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# A Review of Methodological Research on Mediation Effects in China

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## Abstract

Mediation effect can analyze the influence process and mechanism of independent variables on dependent variables, and has become an important statistical method for analyzing relationships among multiple variables. Over the past two decades, mediation effect has become a hot topic in research methodology. This paper systematically summarizes the development history of domestic methodological research on mediation effects from five aspects: testing methods for mediation effects, effect size, mediation effect testing for categorical variables, mediation effect testing for longitudinal data, and model extensions (including multiple mediation, multilevel mediation, moderated mediation, and mediated moderation models). Finally, it discusses and expands upon the progress of international methodological research on mediation effects and future research directions.

## Full Text

## A Review of Methodological Research on Mediation Effects in China

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### Abstract

Mediation effect analysis can reveal the process and mechanism through which independent variables influence dependent variables, and has become an important statistical method for analyzing relationships among multiple variables. Over the past two decades, mediation effect analysis has emerged as a hot topic in methodological research. This article systematically reviews the development of domestic methodological research on mediation effects across five dimensions: testing methods, effect size, mediation analysis with categorical variables, mediation analysis with longitudinal data, and model extensions (including multiple mediation, multilevel mediation, moderated mediation, and mediated moderation). Finally, we discuss recent advances in foreign methodological research on mediation effects and propose directions for future research.

**Keywords:** mediation effect, testing method, effect size, model expansion, categorical variable, longitudinal data

Revealing relationships among variables is a key objective of quantitative research. Mediation effect analysis can explain how an independent variable X influences a dependent variable Y through a mediator variable M, and has become an essential statistical method in multivariate research (Du Anzheng et al., 2014; Gan Yiqun, 2014; Wen Zhonglin & Ye Baojuan, 2014a).

The concept of mediator variables has nearly a century of history in social science research. For example, Woodworth (1928) proposed the "stimulus-organism-response" (S-O-R) model based on "stimulus-response" (S-R) theory, demonstrating that the effect of stimulus on response occurs through internal transformation processes within the organism, making the "organism"a mediator variable.

However, mediator variables did not receive widespread attention until the 1980s, when the stepwise approach for analyzing simple mediation models (one independent variable, one mediator, and one dependent variable) was developed (Baron & Kenny, 1986; Judd & Kenny, 1981). In China, Wen Zhonglin et al. (2004) were the first to introduce analytical methods for mediation models, proposing a testing procedure that combined sequential testing with Sobel testing, which guided and promoted methodological research and applications of mediation effects in China. Since then, mediation analysis has become a research hotspot in psychological statistics domestically (Wen Zhonglin et al., 2021).

The development of methodological research on mediation effects in China is summarized in Table 1 , covering five aspects: testing methods, effect size, mediation analysis with categorical variables, mediation analysis with longitudinal data, and model extensions. Model extensions include multiple mediation models, multilevel mediation models, moderated mediation models, and mediated moderation models. Table 1 categorizes representative literature chronologically, with the first article in each category representing the inaugural study in China. This paper first introduces the simple mediation model, then clarifies related concepts, systematically reviews the development of domestic methodological research on mediation effects, and finally discusses foreign methodological achievements and future research directions.

