**MODERATION ANALYSIS IN BUSINESS RESEARCH: CONCEPTS, METHODOLOGIES, APPLICATIONS, AND EMERGING TRENDS**

**ABSTRACT**

Moderation analysis is an essential statistical technique employed to examine the effect of the strength or direction of the relationship between two variables by a third variable, which is referred to as a moderator. This essay seeks to provide an all-encompassing model of moderation by explaining the definition, outlining different methodologies, and illustrating the practicability in various fields, such as human resource management (HRM), marketing, psychology, finance, and organizational behaviour (OB). In HRM, moderation analysis is used to determine how variables like perceived organizational support affect the relationship between work-life balance policies and employee commitment. In marketing, moderators such as brand trust affect the influence of corporate social responsibility (CSR) efforts on customer loyalty. Likewise, financial research applies moderation to determine how risk tolerance influences the relationship between financial literacy and investment choices. In OB and psychology, moderators like organizational culture and psychological safety are critical in influencing team dynamics and leadership effectiveness. In addition, new trends in moderation analysis, including the use of AI and ML, have improved the capability to identify intricate interactions in diverse fields. The paper addresses these developments and presents future research directions, such as longitudinal modelling and multi-level moderation analysis. By combining these findings, companies and researchers can improve contextual factors affecting decision-making and align strategies to maximize them.

***Keywords: Moderation analysis, interaction effect, Process Macro, Structural Equation Model, Artificial intelligence, Machine Learing, Bayesian Moderation.***

***JEL Classification: C12, C44, M10, M31, G41.***

**I. INTRODUCTION**

Moderation analysis in Structural Equation Modelling (SEM) is a significant statistical technique used to examine if the relationship between two variables is moderated by a third variable, also known as a moderator (Baron & Kenny, 1986). Moderation effects help researchers comprehend under what conditions relationships between variables get stronger, weaker, or even reverse direction (Hayes, 2017). In contrast to mediation, which informs us of how or why an effect occurs, moderation addresses the when or for whom a relationship holds (Frazier, Tix, & Barron, 2004). Moderation is theoretically linked to interaction effects in regression analysis, where the impact of an independent variable (IV) on a dependent variable (DV) is a function of the moderator’s level (Jaccard & Turrisi, 2003). Moderation in SEM is typically explored via multi-group analysis (MGA), latent interaction modelling, or product indicator approaches (Klein & Moosbrugger, 2000; Marsh, Wen, & Hau, 2004). Multi-group analysis divides the sample according to moderator levels and analyses differences in path coefficients across groups (Byrne, 2016). Alternatively, latent interaction modelling allows direct estimation of moderation effects in SEM while maintaining control over measurement error.

One of the challenges in moderation analysis is guaranteeing sufficient statistical power, especially when testing latent interactions since these need larger samples because of increased model complexity (Aiken & West, 1991). Moreover, with the use of product indicators in SEM, non-normality of interaction terms impacts model estimation and fit indices (Little, Bovaird, & Widaman, 2006). Model fit testing is especially significant in moderation analysis, as interactions introduce complexity that affects model convergence and fit statistics such as the Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Tucker-Lewis Index (TLI) (Hu & Bentler, 1999). Researchers should be careful when interpreting fit statistics and modification indices to ensure that the model accurately captures the moderation effect without overfitting (Schermelleh-Engel, Moosbrugger, & Müller, 2003). In addition, theoretical rationale for moderation is required. Researchers need to set definite hypotheses of the anticipated moderating effects grounded on previous literature (Edwards & Lambert, 2007). One of the pitfalls is applying exploratory moderation tests with little theoretical foundation, resulting in spurious results (Frazier et al., 2004).

Some of the recent developments in moderation analysis in SEM are Bayesian methods for more accurate estimation of latent interactions and machine learning methods for detecting non-linear moderation effects. These developments overcome some of the methodological shortcomings of the conventional SEM methods, making moderation analysis more robust. Thus, moderation analysis in SEM is useful to examine conditional relationships between variables, but it must be carefully attended to with respect to statistical power, model specification, theoretical rationale, and interpretation of results. With advancement of SEM methodologies, researchers are able to use powerful statistical tools to enhance precision and applicability of the moderation effects in complex models.

Moderation is a statistical phenomenon that explains when or under what conditions the relationship between an independent variable (IV) and a dependent variable (DV) is weaker or stronger. It occurs when a third variable, the moderator, interacts with the IV in order to influence the strength or direction of the effect on the DV (Baron & Kenny, 1986). In contrast to mediation, where the mechanism of how an effect comes about is detailed through an intermediary variable, moderation concerns the conditional nature of the relationships (Hayes, 2017). The existence of a moderator can strengthen, suppress, or even invert the association between the IV and DV, and has considerable theoretical and practical implications (Frazier, Tix, & Barron, 2004). Moderation is typically examined through interaction terms in regression analysis or multi-group analyses in Structural Equation modelling (SEM) (Marsh, Wen, & Hau, 2004). The magnitude of moderation effects is often contingent upon the appropriate selection and measurement of the moderator variable, which can be either categorical or continuous (Edwards & Lambert, 2007). Moderation is important in such areas as psychology, business studies, and the social sciences since it assists in determining boundary conditions for theoretical models and sharpening predictions of human behaviour (Preacher, Rucker, & Hayes, 2007).

Moderation and mediation are two concepts that differ but frequently overlap in statistical estimation, especially in Structural Equation Modelling (SEM) and regression-based methods. Mediation seeks to describe the how or why an independent variable (IV) influences a dependent variable (DV) by adding a third variable, which is the mediator, to transmit the effect (Baron & Kenny, 1986). Moderation is the opposite, which concerns the when or under what circumstances an IV affects a DV by inserting a moderator variable which changes the strength or slope of the relationship (Hayes, 2017). While mediation implies a causal chain in which the IV affects the mediator, which then affects the DV, moderation involves an interaction effect in which the relationship between the IV and DV depends on the level of the moderator (Edwards & Lambert, 2007). A fundamental statistical difference is in estimation methods: mediation is typically tested through path analysis, indirect effects, or bootstrapping techniques to determine whether the mediator conveys the effect (MacKinnon, Fairchild, & Fritz, 2007), whereas moderation is often examined through interaction terms in regression or multi-group analysis in SEM (Marsh, Wen, & Hau, 2004). Moreover, mediation posits a temporal order by which the IV influences the mediator prior to having an effect on the DV, whereas moderation doesn’t necessitate such temporal precedence and can be cross-sectionally tested (Frazier, Tix, & Barron, 2004). Notwithstanding these differences, both can be combined into a moderated mediation model in which a mediated effect is itself dependent upon a moderator, enriching theory explanations of causal processes (Preacher, Rucker, & Hayes, 2007).

The rest of this paper is organized as follows: Part Two is a review of the literature on moderation, including its conceptual underpinnings, major methodological strategies, and issues in SEM. Part Three outlines the research design, data collection, measurement, and analytical approach. Part Four reports the analysis and main findings. Part Five concludes with the results in the context of prior research and ends with main conclusions and future research directions.

