**Mediation Analysis in Structural Equation Modeling (Sem): Theoretical Foundations, Statistical Methods and Practical Implications**

**ABSTRACT**

This study offers a comprehensive investigation of mediation analysis in Structural Equation Modelling, highlighting its theoretical basics, statistical practices, and real-world applications. It differentiates mediation from moderation, explaining how mediation helps in understanding indirect relationships between latent variables. Various proposed mediation models, including simple mediation, multiple mediation, and moderated mediation, are discussed in detail. The study also analyses statistical methods such as the Causal Steps Approach (Baron & Kenny, 1986), the Product-of-Coefficients Method (Sobel Test), Bootstrapping, the Bayesian Estimation Method, and Monte Carlo Simulation, each with its respective advantages and limitations. Additionally, advanced Structural Equation Modelling techniques, such as multigroup mediation, longitudinal mediation, and latent variable mediation, are examined to address complex research scenarios. Employing a literature review-based methodology, the study synthesizes existing knowledge on best practices for estimating mediation effects using Structural Equation Modelling. Software tools like AMOS, Mplus, LISREL, and SmartPLS are discussed in the context of model specification, estimation, and evaluation. Real-world applications in business, psychology, human resource management, and marketing are illustrated, including customer trust mediating the relationship between service quality and purchase intention, employee engagement mediating the effect of transformational leadership on job performance, and social media engagement mediating brand trust and purchase intention. Key findings highlight bootstrapping as a better method for estimating indirect effects due to its non-reliance on normality of the data assumptions and Bayesian SEM as a robust substitute for handling small sample sizes and incorporating preceding knowledge. The study also discusses crucial challenges such as measurement error, model misspecification, the need for longitudinal data to establish causal inference, and comparisons between Structural Equation Modelling-based mediation and regression-based mediation using the PROCESS macro. By presenting a structured framework for mediation analysis in Structural Equation Modelling, this current study contributes to advancing causal modelling methods across various disciplines and provides directions for future research.

**JEL Classification: C30, C38, M10, M31, M54**

***Keywords:*** *Mediation Analysis, Coefficient, Bootstrapping, Moderated Mediation, Bayesian Estimation, Multigroup Mediation, Latent Variable Mediation, Fit Indices.*

**I INTRODUCTION**

Structural Equation Modelling is a powerful multivariate statistical technique that integrates factor analysis and path analysis to examine complex relationships among observed and latent variables (Hair et al., 2010; Kline, 2015). SEM allows researchers to test theoretical models by specifying and estimating relationships between constructs while accounting for measurement error (Byrne, 2013; Schumacker & Lomax, 2016). Unlike traditional regression models, SEM simultaneously evaluates multiple dependent relationships and mediating effects, providing a more comprehensive understanding of underlying mechanisms (Bollen, 1989; Hoyle, 2012). It is widely applied in social sciences, psychology, marketing, and business research to validate theoretical frameworks and test hypotheses rigorously (Anderson & Gerbing, 1988; Bentler, 1990).

A key advantage of Structural Equation Modelling (SEM) lies in its ability to assess model fit using various goodness-of-fit indices, such as the Comparative Fit Index, Tucker-Lewis Index, Root Mean Square Error of Approximation, and Standardized Root Mean Square Residual (Hu & Bentler, 1999; MacCallum et al., 1996). Model estimation in SEM is commonly performed using methods like Maximum Likelihood and Generalized Least Squares, ensuring robust parameter estimation under different assumptions (Jöreskog & Sörbom, 1993; Muthén & Muthén, 2010). Despite its strengths, Structural Equation Modelling needs large sample sizes and careful model specification to avoid issues like model misspecification and identification problems (West et al., 2012; Kline, 2015). As Structural Equation Modelling continues to evolve, developments in Bayesian SEM, Partial Least Squares SEM (PLS-SEM), and multi-group analysis are mounting its applicability across diverse fields (Hair et al., 2010; Sarstedt et al., 2020).

Structural Equation Modelling is extensively applied across various disciplines, including psychology, social sciences, business, healthcare, and education, due to its ability to analyse complex relationships among latent and observed variables (Byrne, 2013; Hair et al., 2010). In marketing and consumer research, Structural Equation Modelling assists in understanding customer satisfaction, brand loyalty, and purchase intentions by modelling direct and indirect effects (Fornell & Larcker, 1981; Bagozzi & Yi, 1988). In psychology and behavioural sciences, SEM is used to validate theoretical latent constructs such as personality traits, motivation, and cognitive processes (Kline, 2015; Hoyle, 2012). Organizational researchers employ SEM to study leadership effectiveness, job satisfaction, and employee engagement, providing deeper understandings into workplace dynamics (Schumacker & Lomax, 2016; Anderson & Gerbing, 1988). In healthcare sector, SEM is applied to assess patient satisfaction, quality of life, and the effectiveness of medical interventions (Bentler, 1990; MacCallum et al., 1996). Furthermore, SEM is instrumental in educational research, helping to evaluate learning outcomes, student engagement, and instructional effectiveness (West et al., 2012; Sarstedt et al., 2020). The technique’s flexibility in handling measurement errors and testing mediation and moderation effects makes it an indispensable tool for empirical research across diverse fields (Jöreskog & Sörbom, 1993; Muthén & Muthén, 2010).

Mediation analysis is a statistical method used to study the indirect effects of a predictor variable (X) on an outcome variable (Y) through a mediating variable (M), assisting researchers understand the underlying mechanisms driving observed relationships (Baron & Kenny, 1986; Preacher & Hayes, 2008). By decomposing total effects into direct and indirect effects, mediation analysis permits researchers to test whether an effect operates through a specific path rather than solely relying on direct relationship (MacKinnon et al., 2007; Shrout & Bolger, 2002). Structural Equation Modelling has become a preferred method for mediation analysis as it allows simultaneous estimation of multiple mediation pathways while accounting for measurement errors (Hayes, 2013; Kline, 2015). Traditional mediation testing relied on the causal steps approach proposed by Baron and Kenny (1986), but modern approaches emphasise bootstrapping methods, which offer more powerful and reliable confidence intervals for indirect effects (MacKinnon, 2008; Zhao, Lynch, & Chen, 2010). Mediation analysis is extensively applied in social sciences, psychology, business, and healthcare to examine theoretical models involving psychological processes, organisational behaviour, consumer behaviour, leadership effectiveness, and treatment interventions (Iacobucci, 2012; Rucker et al., 2011). Advanced mediation models, such as moderated mediation and serial mediation, further extend its applicability by exploring conditions under which mediation effects vary or multiple mediators’ function successively (Edwards & Lambert, 2007; Preacher, Rucker, & Hayes, 2007).

