seM;
LSM on envy_{se}(gamma12);
LSM on envy_{pc}(gamma11);
PCM on seM (a1);
envy_{pc} on envy_{se} (a1);
envy_{pc} on envyM(a0);
[PCM](a0);
envy_{pc} WITH PCM;
seM WITH envy_{se};
envy_{se} WITH envyM;
envyM WITH seM;
%BETWEEN%
[c] (c0);
c (sig2_{mu1});
MODEL CONSTRAINT: NEW(modtotal ind wmH wmL);
ind = a1*gamma11;
modtotal = a1*gamma11+gamma12;
wmH=c0+a0*gamma11+gamma12*1+gamma11*0.24; !simple slope for high pick-a-point
wmL=c0+a0*gamma11-gamma12*1-gamma11*0.24; !simple slope for low pick-a-point
```

```
loop (seM,-3, 7, 0.01);
plot (effect);
effect = c0+a0*gamma11+(gamma12+a1*gamma11)*seM;
plot: type = plot2;
OUTPUT: CINTERVAL(HPD); !provide highest density interval (HDI) of posterior distribution
```

Note: Figure translations are in progress. See original paper for figures.