**II. LITERATURE REVIEW**

Moderation in Structural Equation Modelling (SEM) refers to a condition where the interaction between two variables is moderated by a third variable, known as the moderator (Baron & Kenny, 1986; Frazier et al., 2004). The interaction effect allows researchers to examine more intricate relationships beyond simple direct effects, and therefore it is a critical analytical tool in psychology, business, and social sciences (Fairchild & MacKinnon, 2009). Moderation is different from mediation because mediation accounts for why or how an effect, whereas moderation asks when or with what conditions an effect is weaker or stronger (James & Brett, 1984). It has become increasingly popular among researchers to use SEM for moderation analysis because it can account for measurement error, evaluate latent variables, and test multiple paths at one time (Hair et al., 2010). Structural Equation Modelling (SEM) had filled these gaps by enabling researchers to simultaneously model latent variables and interaction effects (Jöreskog & Sörbom, 2013). Initially, SEM-based models of moderation drew mainly on mean-centring and product indicator approaches, opening the way for more advanced interaction modelling (Marsh et al., 2004).

Moderation analysis in Structural Equation Modelling (SEM) has come a long way since its development, with early work providing the foundation for current methodologies. This review of literature identifies landmark contributions to the application of moderation in SEM, with particular focus on studies that have been highly cited and referenced. Baron and Kenny’s (1986) seminal paper outlined the conceptual and methodological differences between moderator and mediator variables in social psychological research. They presented a methodological framework for testing these effects, which has been the basis of follow-up SEM research. James and Brett (1984) provided some of the initial understandings of mediators and moderators, presenting their functions and the necessity of testing for mediation in organizational research. Their research has been influential in defining more complex variable relationships in SEM. Jöreskog and Yang (2013) tackled modelling latent variable interactions within SEM paradigms. Jöreskog and Yang suggested methods to estimate interaction effects, improving moderation analysis precision in SEM. Klein and Moosbrügger (2000) developed the Latent Moderated Structural Equations (LMS) technique, which is a maximum likelihood estimation method for latent interaction effects. This method has been crucial in correctly modelling moderation in SEM. Marsh et al., (2004) carried out detailed assessments of a range of estimation approaches and indicator constructions for latent interactions in SEM. Their research has informed researchers on how to choose the right methodologies for moderation analysis. Sardeshmukh and Vandenberg (2017) built on existing methodologies by combining moderation and mediation within a single SEM framework. They explained the LMS approach and offered readable procedures for testing joint hypotheses, considerably advancing the discipline.

Muthén and Muthén (2010) presented sophisticated methods for latent interaction modelling in SEM models. Their contribution highlighted the need to estimate interaction effects between latent variables, which are usually not observed but indirectly measured by indicators. This method has played a crucial role in improving the accuracy of moderation analyses in SEM. Little’s thorough investigation of moderation methods gave researchers sound tools to evaluate complex interactions in SEM (Little, 2013). He provided pragmatic advice on how to test moderation hypotheses, the need to take measurement invariance into account, and potential flaws in neglecting latent variable interaction. His research has been instrumental in taking researchers through the complexities of moderation analysis. Hair et al., (2010) looked at Partial Least Squares Structural Equation Modelling (PLS-SEM), providing insights on managing moderation effects in this framework. They presented different methods to calculate interaction terms, like the product indicator method, where independent and moderator constructs’ indicators are cross-multiplied. Their recommendations have been critical for researchers using PLS-SEM in testing complicated moderating relationships. Sardeshmukh and Vandenberg (2017) built on existing methods by combining moderation and mediation under a single SEM framework. They also talked about the Latent Moderated Structural Equations (LMS) method, which offers readable procedures for testing joint hypotheses. They have greatly contributed to the development of the field with a full method to investigate complex intervariable relationships. Chin, Marcolin, and Newsted (2003) suggested the product indicator method for generating interaction terms in SEM. This method entails the multiplication of indicators of the interacting variables to create product indicators, allowing for the estimation of interaction effects in the SEM framework.

These modern works, building on the works of the founders Muthén & Muthén, Little, and Hair et al., (2010) have contributed altogether to augment the methodological rigor of moderation analysis in SEM. They provide scholars with reliable instruments and best practices to analyse complex intervariable interactions, to bring more valid and dependable conclusions across diverse disciplines. Moderation analysis in SEM has come from lowly regression-based methods to high-level latent interaction methods. Muthén & Asparouhov (2003), Little (2013), and Hair et al., (2010) have all made important contributions to contemporary methodologies such as latent interaction modelling, Bayesian SEM, and multigroup analysis. There needs to be an emphasis on future research integrating machine learning, longitudinal SEM, and nonlinear interactions in order to take the field further.

In spite of the large volume of literature on mediation and moderation in statistical modelling, there are still some gaps in the theoretical and methodological comprehension of their use in Structural Equation Modelling (SEM). For one, whereas numerous studies have examined mediation and moderation separately, there is little research on how they are integrated into one analytical framework, especially in sophisticated moderated mediation models (Edwards & Lambert, 2007; Preacher, Rucker, & Hayes, 2007). The relationship between mediation and moderation is frequently discussed at a conceptual level but does not have solid empirical support from various research areas. Second, methodological difficulties in the estimation of latent interactions in SEM continue, particularly with regard to managing non-normality, sample size needs, and the effects of estimation methods on model fit measures (Marsh, Wen, & Hau, 2004; Klein & Moosbrugger, 2000). Third, current research mainly depends on conventional frequentist methodology, and there is little investigation of Bayesian methodology for the estimation of moderated and mediated effects, which has potentially higher precision and flexibility in parameter estimation. In addition, although mediation is based on causal paths, there is still some controversy regarding whether cross-sectional data can effectively capture causal relations, and more longitudinal studies are needed to confirm mediation effects (MacKinnon, Fairchild, & Fritz, 2007). Finally, there is a paucity of application-focused research that can show how mediation and moderation models can be applied effectively in real-world situations, especially in newer areas like digital consumer behaviour, health analytics, and organizational psychology. Bridging the gaps will make the moderation and mediation analyses more precise, applicable, and stable in SEM-based research.