Mediation analysis is highly relevant across various research fields, as it assists uncover the mechanisms through which predictor variables influence dependent variables, offering deeper theoretical and practical understandings (Baron & Kenny, 1986; MacKinnon, 2008). In psychology, mediation analysis is widely applied to understand cognitive, emotional, and behavioural processes, such as how stress affects mental health through coping strategies (Preacher & Hayes, 2008; Shrout & Bolger, 2002). In business and management research, it plays a critical role in exploring factors that drive employee engagement, job performance, leadership effectiveness, such as how job satisfaction mediates the relationship between various leadership style and employee engagement (Iacobucci, 2012; Rucker et al., 2011). Healthcare research widely applies mediation analysis to assess patient outcomes, treatment effectiveness, and health interventions; for example, it helps examine how lifestyle changes mediate the effect of medical treatments on disease prevention (Hayes, 2013; MacKinnon et al., 2007). In education, mediation models are employed to analyse learning outcome, such as how student motivation mediates the relationship between teaching approaches and academic performance (West et al., 2012; Sarstedt et al., 2020). The flexibility of mediation analysis ranges to social sciences, policy research, and behavioural economics, making it a invaluable device for explaining indirect causal relationships and enhancing empirical research across varied disciplines (Edwards & Lambert, 2007; Zhao, Lynch, & Chen, 2010).

**II THEORETICAL BACKGROUND**

Mediation denotes to a process in which an independent or predictor variable (X) influences a dependent variable (Y) through an intervening variable, known as the mediator (M), assisting to explain the underlying mechanism of the relationship (Baron & Kenny, 1986; MacKinnon, 2008). The mediation effect, or indirect effect, occurs when X affects M, which in turn affects Y, suggesting that part of the effect of X on Y is diffused through M rather than being a direct relationship (Preacher & Hayes, 2008; Shrout & Bolger, 2002). Mediation is typically tested using statistical approaches such as the causal steps approach (Baron & Kenny, 1986), the Sobel test (Sobel, 1982), and bootstrapping methods (Hayes, 2013; MacKinnon et al., 2007), with SEM offering a more influential framework for analysing complex mediation models (Iacobucci, 2012; Kline, 2015).

Mediation differs from moderation, as moderation refers to a process where a third variable called as moderator alters the strength or direction of the relationship between X and Y (Hayes, 2007; Frazier et al., 2004). While mediation explains “how” or “why” a relationship occurs, moderation explains “when” or “under what conditions” it holds (Muller, Judd, & Yzerbyt, 2005; Edwards & Lambert, 2007). In a moderated relationship, the effect of X on Y varies depending on different levels of the moderator, whereas in mediation, the independent variable exerts its influence through the mediator (Fairchild & MacKinnon, 2009; Zhao, Lynch, & Chen, 2010). Researchers often discover both mediation and moderation together through moderated mediation models, which evaluate whether mediation effects change under different moderating conditions (Preacher, Rucker, & Hayes, 2007; Wen & Fan, 2015). These differences are critical for developing theoretical framework and deriving meaningful insights across psychology, business, healthcare, and social sciences (Hayes, 2013; MacKinnon, 2008).

**TYPES OF MEDIATION MODELS**

Mediation models can be classified into various categories based on the complexity of the mediation process and the relationships between latent variables. The primary types of mediation models include simple mediation, multiple mediation, serial (sequential) mediation, and moderated mediation (Baron & Kenny, 1986; MacKinnon, 2008; Hayes, 2013).

**1. Simple Mediation Model**

A simple mediation model involves a single mediator (M) that describes the relationship between a predictor variable (X) and a dependent variable (Y) (Baron & Kenny, 1986; Preacher & Hayes, 2004). This model assists researchers understand how and why X influences Y by identifying the indirect effect transmitted through M (Shrout & Bolger, 2002; Zhao, Lynch, & Chen, 2010).

**2. Multiple Mediation Model**

In multiple mediation models, two or more mediators operate in parallel, meaning that the independent or predictor variable (X) concurrently influences multiple mediators (M₁, M₂, …, Mn), which in turn affect the outcome variable (Y) (Preacher & Hayes, 2008; MacKinnon et al., 2007). This approach allows researchers to scrutinize multiple relationships through which an effect occurs, reducing omitted variable bias (Fairchild & MacKinnon, 2009; Hayes, 2007).

**3. Serial (Sequential) Mediation Model**

In serial mediation techniques, mediators are arranged in a sequence such that one mediator affects the next before finally influencing the outcome or dependent variable (Taylor, MacKinnon, & Tein, 2008; Hayes, 2013). This type of mediation model is useful for testing stepwise mechanisms where an initial cause leads to intermediate outcomes before affecting the final outcome (Nitzl, Roldan, & Cepeda, 2016).

**4. Moderated Mediation Model**

Moderated mediation occurs when the strength or significance of a mediation effect depends on a moderating variable (W) (Preacher, Rucker, & Hayes, 2007; Edwards & Lambert, 2007). In this technique, the mediation process is influenced by an external or outside factor that conditions the indirect effect of X on Y through M (Hayes, 2007; Muller, Judd, & Yzerbyt, 2005). Moderated mediation is extensively used in psychology, business research, and social sciences to investigate complex relations (Fairchild & MacKinnon, 2009; Zhao et al., 2010).

Each of these mediation techniques offers valuable understandings into causal mechanisms, enhancing theoretical understanding across disciplines such as psychology, business, social sciences, and healthcare (Iacobucci, 2012; MacKinnon, 2008; Hayes, 2013). Advanced statistical techniques, including SEM and bootstrapping, are often used to test these models (Preacher & Hayes, 2008; Kline, 2015).