**Table 1** Overview of Domestic Methodological Research Literature on Mediation Effects

- **Testing Methods**: Wen Zhonglin et al. (2004); Wen Zhonglin et al. (2005); Fang Jie et al. (2011); Fang Jie & Zhang Minqiang (2012; 2013); Wen Zhonglin & Ye Baojuan (2014a); Yang Chunyan et al. (2017); Fang Jie & Wen Zhonglin (2018a)
- **Effect Size**: Fang Jie et al. (2012); Wen Zhonglin et al. (2016)
- **Categorical Variables in Mediation**: Liu Hongyun et al. (2013); Fang Jie et al. (2017); Wang Yang & Wen Zhonglin (2018)
- **Longitudinal Data in Mediation**: Liu Guofang et al. (2018); Fang Jie et al. (in press)
- **Multiple Mediation**: Liu Shishun & Ling Wenquan (2009); Fang Jie, Wen Zhonglin, Zhang Minqiang, & Sun Peizhen (2014)
- **Multilevel Mediation**: Fang Jie et al. (2010); Liu Hongyun et al. (2011); Fang Jie, Wen Zhonglin, Zhang Minqiang, & Ren Hao (2014); Fang Jie & Wen Zhonglin (2018a)
- **Moderated Mediation**: Wen Zhonglin et al. (2006); Wen Zhonglin & Ye Baojuan (2014b); Fang Jie, Zhang Minqiang et al. (2014); Fang Jie & Wen Zhonglin (2018b; in press)
- **Mediated Moderation**: Wen Zhonglin et al. (2006); Liu Dong et al. (2012); Ye Baojuan & Wen Zhonglin (2013); Wen Zhonglin & Liu Hongyun (2020); Liu Hongyun et al. (2021)

## 1. Simple Mediation Effect Model

For convenience, assume all variables are continuous and standardized (no intercept in regression equations). The simple mediation model involves estimating the following linear regression equations:

$$Y = cX + \varepsilon_1 \quad (1)$$

$$M = aX + \varepsilon_2 \quad (2)$$

$$Y = bM + c'X + \varepsilon_3 \quad (3)$$

In equation (1), coefficient c represents the effect of X on Y; in equation (2), coefficient a represents the effect of X on M; in equation (3), coefficient b represents the effect of M on Y after controlling for X, and c' represents the direct effect of X on Y after controlling for M. The terms $_1$, $_2$, and $_3$ denote residuals, which are assumed to be normally distributed and independent. Substituting equation (2) into (3) yields:

$$Y = (c' + ab)X + (\varepsilon_3 + b\varepsilon_2) \quad (4)$$

In equation (4), ab represents the mediation effect (indirect effect) of X on Y, c' represents the direct effect, and c = c' + ab represents the total effect. In the case of manifest variables, c = c' + ab.

## 2. Conceptual Distinctions

Mediation effects are also called indirect effects, but the two are not identical. Generally speaking, all mediation effects are indirect effects, but not all indirect effects are mediation effects. Specifically, in models with only one mediator, mediation effect and indirect effect are synonymous. However, when multiple mediators exist, indirect effect can refer to either the effect through a specific mediator (i.e., mediation effect) or the sum of some or all mediation effects (Lu Xiefeng & Han Limin, 2007; Wen Zhonglin et al., 2004; Wen Zhonglin & Liu Hongyun, 2020).

Mediation effect analysis addresses how X influences Y. However, when theory or empirical evidence suggests that X should affect Y, but the regression coefficient c in equation (1) is nonsignificant (indicating no significant effect of X on Y), asking "how does X affect Y?" becomes inappropriate. Instead, the proper question is "why does X not affect Y, and what role does variable M play in this?" This calls for analysis of "suppression effects" to identify what variables suppress the effect (Wen Zhonglin & Ye Baojuan, 2014a). More specifically, suppression occurs when the absolute value of the direct effect c' is larger than that of the total effect c (implying c' and ab have opposite signs) (Wen Zhonglin & Liu Hongyun, 2020). Wen Zhonglin and Ye Baojuan (2014a) further noted that if coefficient c in equation (1) is significant, mediation analysis should be conducted to address "how X affects Y" ; if c is nonsignificant, suppression effect analysis (or more generally, inconsistent mediation) should be considered to address "why X does not affect Y."

For significant mediation effects, if coefficient c' in equation (3) is nonsignificant, this is termed complete mediation; if c' is significant, it is termed partial mediation. However, distinguishing between complete and partial mediation is sometimes inappropriate. First, a complete mediation model does not necessarily have a larger mediation effect than a partial mediation model. Second, the concept of complete mediation may discourage researchers from searching for additional mediators, hindering the development of mediation research. The appropriate approach is to directly report the significance of both mediation and direct effects (Fang Jie et al., 2012; Wen Zhonglin & Liu Hongyun, 2020; Wen Zhonglin & Ye Baojuan, 2014a).