**III. TYPES OF MODERATION**

Moderation in Structural Equation modelling (SEM) can generally be categorized in terms of the incorporation of the moderating variable within the model. It is most commonly defined as observed moderation, where the moderator is an observed variable directly measured, and latent moderation, in which the moderator is conceptualized as a latent construct necessitating specialized estimation procedures (Marsh, Wen, & Hau, 2004; Klein & Moosbrugger, 2000). In addition, moderation may be explored by interaction modelling in which interaction terms are added to SEM equations or multi-group analysis in which groups are contrasted according to the moderator variable (Byrne, 2013). The selection of classification relies on data nature, measurement method, and research purposes, with each form having distinctive advantages and difficulties in identifying moderation effects in SEM models (Maslowsky, Jager, & Hemken, 2015). Below are eminent moderation methods researcher quite frequently applying to their research:

**1. MULTI-GROUP MODERATION**

Multi-group moderation analysis investigates whether the associations between variables are different in different groups, e.g., gender, industry, or region. MULTI-GROUP MODERATION

Multi-group moderation analysis examines whether the relationships between variables differ across distinct groups, such as gender, industry, or geographical location. This method is commonly used in structural equation modelling (SEM) to test whether model parameters (e.g., path coefficients) vary significantly across groups. A critical step in multi-group analysis is ensuring measurement invariance, which verifies that the latent constructs are interpreted similarly across groups (Vandenberg & Lance, 2000). Measurement invariance testing follows a sequential approach: configural invariance (same factor structure), metric invariance (equal factor loadings), and scalar invariance (equal intercepts). The moderation effect is examined by comparing the unconstrained and constrained models using the chi-square difference test (Δχ2) or alternative fit indices like the comparative fit index (CFI) and root mean square error of approximation (RMSEA).

Mathematically, for a structural model:

Where, X is the independent variable, M is the moderator (group), and (X x M) is the interaction term. The moderation effect is significant if β3​ differs across groups. In multi-group SEM, the path coefficients (β) are estimated separately for each group, and invariance is tested by constraining them to be equal across groups:

If Δχ2 is significant, the groups differ in their structural relationships (Byrne, 2016). For example, in a study examining the effect of job satisfaction (X) on job performance (Y) moderated by industry (M), the model is tested separately for manufacturing and service sectors. If the path coefficient of job satisfaction to performance (β1​) is significantly different between the two industries, it suggests a moderation effect, indicating that job satisfaction influences performance differently based on industry type (Muthén & Asparouhov, 2013).

Baseline model for the relationship without moderation element

where: Y= Job Performance, X = Job Satisfaction, β1​ = Path coefficient representing the effect of job satisfaction on job performance, and ε= Error term

Multi-Group Moderation Model

In a multi-group SEM framework, the path coefficient β1​ is estimated separately for each group (M=1 for Manufacturing, M=2 for Services):

For Manufacturing sector (M=1)

For service Sector (M=2)

where: β1,1​ = Effect of job satisfaction on job performance in the manufacturing sector

β1,2​ = Effect of job satisfaction on job performance in the service sector

3. Measurement Invariance Testing Equations: Before testing moderation, measurement invariance is assessed across groups. The following constraints are applied stepwise:

(a) Configural Invariance (Unconstrained Model)

where:

λg​ = Factor loadings are freely estimated for each group g

Fg​ = Latent construct of job performance

εg​ = Error term

(b) Metric Invariance (Constrained Factor Loadings)

where: λ is constrained to be equal across groups (λ1​=λ2​)

(c) Scalar Invariance (Constrained Intercepts)

where: τ = Intercept, constrained across groups (τ1​=τ2​)

4. Moderation Effect Testing

The moderation effect is tested by constraining the path coefficient β1​ to be equal across groups and comparing model fit:

(a) Unconstrained Model (Allowing β1 to Vary Across Groups)

(b) Constrained Model (Forcing β1​ to Be Equal)

(c) Chi-Square Difference Test

The moderation effect is assessed using a chi-square difference test:

where: If is significant, the groups differ in their structural relationships, confirming moderation. Alternative fit indices like CFI, RMSEA, and SRMR are also examined.

Thus, if the path coefficient β1,1 significantly differs from β1,2​,we conclude that industry moderates the relationship between job satisfaction and job performance.

**2.** **INTERACTION EFFECTS IN STRUCTURAL EQUATION MODELLING (SEM)**

Interaction effects in Structural Equation Modelling (SEM) refer to the influence of one latent variable on the relationship between another latent variable and an outcome. These effects are modelled using latent interaction terms, which are multiplicative combinations of latent variables (Marsh, Wen, & Hau, 2004). Unlike traditional regression models, SEM allows for interaction effects while accounting for measurement error, making it a powerful tool for examining moderation (Klein & Moosbrugger, 2000).

A key challenge in estimating latent interactions is that the interaction term is not directly observed but must be computed as a product of latent factor scores. Two common estimation approaches are the Mean-Centered Approach and the Residual-Centered Approach (Little, Bovaird, & Widaman, 2006).

**Mathematical Model for Latent Interaction in SEM**

In a moderated SEM model, the outcome Y is influenced by the predictor X, the moderator M, and their interaction X x M

Where, X is the latent variable (predictor), M is the moderator (latent), and (X x M) is the interaction term (latent). β1​ and β2 are main effects and β3​ is the interaction effect. ε is the error term. Since X x M is unobserved term, it must be predicted indirectly.

**Estimation Approaches for Latent Interaction Terms**

**Mean-Centered Approach (Little et al., 2006)**

Under this approach, each latent variable (X and M) is mean-centered, and the interaction term is created using their deviations from the mean. This reduces multicollinearity and ensures that the main effects (β1​ and β2​) remain interpretable:

The modified SEM equation becomes:

This approach helps in stabilizing parameter estimates but does not eliminate the correlation between the main effects and interaction terms.

**Residual-Centered Approach (Marsh et al., 2004)**

This method addresses potential collinearity issues by regressing out the main effects from the interaction term, ensuring that it represents only the unique variance of the interaction:

The new equation becomes:

where (X×M) residual​ is the residual-centered interaction term. This approach enhances interpretability by removing shared variance with main effects.

**Example of Latent Interaction in SEM**

Suppose a study examines job stress (Predictor), organizational support (Moderator), and their interaction effect on employee performance (dependent variable). The hypothesized model is:

If the interaction term (β3​) is significant, it suggests that the effect of job stress on performance depends on organizational support.

Using the **Residual-Centered Approach**, the interaction term is computed as:

This ensures that the interaction term represents only the unique effect of job stress and organizational support combined, free from multicollinearity.

Therefore, latent interaction modelling offers a robust way to examine moderation effects, accounting for measurement error and increasing proposed model accuracy. The Mean-Centered Approach stabilizes variance, while the Residual-Centered Approach enhances interpretability by eliminating shared variance. Selecting the right estimation method depends on the research background, but both methods contribute to a more accurate understanding of complex interactions (Klein & Moosbrugger, 2000; Little et al., 2006).

**3. PRODUCT INDICATOR APPROACH**

The Product Indicator Approach (PIA) is an extensively applied method in SEM for testing moderation effects between latent variables. It constructs interaction terms by multiplying the observed indicators of the predictor and moderator latent variables (Chin, Marcolin, & Newsted, 2003). This approach is applicable in both Partial Least Squares SEM (PLS-SEM) and Covariance-Based SEM (CB-SEM) (Henseler & Chin, 2010).