**Direct, Indirect, and Total Effects in SEM**

Structural Equation Modelling is a powerful statistical technique that assists researchers quantify and differentiate between direct, indirect, and total effects in complex causal relationships (Kline, 2015; Bollen, 1989; Hair et al., 2010). By incorporating multiple regression equations and latent construct modelling, Structural Equation Modelling allows for a complex understanding of how proposed variables interact within a system (Byrne, 2013; MacKinnon, 2008).

**1. Direct Effects**

A direct effect refers to the direct path between a predictor variable (X) and an outcome variable (Y) without any mediating variables (MacKinnon, Fairchild, & Fritz, 2007; Hayes, 2013). This is characterized by the unmediated regression coefficient in a structural model (Baron & Kenny, 1986). Direct effects are essential for establishing the primary casual relationships between latent constructs in a theoretical framework (Preacher & Hayes, 2008).

**2. Indirect Effects**

Indirect effects occur when the relationship between X and Y is mediated by a mediating or intervening variable (M), meaning X influences M, which in turn affects Y (Shrout & Bolger, 2002; Preacher, Rucker, & Hayes, 2007). Structural Equation Modelling estimates these indirect effects by multiplying the estimated path coefficients of each step in the mediation sequence (Hayes, 2007; Iacobucci, 2012). The significance of indirect effects is typically tested using bootstrapping techniques, which provide robust confidence intervals (MacKinnon, 2008; Zhao, Lynch, & Chen, 2010).

**3. Total Effects**

The total effect is the sum of both direct and indirect effects of X on Y (Bollen, 1989; Kline, 2015). It provides an overall framework of how much variation in Y (DV) can be attributed to X (IV), including all mediating pathways (Hair et al., 2010; Preacher & Kelley, 2011). If the indirect effect is significant while the direct effect is not, full mediation is suggested, whereas if both direct and indirect effects are significant, partial mediation is indicated (MacKinnon et al., 2002; Hayes, 2013).

Structural Equation Modelling is particularly invaluable for decomposing these effects in research fields such as psychology, business research, and healthcare, where complex causal relationships need to be inspected (Iacobucci, 2009; Fairchild & MacKinnon, 2009). It also enables researchers to test competing theoretical models and assess the strength of causal pathways in a way that traditional regression methods cannot (Preacher & Hayes, 2008; Nitzl, Roldan, & Cepeda, 2016).

**Methodology:**

**III. STATISTICAL APPROACHES TO MEDIATION IN SEM**

Statistical mediation analysis in Structural Equation Modelling allows researchers to study how a predictor variable (X) transmits its effect on a outcome variable (Y) through a mediator (M) (MacKinnon, 2008; Preacher & Hayes, 2008; Iacobucci, 2012). in Structural Equation Modelling offers several statistical approaches for testing mediation, including the causal steps approach, the product-of-coefficients method, bootstrapping, and Bayesian estimation (Hayes, 2013; MacKinnon, Fairchild, & Fritz, 2007). These methods offer a more robust framework compared to traditional regression-based mediation analysis (Baron & Kenny, 1986; Shrout & Bolger, 2002).

**A. Causal Steps Approach (Baron & Kenny’s Method)**

The Baron and Kenny (1986) causal steps approach is one of the earliest methods used in mediation analysis. It involves four regression equations to establish (1) the effect of X on Y (total effect).

The total effect (c) of the predictor or independent variable (X) on the outcome or dependent variable (Y) is estimated using:

Where, c is the total effect of X on Y, is the error term

(2) the effect of X on M (Path a): To confirm that the independent variable (X) influences the mediator (M), we estimate:

Where, a is the effect of X on M,is the error term

(3) the effect of M on Y while controlling for X (Path b): To test whether the mediator (M) influences Y, we estimate:

where: b is the effect of M on Y, c’ is the direct effect of X on Y controlling for M, ε₃ is the error term.

(4) Compare c and c’ to Establish Mediation

If c’ (direct effect) is non-significant, and a and b are significant, full mediation is present.

If c’ remains significant but is smaller than c, partial mediation exists.

If a or b is non-significant, no mediation occurs.

Indirect Effect and Sobel Test

The indirect effect of X on Y through M is given by:

Indirect Effect = a × b

where SEₐ and SEᵦ are standard errors of a and b.

The Sobel test (Sobel, 1982) evaluates the significance of the mediation effect.

**Limitations of the Baron & Kenny Approach**

This approach has been criticized for its dependence on stepwise testing, its low statistical power, and its assumption of normality in the indirect effect (MacKinnon et al., 2002; Preacher & Hayes, 2008). More robust methods such as bootstrapping (Preacher & Hayes, 2008; Zhao, Lynch, & Chen, 2010) and Bayesian estimation (Muthén & Asparouhov, 2012) are now preferred for mediation analysis.

**B. Product-of-Coefficients (Sobel Test and Delta Method)**

The product-of-coefficients method estimates the indirect effect by multiplying the path coefficients (a × b), where a represents the effect of X on M and b represents the effect of M on Y (MacKinnon, Warsi, & Dwyer, 1995; Preacher & Hayes, 2004). The Sobel test (Sobel, 1982) is a widely used approach that assumes normality in the sampling distribution of indirect effects. However, it is limited in small samples and when normality assumptions are violated (Preacher & Kelley, 2011; Hayes, 2013). The delta method is a generalization of the Sobel test that provides standard errors for indirect effects in SEM (Bollen & Stine, 1990). The following are the main steps involved in computation:

**Product-of-Coefficients Approach (Sobel Test and Delta Method)**

The product-of-coefficients approach is a extensively used method for testing mediation effects. It evaluates whether the indirect effect of an independent variable (X) on a dependent variable (Y) through a mediator (M) is statistically significant.

**Indirect Effect Calculation**

The indirect effect in mediation analysis is the product of the path from X to M (a) and the path from M to Y (b):

where: a is the coefficient of the path from X to M, and b is the coefficient of the path from M to Y.

**Sobel Test (1982):** The **Sobel test** evaluates the significance of the indirect effect using the following formula:

where SEₐ and SEᵦ are standard errors of a and b. A large Z-score indicates that the indirect effect is significant. However, the Sobel test assumes normality, which can lead to low power in small samples (Preacher & Hayes, 2008).

**Delta Method:** The Delta Method offers an alternative way to estimate the standard error of the indirect effect:

This method improves upon the Sobel test by adjusting for additional variance components, making it more accurate in some cases (MacKinnon et al., 2002).