While mediation analysis examines how X affects Y, when the relationship between X and Y is influenced by a third variable U, U becomes a moderator variable. Moderation analysis examines when X affects Y or when its effect is stronger. The distinction between mediator and moderator variables is detailed in Wen Zhonglin et al. (2005).

### 3.1 Mediation Effect Testing Methods

Early testing methods for mediation effects could be divided into coefficient difference tests and coefficient product tests. The null hypothesis for coefficient difference testing is $H_0$: c - c' = 0, but this approach was abandoned early due to potentially high Type I error rates (Wen Zhonglin et al., 2004). The coefficient product test examines $H_0$: ab = 0 and can be further divided into indirect and direct tests (Figure 1 [Figure 1: see original paper]).

**Figure 1** Mediation Effect Testing Methods

The sequential test, also called joint significance test in some literature, is an indirect method for testing the product of coefficients. It involves sequentially testing coefficient a in equation (2) ($H_0$: a = 0) and coefficient b in equation (3) ($H_0$: b = 0). If both a and b are significant (a $\neq$ 0 and b $\neq$ 0), this is sufficient to conclude that the mediation effect ab is significant (ab $\neq$ 0). However, sequential testing differs from the typical joint significance test in their research hypotheses. The alternative hypothesis for sequential testing is $H_1$: ab $\neq$ 0, whereas for joint significance it is $H_1$: a $\neq$ 0 and b $\neq$ 0. Although the testing procedure is identical, the conclusions differ: rejecting $H_0$ in sequential testing leads to "ab is significantly different from 0," while joint significance concludes "a is significantly different from 0 and b is significantly different from 0," resulting in substantially different Type I error rates.

When the significance level $\alpha$ is 0.05, three scenarios demonstrate that the Type I error rate for sequential testing is less than 0.05 (MacKinnon et al., 2002; see also Wen Zhonglin et al., 2004), whereas the Type I error rate for joint significance is $1 - 0.95^2 = 0.0975$. This distinction has rarely been noted in the literature, leading many to believe that sequential testing does not actually test mediation effects, with some journals even refusing submissions using this method (Gan Yiqun, 2014). Indeed, if sequential testing yields a nonsignificant mediation effect, this method should not be used because it has the lowest statistical power (highest Type II error rate) among the methods shown in Figure 1. Another limitation of sequential testing is that it does not provide confidence intervals for ab.

Direct methods for testing the product of coefficients include Sobel testing, product distribution methods, Bootstrap methods, and Bayesian methods.

The Sobel test assumes normality, but even when each coefficient is normally distributed, their product is typically not normal. Therefore, the Sobel test has obvious limitations and is now rarely used (Fang Jie et al., 2012). The product distribution method assumes that the distribution of ab follows the product distribution of two normal variables, deriving interval estimates for ab. If the interval does not contain 0, the mediation effect is significant. This method' s advantage is that it only requires the estimated values and standard errors of a and b, not the raw data. For more details on product distribution methods, see the review by Fang Jie et al. (2011).

The Bootstrap method is the most widely used direct test for the product of coefficients (Chen Rui et al., 2013; Jiang Chengming et al., 2015; Zhang Han et al., 2016). Bootstrap is a resampling method that can be parametric or nonparametric depending on the resampling target. Parametric Bootstrap resamples parameters (e.g., a and b), with the Monte Carlo method (MC) being one such approach that requires only the estimated values and standard errors of a and b, not raw data. For more on MC methods, see Fang Jie and Wen Zhonglin (2018a). Nonparametric Bootstrap resamples sample data, relying solely on the original sample to generate Bootstrap samples, estimate a and b in each, and derive Bootstrap confidence intervals for ab. If the interval excludes 0, the mediation effect is significant. For higher power, bias-corrected Bootstrap can be used (Fang Jie et al., 2011), but its Type I error rate may exceed the nominal level (e.g., 0.05) under some conditions. Consequently, researchers increasingly recommend uncorrected Bootstrap for mediation analysis unless maximum power is desired (Fang Jie & Wen Zhonglin, 2018a).