**Mathematical Model for Moderation Using Product Indicators**

Let X be the predictor latent variable, M be the moderator latent variable, and Y be the dependent variable. The moderation model is given by:

where: X x M represents the interaction effect, modelled using product indicators. Since X and M are latent constructs, their measurement models include multiple observed indicators:

The interaction indicators are created by multiplying each indicator of X with each indicator of M:

These product indicators serve as observed variables for the latent interaction term X x M, allowing estimation of the moderation effect (β3)

**Ex: The Effect of Training on Employee Performance, Moderated by Job Experience**

Suppose a company wants to analyse how training quality (Independent variable) influences employee performance (dependent variable), and whether this relationship depends on job experience (Moderator).

Independent Variable (X) = Training Quality (measured by X1, X2, X3)

Moderator Variable (M) = Job experience (measured by M1, M2, M3)

Dependent Variable (Y) = Employee Performance.

To test moderation, the Product Indicator Approach constructs interaction terms by multiplying each indicator of training quality with each indicator of job experience:

These product indicators represent the latent interaction variable X x M and are included in the SEM model. If the path coefficient β3 is significant, it confirms that job experience moderates the effect of training on performance. If β3>0, training is more effective for employees with higher experience, if β3<0, training is more effective for employees with less experience, and finally, if β3= 0 job experience does not moderate the training performance relationship.

Major Advantage of this approach is (i) directly estimates latent interactions, without assuming normality, (ii) Compatible with PLS-SEM and CB-SEM, making it versatile, and (iii) allows for complex moderation models, such as nonlinear interactions. However, on the flipside, the concern is multicollinearity, it can arise due to high correlations between product indicators and main effect indicators. A possible solution is mean-centering indicators before multiplication (Henseler & Chin, 2010).

This approach is a robust tool for modelling latent interactions, especially for moderation analysis. By multiplying the observed indicators of predictor and moderator latent variables, it effectively captures interaction effects while maintaining the structural integrity of SEM models. It is particularly useful in PLS-SEM and CB-SEM frameworks, helping researchers analyse complex relationships in social sciences, business, and psychology (Chin et al., 2003; Henseler & Chin, 2010).

**4. LATENT MODERATED STRUCTURAL EQUATIONS (LMS)**

The Latent Moderated Structural Equations (LMS) Approach is an advanced technique in Structural Equation Modeling (SEM) that estimates latent interaction effects directly within the Maximum Likelihood Estimation (MLE) framework (Klein & Moosbrugger, 2000). Unlike the Product Indicator Approach, which constructs interaction terms by multiplying observed indicators, LMS integrates latent interactions into the likelihood function, making it more statistically efficient and reducing biases. However, it is computationally intensive, requiring specialized software such as Mplus or Lavaan in R (Maslowsky, Jager, & Hemken, 2015).

Where, X is the latent variable (predictor), M is the moderator (latent), and (X x M) is the latent interaction term. β1​ and β2 are main effects and β3​ is the moderation term (interaction effect). ε is the error term. To estimate the latent interaction term (X x M), LMS reformulates the likelihood function as:

where: θ = vector of model parameters, is the probability density function considering the non-normality introduced by the interaction term.

Unlike traditional SEM, where latent variables follow a multivariate normal distribution, LMS accounts for non-normality in interaction terms using an adaptive numerical integration method, such as Gauss-Hermite quadrature (Klein & Moosbrugger, 2000).

Ex: Research Scenario: Effect of Leadership Style on Employee Performance, Moderated by Job Autonomy

A company investigates how transformational leadership (X) influences employee performance (Y), considering whether job autonomy (M) moderates this relationship.

**Predictor (X)** = Transformational Leadership, this is measured by three items or indictors X1, X2, and X3. Proposed moderator = Job autonomy measured by three items or indictors M1, M2, and M3. Outcome variable = employee performance measured by three items or indictors Y1, Y 2, and Y3.

First define the model

If β3 is significant, job autonomy moderates the relationship between leadership style and performance.

**Estimate Latent Interaction Term Using MLE**

Instead of multiplying indicators (as in the Product Indicator Approach), LMS incorporates interaction terms directly into the likelihood function. The joint likelihood function is calculated using numerical integration:

The LMS algorithm estimates non-normal latent distributions using adaptive quadrature methods. If β3 >0, transformational leadership is more effective when employees have high job autonomy. If β3 <0, high autonomy weakens the impact of leadership on performance. If β3 = 0, no moderation effect exists.

The major advantage associate with this method is, (i) it is a more precise estimation of interaction effects without relying on observed indicator products, (ii) educes measurement error and avoids the issues of mean-centering used in the Product Indicator Approach, and (iii) statistically more robust than traditional moderation approaches (Maslowsky et al., 2015). On the other hand, (i) it requires numerical integration and high computational power, and (ii) can be implemented in advanced SEM tools like Mplus, EQS, and R (Lavaan).

The Latent Moderated Structural Equations (LMS) Approach is a powerful SEM technique that uses Maximum Likelihood Estimation (MLE) to model latent interaction effects. Unlike traditional moderation methods that rely on multiplying observed indicators, LMS integrates interaction terms directly into the likelihood function, improving accuracy and statistical efficiency. It is particularly useful in psychology, business research, and social sciences, where complex moderation relationships exist (Klein & Moosbrugger, 2000; Maslowsky et al., 2015).

**5. BAYESIAN MODERATION**

Bayesian Structural Equation Modeling (Bayesian SEM) for moderation is an advanced approach that applies Bayesian estimation to capture nonlinear and complex interaction effects between latent variables. Unlike traditional Maximum Likelihood Estimation (MLE), which relies on large samples and normality assumptions, Bayesian SEM is well-suited for small sample sizes and high-dimensional moderation models (Lee & Song, 2012; Van de Schoot et al., 2017). It incorporates prior distributions and uses Markov Chain Monte Carlo (MCMC) simulations for parameter estimation (Gelman 2006).

This approach is particularly beneficial when handling latent variable interactions or hierarchical models where standard SEM techniques (e.g., product indicators, multi-group analysis) may struggle (Lee & Song, 2012).

Mathematical Model Bayesian moderation model is as follows:

Where: Y = Dependent variable, X = Independent variable, M = Moderator Variable, X x M = Interaction term (moderation effect), β3​ = Moderation effect term, and ε = Error term.

 is the residual error, expected to follow a normal distribution. In Bayesian SEM, each parameter (β) has a prior distribution, which reflects prior knowledge or assumptions about the data:

where:= mean of the prior distribution, = variance of the prior distribution, which represents uncertainty.

For variance parameters, an inverse gamma prior is typically used:

where α and β are shape parameters that control the degree of belief in the variance estimates (Gelman, 2006).

Ex: A company studies whether intrinsic motivation (X) with three indicators to measure influences employee productivity (Y) with three indicators to measure, and whether this effect is moderated by workplace flexibility (M) with three indicators to measure.

Step one: Define the model:

with priors for parameters:

,

where non-informative priors (e.g., (0,10) allow data to dominate the estimates.