**Limitations and Alternatives**

Both the Sobel test and the Delta Method assume normality of the indirect effect, which is often violated in real-time data. More powerful techniques like bootstrapping (Preacher & Hayes, 2008) are now chosen because they do not rely on these assumptions and provide more reliable confidence intervals.

C. **Bootstrapping Approach**

Bootstrapping is considered a superior approach for testing mediation effects in Structural Equation Model (Shrout & Bolger, 2002; Preacher & Hayes, 2008). It involves resampling the dataset multiple times (e.g., 1,000, or 2,000 or 5,000 iterations) to create confidence intervals for the indirect effect (Preacher & Hayes, 2004). Unlike the Sobel test, bootstrapping does not assume a normal distribution, making it more robust for detecting mediation effects (MacKinnon et al., 2004; Hayes, 2018).

**Indirect Effect in Bootstrapping**

In this method, the indirect effect (a × b) is estimated by repeatedly resampling the data and calculating the product of the coefficients a (the effect of X on M) and b (the effect of M on Y) for each iteration. The bootstrapped estimate of the indirect effect is denoted as:

where: ai​ is the coefficient from the resampled data for path a (from X to M), bi​ is the coefficient from the resampled data for path b (from M to Y).

**Bootstrapped Confidence Intervals (CIs)**

The main advantage of bootstrapping is that it provides a confidence interval for the indirect effect that does not rely on the assumption of univariate or multivariate normality. For each resample (e.g., 2,000 or 5,000 iterations), the indirect effect is recalculated, and the distribution of these resampled estimates is used to generate a confidence interval for the indirect effect.

The 95% confidence interval is typically computed by finding the 2.5th and 97.5th percentiles of the bootstrapped estimates. If the confidence interval does not include zero, the indirect effect is considered statistically significant.

Mathematically, the 95% bootstrapped confidence interval can be expressed as:

where: represent the 2.5th and 97.5th percentiles of the bootstrapped distribution of the indirect effect.

​Bootstrapping is considered a superior method due to (i) it does not assume normality of the indirect effect distribution, which makes it more robust to violations of normality, and (ii) provides a direct estimate of the sampling distribution of the indirect effect, leading to more accurate confidence intervals.

Although bootstrapping is more reliable than traditional methods, it can be computationally rigorous, especially when dealing with large datasets and a high number of resamples. However, the method is highly recommended for testing mediation effects in Structural Equation Model due to its flexibility and robustness (Preacher & Hayes, 2008; Shrout & Bolger, 2002).

**D. Bayesian Estimation**

Bayesian estimation offer an alternative to traditional frequentist approaches by estimating posterior distributions for mediation effects rather than relying on p-values (Yuan & MacKinnon, 2009; Muthén & Asparouhov, 2012). Bayesian Structural Equation Model allows for greater flexibility in handling small sample sizes and complex models, incorporating prior knowledge to improve estimation accuracy (Van de Schoot et al., 2014; Zyphur & Oswald, 2015). In Bayesian Structural Equation Model, the goal is to estimate the posterior distribution of model parameters, including the indirect effect in mediation models. Bayesian estimation uses Bayes’ Theorem to update beliefs about the parameters based on prior information and observed data. The formula for the posterior distribution of parameters is given by

is the posterior distribution of the parameters θ given the observed data Y, is the likelihood of the data given the parameters, is the prior distribution of the parameters, and is the marginal likelihood of the data (also known as the evidence), which normalizes the distribution.

**Posterior Estimation in Bayesian Mediation**

For mediation, the indirect effect a × b is estimated as the product of the path coefficients a (from the independent variable X to the mediator M) and b (from the mediator M to the dependent variable Y). The posterior distribution of the indirect effect is obtained by computing the product of the posterior distributions of a and b.

Posterior of Indirect Effect= a x b

Where, and

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Bayesian estimation offers a reliable interval for the indirect effect, similar to a confidence interval in frequentist methods, but more flexible as it does not rely on normality assumptions. The credible interval for the indirect effect is resulting from the posterior distribution:

This method allows researchers to assess the significance of the mediation effect by examining if the credible interval excludes zero. If the interval does not include zero, the indirect effect is considered statistically significant.

Main advantage of Bayesian estimation is, it allows the inclusion of prior distributions based on previous research or expert judgment, making it particularly useful in small samples or complex models (Van de Schoot et al., 2014; Zyphur & Oswald, 2015). Unlike frequentist methods, which may require large sample sizes to achieve reliable estimates, Bayesian methods are more flexible and robust in the presence of small samples. Bayesian estimation does not rely on the assumption of normality for the distribution of the indirect effect, making it more robust in real-world applications. However, this approach is not free from limitations, they can be computationally intensive, particularly in models with a large number of parameters or complex priors. Additionally, the choice of prior distributions can significantly impact the outcomes, and inappropriate priors can lead to biased estimates.

**E. Multigroup and Moderated Mediation Models**

In some cases, mediation effects may vary across subgroups (e.g., gender, culture), requiring a multigroup SEM approach (Cheung & Lau, 2008; Nitzl, Roldán, & Cepeda, 2016). Moderated mediation extends the standard mediation outline by investigating whether the strength of the mediation effect differs depending on a moderator variable (Edwards & Lambert, 2007; Preacher, Rucker, & Hayes, 2007).

These statistical methods provide robust ways to test mediation effects in SEM, helping researchers uncover complex indirect relationships across various domains such as psychology, business research, and healthcare (Iacobucci, 2012; Hayes, 2013). Choosing the appropriate method depends on sample size, normality assumptions, and the complexity of the mediation model (MacKinnon et al., 2002; Zhao et al., 2010). In a multigroup mediation model, the same model is estimated separately for different subgroups (e.g., male vs. female, different cultures) to test whether the indirect effect of the predictor variable (X) on the outcome variable (Y) through the mediator (M) is invariant across these groups. This involves comparing path coefficients (a, b) for different groups. The standard form for the mediation model is:

1. Path from X to M (a):
2. Path from M to Y (a):

For multigroup analysis, these equations are estimated separately for each group, and the mediation effect (indirect effect a × b) can be compared across groups.