The Bayesian method, also called Markov Chain Monte Carlo (MCMC), treats parameters as random variables, integrating prior distributions with observed data to obtain posterior distributions via MCMC. Interval estimates derived from the posterior distribution determine significance if they exclude 0. The crucial step is selecting appropriate prior distributions. With small samples or large sampling variance, proper prior information can substantially improve parameter estimation. For more on Bayesian methods, see Fang Jie et al. (2011).

Sequential testing, product distribution methods, Bootstrap, and Bayesian methods each have strengths in mediation analysis (Fang Jie & Wen Zhonglin, 2018a; Fang Jie & Zhang Minqiang, 2012; Fang Jie & Zhang Minqiang, 2013). Wen Zhonglin and Ye Baojuan (2014a) recommend starting with sequential testing; if coefficients a and b are not both significant, Bootstrap should be used. For reporting confidence intervals, Bootstrap is preferable, but the significance of a and b should still be examined. With appropriate prior information, Bayesian methods are also viable (Fang Jie et al., 2011).

### 3.2 Effect Size of Mediation Effects

A significant mediation effect only indicates that the effect is not zero; effect size indices are needed to quantify its magnitude. Fang Jie et al. (2012) reviewed four effect size measures: the ratio of mediation effect to total effect (MP), the ratio of mediation effect to direct effect (MR), the ratio of mediation effect to its maximum possible value ( $^2$), and R$^2${*med*}. *The formula for* $R^2${med} is:

$$R^2_{med} = \frac{\gamma^2_{MY} - \gamma^2_{XY} R^2_{Y.MX}}{1 - \gamma^2_{XY}}$$

where $\gamma${*MY*} *is the correlation between Y and M,* $\gamma${XY} is the correlation between Y and X, and R$^2${*Y.MX*} *is the coefficient of determination from equation (3).* $R^2${med} represents the proportion of variance in Y explained jointly by X and M but not by either alone (Fang Jie et al., 2012; Wen Zhonglin et al., 2016). Additionally, Lachowicz et al. (2018) proposed a new index, , by replacing $\gamma$*{MY} in the* $R^2${med} formula with $\gamma${MY} • $\gamma${XY}:

$$\nu = \frac{\gamma_{MY}\gamma_{XY} - \gamma_{XY}^2 R_{Y.MX}^2}{1 - \gamma_{XY}^2}$$

Wen Zhonglin et al. (2016) noted that $R^2$_{med} lacks monotonicity (i.e., as ab increases, the effect size may decrease), making it unsuitable as a mediation effect size measure. $^2$ also lacks monotonicity and incorrectly uses the maximum possible value of ab as its denominator, rendering it inappropriate (Wen & Fan, 2015). Although has monotonicity, using the standardized mediation effect ab is more interpretable.

Wen Zhonglin et al. (2016) recommend reporting the standardized estimate of ab and using MP as the effect size when ab and c have the same sign. When ab and c have opposite signs, no appropriate effect size measure is available.

### 3.3 Mediation Analysis with Categorical Variables

Most mediation models assume continuous X, M, and Y. For between-subjects designs (where M and Y are measured once) with a binary independent variable, mediation analysis can proceed by coding the categorical variable as 0 and 1 and using equations (1)-(3). For independent variables with k categories ($k \geq 3$), relative mediation effects can be analyzed by dummy coding the variable and testing k - 1 relative mediation effects (Fang Jie et al., 2017).

For two-level within-subject designs (where M and Y are each measured twice) with a binary independent variable (experimental group $X_1$ and control group $X_2$) and continuous M and Y, three new variables are created: diffY, diffM (whose mean equals coefficient a), and sumM (which needs to be centered). Then, coefficient b is obtained from the regression equation. If the Bootstrap confidence interval for ab excludes 0, the mediation effect is significant (Wang Yang & Wen Zhonglin, 2018).