**Bayesian Estimation with MCMC**

Estimate posterior distributions using MCMC simulations (e.g., Gibbs sampling, Hamiltonian Monte Carlo). Software like Stan (via R), JAGS, or Mplus is used to obtain posterior estimates. Assess Model Convergence: Diagnostics such as trace plots, Gelman-Rubin statistic (R-hat), and effective sample size (ESS) ensure that the MCMC chains have converged (Van de Schoot et al., 2017). Interpret Posterior Distributions: Instead of p-values, Bayesian SEM uses Credible Intervals (CIs) (e.g., 95% CI), which indicate the range within which a parameter likely falls. If β3’s CI does not include zero, moderation is supported. Perform Model Comparison: Bayesian model fit indices such as Deviance Information Criterion (DIC) and Watanabe-Akaike Information Criterion (WAIC) help in model selection (Lee & Song, 2012).

Interpret the Posterior Distribution: If the 95% CI for β3​ (moderation effect) does not include zero, moderation is confirmed. The posterior distributions of β3​ tell us the probability that moderation exists. If β3​ ​ is significantly positive, workplace flexibility enhances the effect of motivation on productivity. If β3​ ​ is negative, flexibility weakens the relationship.

The main advantages of associated with Bayesian method for Moderation is it is (i) suitable for Small Sample Sizes: Unlike MLE, which requires large samples, Bayesian SEM works well with limited data (Lee & Song, 2012), (ii) Bayesian models efficiently estimate multiple moderations and nonlinear effects, (iii) Unlike p-values, Bayesian posterior distributions give a full probability estimate of moderation effects, and (iv) Traditional SEM struggles with non-normal data; Bayesian estimation smoothly estimates parameters even in complex models.

Bayesian SEM for moderation offers a flexible and powerful alternative to traditional MLE-based SEM, especially in small samples and complex moderation scenarios. By using Bayesian estimation, researchers can capture latent interactions with better accuracy, avoid assumptions of normality, and obtain probabilistic interpretations of effects (Lee & Song, 2012).

**6. POLYNOMIAL REGRESSION WITH RESPONSE SURFACE ANALYSIS**

Polynomial regression with response surface analysis (RSA) is an advanced analysis technique used to model nonlinear moderation effects in structural equation modelling (SEM) and applied research fields like organizational behaviour and psychology. Unlike traditional linear moderation models that assume a straight-line relationship, polynomial regression captures curvilinear effects and interactions, making it suitable for complex phenomena where relationships change at different levels of predictors (Edwards, 2002; Shanock et al., 2010).

RSA extends polynomial regression by visualizing the interaction effects using three-dimensional surfaces, which help in understanding how two predictors jointly influence an outcome variable beyond simple linear interactions (Edwards & Parry, 1993). The following is the statistical model for PR with RSA:

Where, Y is the outcome variable, X and Z are the predictors, X2 and Z2 are non-linear effects (Quadratic), β0 is the intercept of the equation, β1 to β5 are the coefficients of the equation, and ε is the disturbance term of the equation.

The response surface is then analysed by evaluating the shape of the surface along key axes, such as the line of congruence (LOC) (X=Z) and the line of incongruence (LOIC) (X = −Z). By understanding the curvature, slope, and stationary point of the surface, researchers are able to draw meaningful conclusions regarding the nature of moderation and nonlinear relationships.

Ex: Let us consider an organizational behaviour study investigating how perceived organizational support (predictor) and job satisfaction (the second predictor) together affect employee engagement (dependent variable). Traditional moderation analysis would only assess whether job satisfaction strengthens or weakens the relationship between organizational support and engagement. However, response surface analysis allows for detecting curvilinear relationships, revealing whether extremely high or low levels of job satisfaction change the effect of organizational support on engagement (Edwards & Parry, 1993). The following is the proposed model of the problem:

X2 and Z2 are non-linear effects (Quadratic terms of the equation)

A. At Line of Congruence (X=Z): At this level both the predictors are equal:

Inference: if β3 +β4 +β5 >0, the curve slopes upward, signifying that employee job engagement is highest when both predictors of the study perceived organisational support and job satisfaction are **high**.

Inference: if β3 +β4 +β5 <0, the curve slopes downward, indicating that employee job engagement may decline at extreme levels, even though both predictors are aligned

B. Line of Incongruence X=-Z). At this point the predictors X and Z are misaligned (for example low perceived organisational support and high job satisfaction, or vice versa), the following is the equation:

Inference: if β3 -β4 +β5 <0, the curve slopes downwards, signifying that employee job engagement is lower when there is misalignment between perceived organisational support and job satisfaction.

if β3 -β4 +β5 >0, the curve slopes upwards, signifying the mismatch between perceived organisational support and job satisfaction, in some cases increases job engagement.

RSA provides deeper insights beyond traditional moderation analysis. If the analysis reveals an upward curvature along LOC, it suggests that engagement is maximized when organizational support and job satisfaction are both high. Conversely, if the LOIC shows a downward curvature, engagement is significantly reduced when there is a misalignment between the two variables.

**Hierarchical Structural Equation Modelling (HSEM) for Moderation**

Hierarchical Structural Equation Modelling (HSEM) is a sophisticated statistical method for estimating moderation effects in multi-level data structures, e.g., longitudinal or nested data (e.g., team members vs. employees at the company level, students in a school vs. students across schools). Contrary to single-level SEM that postulates that all variables belong to one and the same level, HSEM accommodates hierarchical dependencies by modelling relations at different levels of analysis. This technique is especially helpful in organizational behaviour, education, and psychology, where there are variables at various levels (individual, team, organization) that interact to affect an outcome (Preacher et al., 2010). In moderation analysis, HSEM assists in establishing if a higher-level (group-level) moderator affects the relationship between lower-level predictors and outcomes. This method extends standard multilevel modelling (MLM) by incorporating latent variables and measurement error corrections, thus being an effective tool for investigating complex moderation effects (Hox, 2010).

**The following is the statistical model of HSEM**

HSEM has two levels: (i) Individual level and (ii) Group level

Level1: Individual level: It is also known as Within-level model.

Where, Yij is dependent variable for individual i in cluster j, Xij is independent variable at the individual level, βoj is the intercept of the cluster or group j, β1 is coefficient, and eij is the error term of the equation.

Level 2: It is also known between-level model

Where, Zj is the proposed moderator at group level, γ00 mean (grand) of dependent variable across group, γ01 effect of the proposed moderator Zj, γ10 effect (average) of predictor on dependent variable across group, u0j and u1j are error terms.

Example: A manager is examining productivity of employees (dependent variable) predicted by independent variable job autonomy, with leadership style (term level moderator). Furthermore, employees (i) are nested within teams (j).

First Level or Induvial level, we are assuming employees within groups experience varying degrees of job autonomy.

Second level also known as group level: term level moderator (leadership style) affects how job autonomy explains productivity.

Where, Yij is dependent variable (productivity of employees) for individual i in cluster j, Xij is independent variable (job autonomy) at the individual level, βoj is the intercept of the cluster or group j, β1 is coefficient represents the impact of job autonomy on employee productivity, and eij is the error term of the equation (at individual level).