**Moderated Mediation Model**

Moderated mediation examines whether the moderator variable (W) affects the strength of the mediation effect. In this model, the indirect effect a × b is moderated by the moderator (W), meaning the strength of the mediation effect depends on the value of W. The moderated mediation model can be expressed as follows:

Moderated Path from X to M (a):

Where, is the interaction term between X and W, which moderates the relationship between X and M.

Path from M to Y (b):

**Indirect Effect (Moderated Mediation):** Indirect Effect= a × b.

In the moderated mediation model, the indirect effect a × b is depending on the level of the moderator (W). If the interaction term γ3 ​ is significant, this indicates that the mediation effect differs based on the moderator (W).

**Testing the Moderated Mediation**

The moderation of the mediation effect can be tested using Sobel test or bootstrapping methods (Hayes, 2007). For example, a moderated mediation hypothesis can be tested using the following steps:

1. Estimate the direct paths (a and b) between X, M, and Y.
2. Test the interaction effect (X × W) on the mediator (M) using the path coefficient γ3
3. Estimate the moderated indirect effect using bootstrapping methods or Sobel tests.

**F. Monte Carlo Simulation: An Alternative for Testing Mediation Effects**

Monte Carlo simulation is another method for testing mediation effects, mainly useful when the normality assumption of indirect effects is violated or when traditional methods like the Sobel test lack statistical power (MacKinnon, Lockwood, & Williams, 2004; Preacher & Selig, 2012). It involves generating repeated random samples from estimated distributions of the path coefficients to approximate the sampling distribution of the indirect effect. This approach provides more accurate confidence intervals (CIs) than conventional methods (Tofighi & MacKinnon, 2016).

**Monte Carlo Procedure for Mediation Testing**

The Monte Carlo technique estimates the distribution of the indirect effect (a × b) by simulating multiple values based on the estimated parameters:

(i) Estimate Path Coefficients: Calculate the estimates of a and b from SEM or regression analysis. (ii) Simulate New Samples: Generate a large number (e.g., 10,000) of random samples for a and b based on their estimated means and standard errors. (iii) Compute Indirect Effects: Multiply simulated values of a and b in each sample to generate a distribution of the indirect effect. (iv) Construct Confidence Intervals: Determine the confidence intervals (typically 95%) for a x b using the percentiles of the simulated distribution. (v) Assess Significance: If the confidence interval does not include zero, the mediation effect is considered significant.

**Mathematical Representation of Monte Carlo Simulation for Mediation**

In a standard mediation model, the relationships between variables can be expressed as follows:

1. Path from the independent variable (X) to the mediator (M) (a path):
2. Path from the mediator (M) to the dependent variable (Y) (b path):
3. Direct effect of X on Y (c’ path):
4. Total effect of X on Y (c path):
5. Indirect effect (mediation effect):

**G. Maximum Likelihood (ML) Estimation of Indirect Effects**

Maximum Likelihood (ML) estimation is one of the most widely applied methods for estimating indirect effects in Structural Equation Modelling (Bollen, 1989; Kline, 2015). Maximum Likelihood estimation finds the parameter values that maximize the likelihood of the observed data, assuming a given statistical model. It is extensively used because it provides efficient and asymptotically unbiased estimates, especially when data follow a multivariate normal distribution (Hoyle, 2012; MacKinnon, 2008).

**Mathematical Representation of Maximum Likelihood Estimation for Indirect Effects**

In a mediation model, the relationships between variables are defined as:

1. Equation for the effect of the independent variable (X) on the mediator (M) (path a):
2. Equation for the effect of the mediator (M) on the dependent variable (Y) (path b):
3. Equation for the direct effect of X on Y (path ):
4. Total effect of X on Y (path c):
5. Indirect effect (Mediation effect):

**ML Estimation Process in SEM**

Define the Likelihood Function: The likelihood function is formulated based on the assumed probability distribution of the observed data. If we assume normality, the likelihood function for SEM can be expressed as:

Where θ represents the parameters (i.e., path coefficients a, b, c′) and  is the joint probability density function of the observed variables.

Estimate Model Parameters:

ML estimation finds the parameter values that maximize the likelihood function:

**Obtain standard errors and confidence intervals:**

The standard errors of the estimated indirect effect are derived using the Delta Method or Bootstrapping, which provides robust confidence intervals (Sobel, 1982; MacKinnon et al., 2002).

The standard error of the indirect effect can be approximated as:

Assess Model Fit:

SEM software (e.g., AMOS, SmartPLS, Mplus, Lavaan in R) provides fit indices such as CFI, TLI, RMSEA, and SRMR to evaluate model adequacy before interpreting mediation effects (Hu & Bentler, 1999).

**H. Longitudinal Mediation Models**

Longitudinal mediation techniques extend traditional mediation analysis by integrating temporal ordering, which assists establish causal relationships between latent variables over time (Cole & Maxwell, 2003; Preacher, 2015). These models use panel data technique, meaning repeated observations of the same individuals or entities across multiple time points, allowing for more precise mediation analysis results compared to cross-sectional designs. By analysing data over multiple time points, longitudinal mediation reduces the risk of reverse causality and strengthens causal inference (Little, 2024). Since individuals are observed over time, time-invariant confounders can be controlled, leading to more accurate estimates (Maxwell & Cole, 2007). Integrating lagged effects enhances model accuracy and allows for dynamic relationships between latent variables (Selig & Preacher, 2009).

**Mathematical Representation of Longitudinal Mediation**

In a three-time-point longitudinal mediation model (T1, T2, T3), the predictor X, mediator M, and outcome variable Y are measured at different time points to capture their causal pathways:

Effect of X on M over time (Path a)

Effect of M on Y over time (Path b)

Direct effect of X on Y over time (Path ‘c′):

Total effect (c)

Indirect Effect (Mediation Effect):

**Estimation Methods for Longitudinal Mediation:** (i) Cross-Lagged Panel Model (CLPM): Examines reciprocal causation between variables over time (Finkel, 1995), (ii) Latent Growth Curve Model (LGCM): Captures individual differences in mediation trajectories over time (Duncan et al., 2006), and (iii) Autoregressive Latent Trajectory Model (ALT): Combines CLPM and LGCM for a more robust mediation framework (Bollen & Curran, 2006).