When M and/or Y are categorical, logistic regression should replace linear regression (Liu Hongyun et al., 2013). Special attention must be paid to coefficient scaling. For example, when Y is categorical and X and M are continuous, coefficient a from equation (2) (on a continuous scale) and coefficient b from equation (3) (on a logit scale) are not on the same metric, so they cannot be multiplied directly. Instead, coefficients should be transformed to a_Z = a/SE(a) and b_Z = b/SE(b), with the mediation effect size being a_Z × b_Z, and its significance tested accordingly (Fang Jie et al., 2017). When Y is an ordinal variable with at least 5 categories, standard linear regression may be used (Liu Hongyun et al., 2013).

### 3.4 Mediation Analysis with Longitudinal Data

Previous mediation analyses often used cross-sectional data, which are unsuitable for causal inference, necessitating longitudinal data collection and analysis (Wen Zhonglin, 2017). Liu Guofang et al. (2018) introduced mediation testing based on cross-lagged panel models (more appropriately called autoregressive lag models), latent growth models, and latent change score models. Fang Jie et al. (in press) further identified four trends in longitudinal mediation analysis: (1) examining time-varying mediation effects, such as continuous-time models and multilevel time-varying coefficient models; (2) examining individually varying mediation effects, such as random-effects cross-lagged panel models and multilevel autoregressive mediation models; (3) integration of mediation models, such as combining cross-lagged panel models with multilevel models to create multilevel autoregressive mediation models; and (4) using Bootstrap and Bayesian methods for longitudinal mediation analysis.

Fang Jie et al. (in press) noted that multilevel linear models and latent growth models do not consider the temporal ordering of variable influences, so longitudinal mediation analysis using these models remains essentially cross-sectional, requiring extra-statistical justification for causal claims (Wen Zhonglin, 2017). Only cross-lagged panel models, multilevel autoregressive mediation models, and continuous-time models support longitudinal causal inference because they incorporate both temporal precedence and autoregressive effects. They proposed a flowchart for longitudinal mediation analysis: if the goal is not longitudinal causal inference, use multilevel linear or latent growth models; if the goal is longitudinal causal inference with time-varying effects, use continuous-time models; otherwise, use cross-lagged panel or multilevel autoregressive mediation models.

### 3.5.1 Multiple Mediation Models

Complex phenomena often require multiple mediators to adequately explain the effect of X on Y, necessitating multiple mediation models (Figure 2 [Figure 2: see original paper]). Based on whether mediators influence each other, these models can be classified as parallel (no mediator-to-mediator relationships, remove $M_1 \rightarrow M_2$ path in Figure 2) or chain (mediators influence each other, see Figure 2). Mediation effects in multiple mediation models fall into three categories: (1) specific mediation effects for particular paths of interest (typically products of two coefficients like $b_1a_1$, but chain models allow products of multiple coefficients like $b_3a_2a_1$, which is unique to multiple mediation); (2) total mediation effect, the sum of all mediation effects; and (3) contrast mediation effects, the difference between two path-specific effects (e.g., $b_1a_1$ - $b_2a_2$). If two mediation effects have opposite signs, the contrast is based on absolute values (e.g., $|b_1a_1|$ - $|b_2a_2|$) (Fang Jie, Wen Zhonglin, Zhang Minqiang, & Sun Peizhen, 2014; Liu Shishun & Ling Wenquan, 2009; Wen Zhonglin & Liu Hongyun, 2020).

**Figure 2** A Multiple Mediation Model

Liu Shishun and Ling Wenquan (2009) first introduced multiple mediation models to China, using Sobel tests for manifest variable analysis. Fang Jie, Wen Zhonglin, Zhang Minqiang, and Sun Peizhen (2014) recommended using Bootstrap with auxiliary variables for latent variable multiple mediation analysis. Comparisons of testing methods for multiple mediation are reviewed in Fang Jie et al. (2011), multi-category independent variables are addressed in Fang Jie et al. (2017), and two-level repeated measures multiple mediation is discussed in Wang Yang and Wen Zhonglin (2018).