Second level we have the following set of equations for between-team model

Where, Zj is the proposed moderator in this case leadership style exhibited by the manager (transactional or transformational) at group level, γ00 mean (grand) of dependent variable across group, γ01 effect of the proposed moderator (leadership style), Zj, γ10 effect (average) of predictor (job autonomy) on dependent variable (productivity) across group, γ11 moderation effect of the proposed moderator (transactional (coded as 1) or transformational (coded as 2)) impact on job autonomy’s (predictor variable) impact. u0j and u1j are error terms.

Inference: if β1 >0, (this indicates the direct effect of job autonomy) the predictor (job autonomy) influences outcome variable (productivity) positively.

If, >0, (indicates the effect of leadership style on productivity) inferred as the groups or teams with transformational leadership styles have higher productivity (overall).

In the next level, moderation effect will be tested as follows:

If, >0, the predictor (job autonomy) effects employee productivity positively. If, <0, the leadership style (transformational leadership) weakens the relationship between job autonmy (predictor) and employee productivity (outcome variable).

Hierarchal Structural Equation Modelling signifies that leadership style (transactional or transformational) moderates the proposed relationship between job autonomy and employee productivity, with transformational leadership intensifying the positive effects. This multilevel method captures for distinctions or variations across groups, making it superior to single-level Structural Equation Modelling or elementary moderation models.

**8. MODERATED MEDIATION**

Moderated mediation is a statistical approach that integrates both moderation and mediation within a single framework. It examines whether the strength of a mediated relationship (i.e., the indirect effect of a focal predictor variable on an outcome variable via an intermediate or mediator variable) depends on the level of a moderator (Edwards & Lambert, 2007; Preacher, Rucker, & Hayes, 2007). In simpler terms, it tests under what circumstances and for which person the mediation effect occurs. This method is very useful in behavioural, psychological, and business research where mediation effect not necessarily the same in all the circumstances but may vary depending upon the conditions on contextual differences.

Statically, the moderated mediation process can be understood by the following equations:

1. Effect of predictor (IV) on the mediator (M) (path a)

In the above equation β3 indicates whether the effect of predictor on moderator in moderated by W the moderating variable.

2. Effect of Mediating variable (M) on outcome variable (Y) regulating for predictor variable (X) (path b):

In the above equation, β7 is called the interaction term, signifying whether the effect of mediating variable on dependent variable is moderated by the proposed moderator.

3. Conditional Indirect Effect Path:

The indirect effect of independent variable (X) on outcome variable (Y) via proposed mediating variable, conditional on Moderating variable, is given mathematically as follows:

In the above equation if the coefficients β3 or β7 statistically significant, then the effect of mediating variable varies based on the level of the proposed moderator (W), confirming the effect of moderated mediation in the proposed relationship.

Ex: In a study a researcher is examining the relationship between work stress (focal predictor) on an outcome variable, job performance (Y) by using job satisfaction as the intervening variable (mediator). In addition, he is using personality type or emotional stability as a moderator (W).

To investigate the above relationship the researcher has set the following set of equations to be tested:

Path a: The effect of work stress (predictor) on work satisfaction (mediator variable)

Where β1 indicates the direct effect of predictor on job satisfaction and β2 direct effect of moderator emotional stability on job satisfaction (mediating variable). However, the coefficient β2 signifies the interaction effect, exhibiting whether the effect of work stress (predictor) on mediator job satisfaction is contingent on emotional stability of the employee. If the coefficient β1 is statistically significant, the moderator emotional stability moderates the influences the relationship between job stress on job satisfaction.

Path b: In path b we are investigating the influence of job satisfaction (moderator) on job performance of the employees (outcome variable), controlling for work stress that is focal predictor of the equation.

Where, β4 the coefficient signifies the influence of job satisfaction (M) on job performance (Y) of the employees, similarly the coefficient β5 denotes the direct effect of work stress (X) on performance of the employees (Y), the coefficient β6 denotes the impact of the moderator emotional stability on outcome variable job performance. However, the coefficient β7 denotes the interaction effect, signifying whether the impact of mediator (job satisfaction) on outcome variable (job performance) depends on moderating variable (emotional stability).

In the next step, we need to investigate for conditional indirect effect of predictor (work stress) on work performance (outcome variable) via job satisfaction (mediating variable), conditional on emotional stability of the employee (moderator) by applying the following equation:

The above equation denotes the product of path a (tested above, to know the impact of predictor on mediator) and path b (tested above, to know the impact of mediator on outcome variable). Where the moderating variable W indicates the mediation effect on outcome variable varies depending upon the moderating variable emotional stability. If β3 or β7 is statistically significant, then the conclusion is that the mediation effect of job satisfaction depends on emotional stability of the employee (evidence for moderated mediation).

**IV STEPS INVOLVED IN MEDIATION ANALYSIS IN SEM**

Moderation analysis in Structural Equation Modelling (SEM) is applied to investigate whether the relationship between an independent variable and a dependent variable varies based on the level of a third variable (moderator). The calculation of moderation analysis in SEM typically follows the following steps:

**STEP 1: MODEL SPECIFICATION**

Model specification includes the description of hypothesized associations between variables under investigation to enable clarity in causality. An independent variable (IV) refers to the assumed influence factor that impacts an outcome, and the dependent variable (DV) represents the outcome of measurement. The moderator variable (MV) alters the direction or strength of relationship between the IV and DV. For instance, in research that is investigating the influence of workload (IV) on job performance (DV), job autonomy (MV) can act as a moderator. If the workers are highly autonomous, the negative effect of workload on performance will be less, while low autonomy will enhance the negative effects. This interaction highlights how moderators can alter the primary relationship between IV and DV.

**STEP 2: DATA PREPARATION**

Preparation of data is an important step to get an accurate and trustworthy analysis. All the variables are first measured in the right way, consistent with the theoretical framework of the study. If the model contains interaction terms, the independent variable (IV) and the moderator variable (MV) should be mean-centered (standardised) so as to minimise multicollinearity that causes distortion of the regression estimates. Besides that, missing values should be assessed with caution and dealt with an appropriate imputation method, either mean substitution, multiple imputation, or regression imputation, depending on missing values’ extensiveness and type. In a study exploring the impact of training hours (IV) on workers’ productivity (DV) with motivation (MV) being a moderator as an example, standardizing the training hours and motivation will better enable their interaction to be understood. Treating missing data effectively avoids biases and enhances the reliability of the findings.

**STEP 3: CONSTRUCTING INTERACTION TERM**

Building interaction terms is necessary to test moderation effects in a model. This entails the creation of a new variable through the multiplication of the independent variable (IV) and the moderator variable (MV) (i.e., IV \* MV) to measure their combined effect on the dependent variable (DV). If the variables are latent constructs, product indicators must be created by multiplying corresponding item scores of IV and MV. This method has the benefit that moderation effects can be properly accounted for in structural equation modelling (SEM). To illustrate, where work stress (IV) and job satisfaction (DV) have been examined using emotional intelligence (MV) as a moderator variable, an interaction term (work stress \* emotional intelligence) is constructed to specify whether emotional intelligence moderates or buffers the inverse effect of stress on job satisfaction. This is an important step in properly interpreting moderation effects in empirical studies.