I. **Latent Variable Mediation in Structural Equation Modelling (SEM)**

Latent variable mediation in SEM enhances traditional mediation analysis by accounting for measurement error through the use of latent constructs (Little, 2024; Kline, 2015). Unlike observed variable mediation, where mediation effects are assessed using single observed indicators, latent variable mediation incorporates several observed indicators for each construct, leading to more precise and unbiased estimates (MacKinnon, 2008). The following are the advantages associates with LVM: (i) By using multiple indicators per construct, latent variables provide more reliable estimates of mediation effects (Bollen, 1989), (ii) it allows researchers to test the structural model while simultaneously modelling measurement error, leading to better model fit (Hoyle, 2012), and studies involving psychological, business research, or social science constructs benefit from latent variable mediation due to improved construct validity (Cheung & Lau, 2008).

**Mathematical Representation of Latent Variable Mediation**

In a standard mediation model with observed variables, mediation is expressed as:

Effect of independent variable X on mediator MMM (Path a)

Effect of mediator M on dependent variable Y (Path b):

Direct effect of X on Y (Path ‘c′)

Total effect (c):

Indirect effect (Mediation Effect):

However, when using latent variables, each construct (X,M,Y) is measured using multiple observed indicators. For example, if X has three observed indicators (X1,X2,X3), the measurement model is:

Similar equations apply to the mediator M and outcome variable Y. These measurement equations are integrated into the structural model, confirming the mediation effects are estimated after accounting for measurement error (Byrne, 2013). Latent mediation effects are tested using various software such as AMOS, LISREL, Mplus through maximum likelihood estimation or Bayesian estimation (Muthén & Asparouhov, 2012). Common fit indices such as CFI, TLI, AGFI, NFI, RMSEA, and SRMR help assess model adequacy (Hu & Bentler, 1999).

**IV. MODEL FIT AND EVALUATION**

**Model Fit and Evaluation in Mediation Models using SEM**

Assessing model fit is a vital step in Structural Equation Modelling to find out how well the hypothesized proposed mediation model line up with the observed dataset. Researchers use several fit indices to assess model adequacy, which can be generally classified into (i) absolute fit measures, (ii) incremental fit indices, and (iii) parsimonious fit indices (Hu & Bentler, 1999; Kline, 2015). Furthermore, reporting standardised vs. unstandardised coefficients confirms clear interpretation of mediation effects.

**1. Absolute Fit Measures**

Absolute fit indices assess how well the hypothesised mediation model replicates the observed dataset without comparing it to a substitute model (Bentler & Bonett, 1980).

Chi-Square (χ²) Test: The χ² test assesses the difference between the observed and expected covariance matrices. A non-significant χ² suggests good model fit, but Chi-square is highly sensitive to sample size (Bollen, 1989).

Relative Chi-Square (χ²/df or CMIN/df) (Sathyanarayana, & Mohanasundaram. 2024): To account for sample size sensitivity, the relative chi-square (χ2/df) is used. Lower values indicate better fit:

χ2/df<3 = Good fit, χ2/df<5 = Acceptable fit

Where df is the model’s degrees of freedom (Wheaton et al., 1977; Kline, 2015).

Goodness of Fit Index (GFI)

GFI measures how much of the covariance in the data is explained by the model (Jöreskog & Sörbom, 1993).

GFI ≥ 0.90 = Acceptable fit, GFI ≥ 0.95 = Excellent fit

Normed Fit Index (NFI)

NFI compares the proposed model to a null model where variables are uncorrelated (Bentler & Bonett, 1980).

NFI ≥ 0.90 = Acceptable fit, NFI ≥ 0.95 = Excellent fit

ii. Root Mean Square Error of Approximation (RMSEA)

RMSEA estimates the model’s approximation error per degree of freedom (Steiger, 1990). Lower values indicate a better fit:

RMSEA < 0.05 = Good fit, 0.05 ≤ RMSEA ≤ 0.08 = Acceptable fit, and RMSEA > 0.10 = Poor fit.

iii. Standardized Root Mean Square Residual (SRMR)

SRMR measures the average difference between observed and predicted correlations. A lower SRMR (≤ 0.08) indicates better model fit (Hu & Bentler, 1999; Sathyanarayana, and T. Mohanasundaram. 2024).

**2. Incremental Fit Indices**

Incremental fit indices compare the proposed mediation model against a baseline model (usually an independence model) to assess relative improvement (Bentler, 1990).

i. Comparative Fit Index (CFI)

CFI accounts for sample size limitations and compares the tested model with the null model (Bentler, 1990). Values closer to 1.0 indicate good fit:

CFI ≥ 0.95 = Excellent fit and 0.90 ≤ CFI < 0.95 = Acceptable fit

ii. Tucker-Lewis Index (TLI)

TLI penalizes model complexity and rewards parsimony (Tucker & Lewis, 1973). Like CFI, values ≥ 0.95 indicate good fit.

TLI penalizes complex models and rewards parsimony (Tucker & Lewis, 1973). Like NFI, values closer to 1.0 indicate a better fit:

TLI ≥ 0.95 = Good fit. In addition, we have Normed Fit Index, Relative Fit Index, and Incremental Fit index (Sathyanarayana, and T. Mohanasundaram. 2024).

**3. Parsimonious Fit Indices**

These indices balance model fit with simplicity, discouraging overfitting by penalizing complex models (Burnham & Anderson, 2011).

i. Akaike Information Criterion (AIC): AIC helps compare non-nested models, with lower values indicating a better model (Akaike, 1974).

ii. Bayesian Information Criterion (BIC).

BIC is similar to AIC but penalizes complexity more aggressively based on sample size (Schwarz, 1978). In addition, we have Parsimonious Normed Fit Index, and Parsimonious Goodness-of-Fit Index (Sathyanarayana, and T. Mohanasundaram. 2024).