### 3.5.2 Multilevel Mediation Models

Nested data structures are common in social sciences (e.g., students nested in classrooms). These violate independence assumptions, requiring multilevel models for mediation analysis to overcome limitations of ordinary least squares regression (Fang Jie et al., 2010). Multilevel mediation models combine multilevel and mediation models. Common configurations include 2-2-1, 2-1-1, and 1-1-1 models (numbers indicate levels of X, M, and Y, respectively). The 2-1-1 and 1-1-1 models can be fixed or random depending on whether path coefficients vary across level-2 units. In 2-1-1 random mediation models, the random effect b (subscript j denotes level-2 unit, e.g., classroom) indicates that the effect of level-1 M on level-1 Y varies across level-2 units, expressed as b = b + . The 1-1-1 random mediation model includes random effects a , b , c' , and random mediation effect a b (Liu Hongyun et al., 2011).

Fang Jie et al. (2010) first introduced multilevel mediation models to China, discussing manifest variable analysis. For 2-1-1 and 1-1-1 models, centering level-1 predictors at group means while including group means in level-2 intercept equations effectively separates between-group and within-group mediation effects. Specifically, 2-1-1 models have only between-group mediation, while 1-1-1 models have both. Liu Hongyun et al. (2011) noted that using fixed mediation models when random effects are present yields incorrect estimates and test results.

When data come from I employees in J companies randomly sampled from populations of companies and employees, respectively, centering level-1 variables (e.g., employee psychological capital) at group means and placing group means in level-2 intercept equations assumes that observed group means equal unobservable population means, introducing sampling error—bias due to sampling from populations (Fang Jie, Wen Zhonglin, Zhang Minqiang, & Ren Hao, 2014). Treating group means as unobservable latent variables and using multilevel structural equation modeling (MSEM) better controls sampling error. Fang Jie et al. proposed a flowchart: first use MSEM for latent variable multilevel mediation; if results are nonsignificant and the dependent variable is at level 1, then use multilevel models for manifest variable analysis.

Nonparametric Bootstrap is difficult to implement in multilevel mediation. Fang Jie and Wen Zhonglin (2018a) recommended Bayesian methods when appropriate prior information is available, and MC methods when it is not, as MC performs comparably to other methods without requiring raw data, making it computationally faster. Method comparisons are reviewed in Fang Jie et al. (2011).

### 3.5.3 Moderated Mediation Models

Moderated mediation occurs when the mediation process (X→M→Y) is influenced by a moderator Z, such that the mediation effect varies with Z' s values. Wen Zhonglin et al. (2006) discussed using sequential testing for models where the latter path (M→Y) is moderated. Wen Zhonglin and Ye Baojuan (2014b) systematically reviewed six moderated mediation models (three moderating only the mediation effect and three moderating both mediation and direct effects), evaluating three testing approaches—sequential testing, coefficient product interval testing, and mediation effect difference testing—and provided a testing flowchart. They recommended sequential testing first; if moderated mediation is nonsignificant, use coefficient product interval testing (nonparametric Bootstrap); if still nonsignificant, use mediation effect difference testing (nonparametric Bootstrap). Fang Jie, Zhang Minqiang et al. (2014) explained coefficient product interval testing using Bayesian methods. Liu Hongyun et al. (Liu, Yuan et al., in press) integrated moderated mediation with two-level regression moderation models (Yuan et al., 2014), proposing a two-level moderated mediation model and effect size measures.

Fang Jie and Wen Zhonglin (2018b) further explained latent moderated structural equation methods for latent variable moderated mediation analysis. The latent moderated structural equation approach (Klein & Moosbrugger, 2000) has the advantage of not requiring product indicators and can be conveniently implemented in Mplus. Fang Jie et al. recommended testing latent moderated mediation if the baseline model (without moderation) is acceptable; otherwise, use manifest variable analysis.