**STEP 4: MODEL ESTIMATION**

Model estimation consists of testing the relationships hypothesised through specifying and estimating the structural model. The starting point is specifying a baseline model (lacking the moderation effect) to estimate the direct links between the independent variable (IV) and the dependent variable (DV). Secondly, the interaction term (IV \* MV) is added in the structural model to test for the moderation effect. The model can be estimated with the help of software such as AMOS, Mplus, or SmartPLS, depending on whether covariance-based (CB-SEM) or variance-based (PLS-SEM) modelling is desired. The estimation approach, for example, Maximum Likelihood (ML) in CB-SEM or Partial Least Squares (PLS) in PLS-SEM, relies on data properties and model complexity. For instance, if a study investigates the impact of leadership style (IV) on employee engagement (DV) with organisational culture (MV) as a moderator, estimating the model with and without the interaction term assists in establishing whether culture significantly moderates the IV-DV relationship.

**STEP 5: ASSESSING MODEL FIT**

Model fit evaluation is essential in order to provide assurance regarding the validity of the structural model as estimated. Of primary importance are the fit indices like the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) to identify the degree of representation of the data by the model. The fit of the model should be compared prior to and following the addition of the interaction term to determine if moderation enhances or reduces model fit. Ideally, adding the interaction should not substantially reduce model fit. For instance, in research testing the effect of workload (IV) on job satisfaction (DV) with organizational support (MV) as a moderator, an appropriately fitting model should have good CFI (≥0.90), TLI (≥0.90), and RMSEA (≤0.08) values even after adding the interaction term (Sathyanarayana & Mohanasundaram, 2024; Sathyanarayana & Mohanasundaram, 2025). Having good model fit enhances the robustness of moderation analysis.

**STEP 6: INTERPRETING MODERATION EFFECTS**

The interpretation of interaction effects involves looking at the coefficient of the interaction term. It is to determine if the moderator significantly affects the relationship between the IV and the DV. In case the interaction term is significant, this implies that the effect of IV on DV is contingent upon the moderator variable (MV). To better view this effect, a simple slope analysis can be conducted, wherein the IV-DV relationship across different levels of the moderator (e.g., low, medium, and high MV) may be examined. Also, interaction plots can be made to view how the relationship varies at various levels of MV. Moreover, interaction plots can be drawn to see how the relationship varies at varying levels of MV. For instance, in research that investigates the effect of work stress (IV) on job performance (DV) with coping strategies (MV) as a moderator, a significant interaction term indicates that employees with good coping strategies have a weaker negative impact of stress on performance than those with bad coping strategies. Such analyses also offer greater insight into the nature of moderation effects.

**STEP 7: POST-HOC AND ROBUSTNESS TEST**

Post-hoc and robustness tests guarantee the validity of moderation analysis outcomes. If the moderator variable (MV) is categorical, a multi-group moderation analysis must be performed to examine if the interaction between the independent variable (IV) and dependent variable (DV) varies across groups. It is also necessary to test for multicollinearity, especially in interaction models, with variance inflation factors (VIF) to guarantee that predictors are not highly correlated. To improve the robustness of results, bootstrapping (e.g., with 5,000 resamples) can be used to evaluate the stability and confidence intervals of interaction effects, minimizing sampling bias. For instance, in research examining the effect of workload (IV) on job satisfaction (DV) and how job autonomy (MV) moderates it, multi-group analysis would test employees with high versus low autonomy, whereas bootstrapping would verify if the moderation effect holds across samples. These tests enhance the reliability and generalizability of moderation findings.

**STEP 8: REPORTING THE RESULTS**

Presenting results involves presenting the findings of the moderation analysis precisely. Moderation effects must be presented clearly using tables and figures, for example, interaction plots to present how the independent variable (IV) influences the dependent variable (DV) across moderator variable (MV) levels. Output should be in the form of standardized coefficients, p-values (reporting significance levels), and effect sizes (such as Cohen’s f² for moderation effects) in order to convey the strength and significance of the interaction. Finally, theoretical and practical implications must be addressed setting out how the results add to current knowledge and how they can be used in practice. For instance, if a study discovers that emotional intelligence (MV) is a moderator of work stress (IV) and job performance (DV), organizations would utilize this knowledge to develop training modules that improve employees’ emotional intelligence, thus mitigating the performance-impeding effects of stress. Such systematic reporting assures brevity and efficacy.

**V. DISCUSSION AND CONCLUSION**

Moderation is extensively investigated across various business domains to capture context-dependent effects and enhance theoretical understanding (Baron & Kenny, 1986; Edwards & Lambert, 2007). Furthermore, the moderation technique has gained considerable attention due to its ability to examine the limits shaping theoretical and managerial insights (Hayes, 2007).

Moderation is widely studied in psychology to examine third-variable influences on large effects between personality factors, resilience, job stress management, and work performance. Emotional intelligence, for instance, moderates job stress and performance (Goleman, 1998; Joseph & Newman, 2010), and self-efficacy moderate’s burnout following high job demands (Schaufeli & Bakker, 2004). Personality factors also serve to moderate the associations, like conscientiousness acting as a moderator of job autonomy on performance (Barrick & Mount, 1991) and extraversion moderating the influence of workplace social support on job satisfaction (Judge & Bono, 2001). These experiments demonstrate the pivotal importance of moderation in organizational behaviour. Moderation forms the nucleus of Organizational Behaviour (OB) research since it allows the specification of circumstances under which organizational relationships and behaviours function optimally. Rather than anticipating cause-and-effect associations in general, moderation accounts for when and for whom leadership behaviors, teamwork, and employees’ actions result in different outcomes. For example, organizational culture is a buffer between transformational leadership and job satisfaction (Hartnell et al., 2016; Hoch et al., 2018), while psychological safety moderates the team diversity-performance relationship (Newman et al., 2017; Edmondson & Lei, 2014). Emotional intelligence raises leader-member exchange (Jordan & Troth, 2021), whereas trust serves to moderate virtual collaboration and team performance (Bartsch et al., 2021). With increasingly digitalized and AI-led workplaces, moderation continues to play an important role in adapting leadership, engagement, and organizational strategy to particular settings.