**V. STEPS IN CONDUCTING MEDIATION ANALYSIS USING SEM**

Mediation analysis in Structural Equation Modelling comprises evaluating how an predictor variable (X) influences a outcome variable (Y) through a mediator (M). Structural Equation Modelling provides a strong framework for testing mediation effects by integrating measurement errors, latent constructs, and direct/indirect paths (Preacher & Hayes, 2008; MacKinnon, 2008). The following five steps outline the SEM-based mediation process: The mediation process follows five key steps, as outlined below:

**1. Model Specification: Defining the Theoretical Model and Drawing the SEM Diagram**

Before estimating mediation effects, a clear theoretical framework must be established. Researchers should specify:

The independent variable or focal predictor (X)

The mediator (M)

The dependent or outcome variable (Y)

Any covariates or control variables

**2. Model Estimation**

Using SEM Software to Estimate Parameters

Once the model is specified, the next step is to estimate the parameters using SEM software. The estimation method typically used is:

Maximum Likelihood Estimation (MLE): Assumes multivariate normality (Kline, 2015), Robust Maximum Likelihood (MLR): Used when normality is violated (Satorra & Bentler, 1994), and Partial Least Squares (PLS-SEM): Suitable for smaller samples and non-normal data (Hair et al., 2010).

**Software options:** AMOS (IBM SPSS) – Graphical interface, used for covariance-based SEM Mplus – Supports categorical data, latent growth modelling, JASP, Stata, LISREL – Known for confirmatory factor analysis, SmartPLS – Used for variance-based SEM. During estimation, factor loadings, path coefficients, and error variances are calculated (Bollen, 1989).

**3. Model Evaluation**

Checking Model Fit Indices and Modification Indices: After estimation, researchers assess whether the model fits the data well using fit indices (Hu & Bentler, 1999): If the model fit is poor, modification indices (MI) suggest adding new paths or correlations to improve fit (Saris et al., 2009). Nevertheless, modifications must be theoretically justified to avoid overfitting (MacCallum et al., 1992).

**4. Testing Indirect Effects**

**Using Bootstrapping for Confidence Intervals**

Mediation is confirmed when the indirect effect (a × b) is statistically significant. Traditional methods (e.g., Sobel test) assume normality, but bootstrapping is preferred because it does not (Preacher & Hayes, 2008).

Indirect Effect = a × b

**Bootstrapping Method**

Resampling (5000+ samples)

Bias-corrected confidence intervals (95%)

Significant mediation if 95% CI does not include zero

Bootstrapping is available in Mplus, AMOS (via PROCESS macro), LISREL, and SmartPLS (Cheung & Lau, 2008).

**Result and Discussion:**

**5. Reporting Results**

Presenting Path Coefficients, Standard Errors, and Significance Values

When reporting results, include:

Path Coefficients (𝛽): Standardized values allow comparison across variables.

Standard Errors (SE): Indicates the variability of estimates.

Confidence Intervals (CI, 95%): Ensures robust inference.

Significance Values (p-values): Determines statistical significance.

Table 1: Path Coefficients, Standard Errors, Confidence Intervals and Significance Values

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Path** | **Estimate (β)** | **SE** | **95% CI** | **p-value** |
| X→M (a) | 0.40 | 0.05 | [0.30, 0.50] | < 0.001 |
| M→Y (b) | 0.35 | 0.06 | [0.22, 0.48] | < 0.001 |
| X→Y (c’) | 0.10 | 0.04 | [-0.02, 0.22] | 0.12 |
| Indirect Effect (a × b) | 0.14 | 0.03 | [0.08, 0.22] | < 0.001 |

**Interpretation as per APA format (Sathyanarayana S and Mohanasundaram T, 2025).**

The effect of X (predictor) on Mediator (M) (path a): The path coefficient for the effect of IV on M (mediator) was significant, β= 0.40, SE = 0.05, p=0.000 (<0.001) 95% CI [0.30, 0.50]. Since the confidence interval does not include zero, this suggests a statistically significant positive effect of X (predictor) on Mediator (M) (path a).

The effect of M (moderator) on outcome variable (Y) (path b): The path coefficient for the effect of M (mediator) on IV (dependent variable) was significant, β= 0.35, SE = 0.06, p=0.000 (<0.001) 95% CI [0.22, 0.48]. Since the confidence interval does not include zero, this suggests a statistically significant positive effect of M (mediator) on DV (dependent variable) was significant (path b).

The direct effect of X (predictor) on outcome variable (Y) (path c’): The path coefficient for the effect of M (predictor) on IV (dependent variable) was not statically significant, β= 0.10, SE = 0.04, p=0.12 (>0.05) 95% CI [-0.02, 0.22]. Since there is a zero in confidence interval, this suggests no statistically significant relationship between predictor and outcome variable (dependent variable) was significant (path c’).

The indirect effect of (a x b) on outcome variable: The indirect effect of a x b is statically significant, β= 0.14, SE = 0.03, p=0.000 (<0.001) 95% CI [0.08, 0.22]. Since the confidence interval does not include zero, this suggests a statistically significant positive indirect effect of focal predictor via mediator on dependent variable and statistically significant. Results indicate a full mediation**.**

**Few examples:**

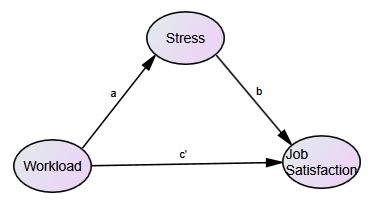
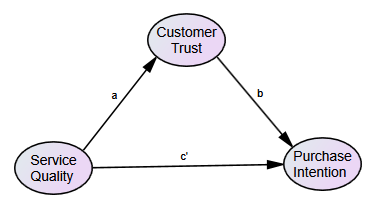
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Fig 2. Job Stress on the relationship between work Load and Job Satisfaction

Fig 1: Testing the mediation effect of Customer trust on the relationship between service quality and purchase intention.

**1. Testing the mediation effect of customer trust on the relationship between service quality and purchase intention**

where: a = Impact of service quality on trust, b = Impact of trust on purchase intention, c′ = Direct effect of service quality on purchase intention, and a × b = Indirect effect (mediation effect).

**2. Testing the mediation effect of Job Stress on the relationship between work Load and Job Satisfaction.**

where: a = Impact of workload on stress, b = Impact of stress on job satisfaction, c′ = Direct effect of workload on job satisfaction, a × b = Indirect effect (mediation effect)

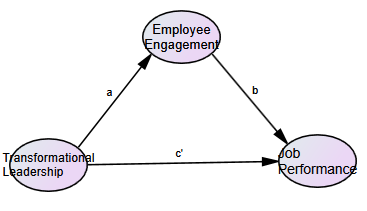
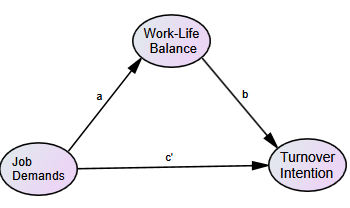
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Fig 4: Work-Life Balance on the relationship between Job Demands and Turnover Intention

Fig 3: Testing the mediation effect of Employee Engagement on the relationship between Transformational Leadership and Job Performance.