Fang Jie and Wen Zhonglin (in press) integrated multilevel mediation and moderation, creating 12 types of moderated multilevel mediation models (2 multilevel mediation types $\times$ 2 moderator levels $\times$ 3 moderated paths). They explained manifest variable testing for all 12 types and systematically described latent variable testing using multilevel structural equation models, including orthogonal decomposition, random coefficient prediction, latent moderated structural equation, and Bayesian plausible value methods. The core issue is handling latent interaction terms. With adequate sample sizes, latent moderated structural equation methods are recommended; with small samples, Bayesian plausible value methods are preferred.

### 3.5.4 Mediated Moderation Models

Mediated moderation means that X' s effect on Y is moderated by Z, and this moderation effect (at least partially) operates through mediator M (Figure 3 Figure 3: see original paper), known as mediated moderation Type I (Liu Dong et al., 2012; Wen Zhonglin et al., 2006). Wen Zhonglin et al. (2006) discussed sequential testing for Type I models. The testing steps are identical to those for models where the first half of the mediation path (X→M) is moderated, but the theoretical framing and interpretation differ (Wen Zhonglin & Ye Baojuan, 2014a). For mediated moderation, the focus is on the moderation effect and whether it operates through M; for moderated mediation, the focus is on the mediation effect and whether it is moderated.

Ye Baojuan and Wen Zhonglin (2013) systematically reviewed five methods for testing mediated moderation and provided a flowchart: first test whether X' s effect on Y is moderated by Z; if significant (with $\Delta R^2 \geq 2\%$), use sequential testing; if mediated moderation is nonsignificant, use coefficient product interval testing (nonparametric Bootstrap or Bayesian).

Wen Zhonglin and Liu Hongyun (2020) integrated testing procedures for moderated mediation and mediated moderation into a comprehensive flowchart. If X' s effect on Y is not moderated by Z, only moderated mediation should be considered. If moderation is present, either mediated moderation or moderated mediation can be considered, depending on the researcher' s theoretical framework.

Liu Dong et al. (2012) noted that when Z' s moderating effect is transmitted through M, this is mediated moderation Type II (Figure 3 Figure 3: see original paper). Kwan and Chan (2018) showed that Type II is equivalent to a moderated mediation model where Z is the independent variable and X is the moderator of the latter path. Liu Hongyun et al. (2021) further integrated Type II with two-level regression moderation models (Yuan et al., 2014), proposing a two-level mediated moderation model and new effect size measures for indirect moderation effects.

Liu Dong et al. (2012) also integrated multilevel mediation and moderation, proposing three mediated multilevel moderation Type I models and two Type II models. Type I includes: level-2 X and Z moderation transmitted through level-1 M to level-1 Y, through level-2 M to level-1 Y, and level-1 X and Z moderation through level-1 M to level-1 Y. Type II includes level-2 Z moderation of level-1 X→Y transmitted through level-2 M or level-1 M.

## 4. Discussion and Extensions

This article systematically reviewed the development of domestic methodological research on mediation effects across five dimensions: testing methods, effect size, categorical variable mediation, longitudinal data mediation, and model extensions, serving as a guide for readers. Combined with recent foreign methodological research, several areas warrant further exploration.

### 4.1 Experimental Design for Mediation Analysis

Only two domestic studies address experimental mediation designs. Liu Guofang (2018) introduced three designs: double randomization, concurrent double randomization, and parallel designs. Wang Yang and Wen Zhonglin (2018) explained two-level within-subject mediation analysis (see Section 3.3). Miočević et al. (2018) noted that for experimental designs manipulating X and measuring M and Y once each, potential outcomes mediation analysis can be conducted within a counterfactual framework. For example, in a word memory experiment examining memory strategy (experimental group: associative memory; control: repetitive memory) → association strength → number of words recalled, before random assignment each student has two potential outcomes: Y(1) under associative memory and Y(0) under repetitive memory. If assigned to the experimental group, Y(1) is observed while Y(0) becomes the counterfactual outcome.