Moderation is extensively studied in psychology to examine third variables that affect strong relationships between personality traits, coping with stress, resilience, and work performance. For instance, emotional intelligence moderates the effect of job stress on performance (Goleman, 1998; Joseph & Newman, 2010), whereas self-efficacy minimizes burnout resulting from over-demanding jobs (Schaufeli & Bakker, 2004). Personality traits are moderators as well, i.e., conscientiousness moderating job autonomy’s influence on performance (Barrick & Mount, 1991) and extraversion enhancing workplace social support’s influence on job satisfaction (Judge & Bono, 2001). These studies underscore the significance of moderation in workplace dynamics. Moderation is at the heart of Organizational Behaviour (OB) research since it enables the determination of conditions under which workplace relationships and behaviours are most effective. Instead of assumed all-encompassing cause-and-effect connections, moderation identifies when and for whom leadership styles, team performance, and employee actions lead to differing outcomes. Organizational culture, for example, moderates the impact of transformational leadership on job satisfaction (Hartnell et al., 2016; Hoch et al., 2018), whereas psychological safety mediates the connection between team diversity and performance (Newman et al., 2017; Edmondson & Lei, 2014). Emotional intelligence supports leader-member exchange (Jordan & Troth, 2021), and trust acts as a moderator between virtual work and team performance (Bartsch et al., 2021). In the face of conflicting workplaces driven by AI and digitalization, moderation continues to have a critical role in informing leadership, organizational, and employee engagement strategies contextually.

Moderation is important in marketing research as it assists in streamlining brand perception, analysis of consumer behaviour, and digital marketing approaches. Moderation highlights circumstances under which marketing variables interact, making interventions more effective. For instance, social influence intensifies the effectiveness of internet reviews in influencing purchasing decisions (Chevalier & Mayzlin, 2006), whereas brand trust mediates the CSR-locales link by amplifying loyalty only when trust exists (Chaudhuri & Holbrook, 2001; Fatma et al., 2018). Consumer interaction mediates the efficacy of targeted adverts (Lambrecht & Tucker, 2013), whereas authenticity in influencer marketing enhances the success of brand endorsement (Jin et al., 2019). Moreover, cross-cultural differences determine international branding policies (De Mooij & Hofstede, 2010). With AI and data-driven personalization emerging, moderation analysis is still fundamental to developing responsive, consumer-oriented marketing strategies.

Moderation analysis in financial research assists in analysing how different factors shape investment behaviour, risk management, corporate governance, and finance decision-making. For instance, risk tolerance conditions the relationship between investment choice and financial literacy in a way that financially literate people are likely to engage in higher risks (Van Rooij et al., 2011; Lusardi & Mitchell, 2014). Market conditions also influence the influence of corporate governance in company performance so that its effect is more pronounced in periods of recessions (Shleifer & Vishny, 1997; La Porta et al., 2000). Investor sentiment moderates’ earnings announcements’ influence on stock returns (Baker & Wurgler, 2006), and financial distress lowers consumer credit use even with good credit conditions (Gathergood, 2012). Regulatory systems define the CSR-financial performance relationship (Flammer, 2015), and inflation expectations enhance monetary policy’s impact on stock market volatility (Bekaert et al., 2013). By comprehending these moderating effects, one can make better investments, risk estimates, and financial plans in dynamic markets.

Moderation analysis in HRM studies enables the identification of intricate relationships that affect employee motivation, retention, job satisfaction, and performance. For instance, the construct perceived organizational support acts as a mediator of work-life balance practices’ constructive impact on the commitment of employees (Eisenberger et al., 1986; Rhoades & Eisenberger, 2002). Likewise, job autonomy off-sets the harmful impact of job demands on the health of employees (Bakker & Demerouti, 2007; Schaufeli et al., 2009). Satisfaction of psychological contract is the missing link that authenticates reward-for-performance’s association with employees’ motivation (Rousseau, 1995; Bal et al., 2008), while transformational leadership authenticates organizational justice power’s influence in the creation of job satisfaction (Judge & Piccolo, 2004). Career development prospects diminish turnover intentions despite low job satisfaction (Weng & McElroy, 2012), and emotional intelligence also mediates the impact of workplace conflict on performance (Jordan & Troth, 2021). Furthermore, organizational culture strengthens the positive effect of diversity management on team performance (Ely & Thomas, 2001). Flexible work arrangements minimize levels of burnout even if work is very stressful (Tavares, 2017), and clarity of goals enhances the quality of feedback influencing productivity (Locke & Latham, 2002). Understanding these moderation effects enables HR professionals to align policies to create improved employee well-being, participation, and business success.

Moderation analysis is a crucial component of business research as it determines contextual conditions that affect relations between important variables. The conclusions in psychology, organizational behaviour, marketing, finance, and human resource management imply that moderation contributes to the effectiveness of models as predictors by responding to external stimuli (Hayes, 2007; Baron & Kenny, 1986). From an empirical standpoint, subsequent research could investigate the incorporation of machine learning models within moderation analysis to measure complicated, non-linear interactions (Aguinis et al., 2010). Newer computational methods like neural networks and decision trees have the potential to offer more nuanced understanding of the functioning of moderators across varied settings (Shmueli & Koppius, 2011). Cross-cultural research also has the ability to further enrich our knowledge on moderation effects within international business settings (Taras et al., 2010).

From a management perspective, it is possible to create more efficient employee engagement, consumer behaviour, and financial decision-making strategies if businesses understand the moderation effects. For instance, HR managers can adjust employee retention strategies according to the level of job autonomy and the level of perceived organizational support (Bakker & Demerouti, 2007). Likewise, marketing professionals can use brand trust and social influence to maximize consumer engagement (Chevalier & Mayzlin, 2006). Financial analysts also stand to gain by adding risk tolerance as a central moderator when making recommendations to clients regarding investment choices (Lusardi & Mitchell, 2014).

Although it has its merits, moderation analysis has its own weaknesses. Measurement errors and sample size limitations may compromise the reliability of findings, and therefore more robust data collection strategies are needed (Aguinis et al., 2010). Use of self-reported information may also pose bias risks, which necessitates the use of multi-source verification methods (Podsakoff et al., 2003). Future studies should overcome these shortcomings by using longitudinal designs and utilizing big data analytics to enhance the accuracy of moderation effects.

The recent developments in moderation analysis have been fuelled by the convergence of artificial intelligence (AI) and machine learning (ML), which allows for researchers to detect intricate, non-linear interactions between variables more accurately (Kuhn & Johnson, 2019). The technologies improve predictive power and enable the real-time identification of moderation effects in large datasets, especially in marketing, finance, and human resource management. Furthermore, meta-analytic research has yielded a more generalizable understanding of how moderators work in various industries, organizational settings, and cultures, providing more generalizable results (Aguinis et al., 2010). Researchers are increasingly turning to multi-level moderation analysis, exploring how individual, team, and organizational levels interact to impact important business outcomes (Preacher et al., 2016). Future studies must then develop practical applications for such advances in decision-making, including using AI-based moderation insights to customize leadership interventions, maximize customer interactions, and improve risk management. Additionally, the combination of longitudinal studies with dynamic modelling will further sharpen our understanding of how moderation effects change over time, ultimately enhancing data-driven business strategies and policy-making (Antonakis et al., 2010). Thus, moderation continues to be a key instrument for developing theoretical and managerial knowledge across business fields. By combining fresh analytic methods and overcoming current hindrances, future research can further uncover how business results are shaped by contextual determinants.

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