**3. Testing the mediation effect of Employee Engagement on the relationship between Transformational Leadership and Job Performance.**

where: a = Impact of transformational leadership on job engagement, b = Impact of job engagement on job performance, c′ = Direct effect of transformational leadership on job performance, and a × b = Indirect effect (mediation effect).

**4. Testing the mediation effect of Work-Life Balance on the relationship between Job Demands and Turnover Intention.**

where: a = Impact of Job demands on work-life balance, b = Impact of work-life balance on turnover intention, c′ = Direct effect of job demands on turnover intention, and a × b = Indirect effect (mediation effect).

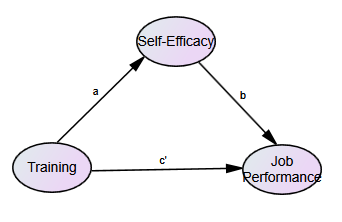
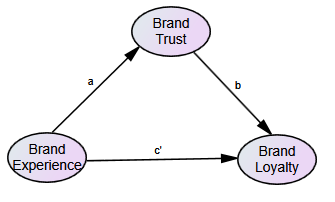
 

Fig 6: Brand Trust on the relationship between Brand Experience and Brand Loyalty

Fig 5: Testing the mediation effect of Self-Efficacy on the relationship between Training and Job Performance

**5. Testing the mediation effect of Self-Efficacy on the relationship between Training and Job Performance.**

where: a = Impact of training on self-efficacy, b = Impact of self-efficacy on job performance, c′ = Direct effect of training on job performance, and a × b = Indirect effect (mediation effect).

Required Equations are as follows:

Effect of predictor on mediator:

Effect of mediating variable on dependent variable

**6. Testing the mediation effect of Brand Trust on the relationship between Brand Experience and Brand Loyalty.**

where: a = Impact of Brand Experience on Brand Trust, b = Impact of Brand Trust on Brand Loyalty, c′ = Direct effect of Brand experience on Brand Loyalty, and a × b = Indirect effect (mediation effect).

Required Equations are as follows:

Effect of predictor on mediator:

Effect of mediating variable on dependent variable

**CONCLUSION:**

Mediation analysis using Structural Equation Modelling is a influential method that permits researchers to examine complex relationships between various latent variables while accounting for indirect effects. The procedure includes model specification, estimation, evaluation, and testing indirect effects, with a emphasis on fit indices and bootstrapping methods for robust inference. Structural Equation Modelling has comprehensive applications in business research, psychology, organisational behaviour, HR, and marketing, demonstrating its flexibility in real-world research. Despite its advantages, Structural Equation Modelling -based mediation analysis faces numerous challenges, including measurement errors, model misspecification, and the difficulty of establishing causal relationships. Addressing these challenges necessitates rigorous model validation, longitudinal research designs, and advanced statistical methods such as cross-lagged panel models, latent growth curve modelling, and instrumental variable approaches. Additionally, the comparison between Structural Equation Modelling -based mediation and regression-based mediation (PROCESS macro) highlights key trade-offs in measurement precision, model complexity, and usability. While Structural Equation Modelling provides a inclusive framework for latent variable modelling, PROCESS remains a widely used tool for simpler mediation analyses.

One of the key challenges in SEM-based mediation analysis is managing measurement errors and model misspecification. Latent variables are often measured using items or observed indicators, but these are imperfect representations, leading to attenuation bias and distorted path coefficients (MacCallum & Austin, 2000; Brown, 2015). Model misspecification, such as overlooking a pertinent mediator or counting an irrelevant one, can introduce Type I or Type II errors, affecting the validity of causal claims (Tomarken & Waller, 2003). Common Method Bias is another major issue, where primary data collected from the same respondents lead to false correlations between latent constructs (Podsakoff et al., 2003). Addressing these issues necessitates rigorous confirmatory factor analysis to measure construct validity, applying multi-trait multi-method (MTMM) approaches to separate measurement error from true score variance (Campbell & Fiske, 1959), and testing for model fit using indices like Chi-Square, GFP, AGFI, CFI, RMSEA, and SRMR (Hu & Bentler, 1999).

Another important challenge is the need for longitudinal data to establish causal inference, as most mediation studies depend on on cross-sectional data that only capture associations rather than causal relationships (Maxwell & Cole, 2007). Reverse causality is a major concern since the dependent variable (Y) might influence the mediator (M) rather than the other way around (Cole & Maxwell, 2003). Additionally, unobserved confounders may influence both the independent variable (X) and the mediator, leading to spurious mediation effects (Hayes & Scharkow, 2013). A promising approach to overcoming these limitations is longitudinal mediation modelling (MacKinnon, 2008), which permits researchers to track mediation effects over time. Cross-lagged panel models (CLPM) are useful for evaluating whether changes in Independent Variable (X) predict changes in Mediating Variable (M) and subsequently Outcome Variable (Y) (Selig & Preacher, 2009). Furthermore, latent growth curve modelling (LGCM) helps evaluate mediation dynamics across different time points (Bollen & Curran, 2006), while instrumental variable (IV) methods strengthen causal claims by reducing endogeneity (Angrist & Pischke, 2009).

Looking ahead, future research should focus on integrating Bayesian methods, machine learning techniques, and hybrid methods that integrate the flexibility of regression with the strength of Structural Equation Modelling. By refining model selection, refining causal inference, and integrating more robust data structures, Structural Equation Modelling -based mediation analysis can continue to improve theoretical and empirical insights across various disciplines. Researchers should also prioritize replication studies and methodological advancements to further solidify mediation analysis as a gold standard in quantitative research. Consequently, while mediation analysis in Structural Equation Modelling is not without its challenges, its continued evolution offers exciting opportunities for both theory and practice. By adopting rigorous methodologies and accepting future innovations, researchers can answer deeper understandings into the complex mechanisms driving human behaviour, business decisions, policy making, and organisational outcomes.

**Disclaimer (Artificial intelligence)**

Option 1:

Author(s) hereby declares that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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