### 4.2 Controlling for Confounders in Mediation Analysis

In simple mediation models, if variable T causes both M (T→M) and Y (T→Y), T is a confounder of the M→Y relationship. Confounders can be pre-treatment (occurring before X, assumed unaffected by X) or post-treatment (occurring after X, potentially affected by X) (Figure 4 [Figure 4: see original paper]). For example, in a model where education (X) affects blood pressure (Y) through unhealthy diet (M), socioeconomic status (T) is a post-treatment confounder because education influences socioeconomic status.

**Figure 4** Simple Mediation Model with Confounder T (adapted from Fritz et al., 2016)

Fritz et al. (2016) found that omitted confounders bias the M→Y relationship, overestimating mediation effects. Tofighi et al. (2013; 2016) found that omitted level-2 confounders bias both within-group and between-group mediation estimates in 1-1-1 models. Talloen et al. (2016) found similar bias in 2-1-1 models. Therefore, confounders must be controlled.

For pre-treatment confounder T in simple mediation, add T as a covariate to equations (1)-(3). For example, equation (2) becomes $M = aX + gT + {}_2$, and equation (3) becomes $Y = bM + c' X + g' T + {}_3$, testing a_T × b_T (Fritz et al., 2016). Post-treatment confounders should be treated as new mediators, adding X→T→M, X→T→Y, and X→T→M→Y paths.

### 4.3 Robust Mediation Analysis

Linear regression mediation analysis assumes homoscedastic and normal residuals, which are often violated. Robust methods reduce bias from assumption violations. Their advantage is insensitivity to deviations from ideal statistical assumptions (Zu & Yuan, 2010), hence the term robust mediation analysis. Methods include Robust M-estimation (Zu & Yuan, 2010), median regression (Yuan & MacKinnon, 2014), and Robust Bootstrap (Alfons et al., in press).

Robust M-estimation approximates maximum likelihood estimation under normality by weighting data according to distance from the center (e.g., mean), giving extreme values lower weight and reducing their influence (Zu & Yuan, 2010).

Traditional linear regression is mean regression, which is sensitive to outliers and performs poorly with skewed or heavy-tailed distributions (Yuan & MacKinnon, 2014). Median regression uses the median, which is robust to outliers, and requires only residual independence, not homoscedasticity or normality, using least absolute deviations estimation.

Robust Bootstrap uses weighted least squares (weights in [0,1], with smaller weights for more distant data) to estimate $\hat{a}$ and $\breve{b}$ in each Bootstrap sample, then applies linear correction to account for uncertainty in robust weights (Alfons et al., in press).

### 4.4 Power Analysis for Mediation Effects

Power analysis can be post-hoc (given sample size, $\alpha$, and observed effect sizes a, b, c' , compute power) or a priori (given desired power $\geq 0.8$, $\alpha$, and predicted effect sizes from prior research, pilot studies, meta-analysis, or expert knowledge, compute required sample size). Post-hoc analysis is generally less meaningful. Schoemann et al. (2017) developed a web tool for both types of power analysis for simple and multiple mediation. Liu and Wang (2019) noted that Schoemann' s tool does not account for uncertainty in predicted a, b, and c' values, and developed a new tool incorporating this uncertainty.

Current methodological research integrates mediation analysis with new statistical techniques. Serang et al. (2017) proposed regularized exploratory mediation analysis using Lasso estimation, retaining only significant mediation paths in parallel multiple mediation models. Serang and Jacobucci (2020) extended this to dichotomous outcomes. Gonzalez et al. (2018, 2021) integrated bifactor analysis with mediation analysis, examining how mediator measurement (reliability and error) affects conclusions. Hsiao et al. (in press) combined latent class analysis with mediation analysis. Others have integrated social network analysis with mediation (Che et al., 2021; Liu, Jin et al., in press). These advances enable deeper understanding and application of mediation effects, and continued methodological research will further enhance our understanding of mediation-related issues.

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### References

[The references section contains both Chinese and English citations and should be preserved exactly as in the original, maintaining all formatting and details.]

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