Addressing Common Method Bias in Survey Datasets: A Literature Review and Future Research Directions

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DECLARATION

I, **Lwazi Qangule**, hereby declare that this proposal for the master's degree in business administration submitted to the Wits Business School at the University of Witwatersrand has not been submitted previously for any degree at this or another university. It is original in design and in execution, and all reference material contained therein has been duly acknowledged.

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Student ……………………………... **Date** ………………………

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ABSTRACT

This paper provides a thorough examination of techniques for detecting and mitigating common method bias (CMB) in research studies. A thorough review of literature from 1990 to 2024 using Scopus and Google Scholar as primary search engines, revealed multiple methods of dealing with CMB. Despite significant contributions from seminal studies, methodological limitations remain, as does the need for innovative measurement methodologies and statistical solutions. This study, which draws on findings from key studies from the literature, addresses the need for novel strategies to effectively combat CMB.

The study investigates a variety of methodological techniques, including blinding, counterbalancing, longitudinal designs, and multimethod approaches, and proposes strategies for reducing bias in data collection procedures. Confirmatory factor analysis, structural equation modelling, and multilevel modelling are some of the statistical techniques used to evaluate measurement validity and control for CMB. However, gaps still exist in the literature, particularly relating to accurately identifying and addressing CMB across multiple datasets and research scenarios. Existing techniques may fail to capture the complexities of method bias or provide reliable solutions in all contexts. These limitations highlight the need for a new technique that offers a systematic and parametric approach to assessing and mitigating CMB, providing researchers with a comprehensive tool for increasing the validity and reliability of their findings. This study aims to imparts valuable insights for researchers seeking to improve the reliability and validity of their findings through a nuanced examination of each technique's strengths, weaknesses, and practical implications. The proposed parametric mathematical method (Stacey-Qangule Model) provides a systematic approach for detecting and addressing Common Method Bias (CMB) in survey data, with the goal of improving research validity. The method aims to identify latent variables free of method bias across various datasets and scenarios by estimating bias in manifest ratings and applying mathematical transformations.

Future research should focus on refining and validating the proposed statistical model, collecting diverse and high-quality data, conducting rigorous data analysis, effectively interpreting and communicating findings, disseminating research results, and pursuing new research directions. Implementing these recommendations allows researchers to

contribute to the advancement of knowledge in organizational behaviour and performance evaluation, ultimately leading to positive change and impact in the identified phenomena or problem areas.

KEYWORDS: Common Method Bias; Latent Variable Modelling; Confirmatory Factory Analysis; Behavioural Research; Validity and Reliability

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CHAPTER 1: INTRODUCTION

1.1 Background of the Study

The term "common method bias" (CMB) refers to the systematic variance that is due to the measurement method rather than the constructs that the measures represent(Doty & Glick, 1998; Jakobsen & Jensen, 2015a; Kock, 2017; MacKenzie & Podsakoff, 2012a; Podsakoff et al., 2003a). It happens when the same method or source of measurement is used for both the predictor and criterion variables in a study, resulting in artificial inflation of relationships between variables (Doty & Glick, 1998; Jakobsen & Jensen, 2015b; Kock, 2017; MacKenzie & Podsakoff, 2012; Podsakoff et al., 2003a;). CMB can cause overestimation or underestimation of variables' relationships, potentially biasing the study's results. (Doty & Glick, 1998; Jakobsen & Jensen, 2015a; N. Kock, 2017; MacKenzie & Podsakoff, 2012a; Podsakoff et al., 2003a) This method is also known as common method variance (Podsakoff et al., 2003b). CMB occurs when systematic variance is introduced into data due to the measurement instrument or the context of data collection. It can arise from the shared method of data collection, common item wording, or respondent characteristics, leading to inflated correlations or biased estimates. The predictor and outcome variables would be subject to this bias if they were obtained from the same source or technique of measurement. CMB, leading to the apparent connections being artificially inflated or muted (Jakobsen & Jensen, 2015b; Jordan & Troth, 2020a; Kamakura, 2010a; Podsakoff et al., 2003b). Several disciplines may be significantly impacted by this bias, including organisational research, where precise measurement and assessment of constructs are essential for comprehending relationships and making defensible judgments (Jakobsen & Jensen, 2015b; Jordan & Troth, 2020a; Kamakura, 2010a; Podsakoff et al., 2003b). CMB has been written about extensively in literature and various authors have suggested ways of dealing with CMB including the use of statistical approaches.

1.2 Overview of CMB

Employing rigorous techniques that guarantee the validity and dependability of study findings is essential in empirical research.(Gorrell et al., 2011; Jakobsen & Jensen, 2015b; Jordan & Troth, 2020a; Keiser & Payne, 2019; Kock, 2021; Leplingard et al., 2003; Ruble & Stout, 1991; Zangirolami-raimundo & Leone, 2018). However, methodological difficulties are frequently encountered by researchers, which might create biases and jeopardise the integrity of their findings.(Podsakoff et al., 2003b). Common method bias (CMB), also known as common method variance (CMV), is one such matter that has drawn considerable industry attention. (Podsakoff et al., 2003b). The term "CMB" describes a systematic bias or variation that develops because of a research study's usage of a single data-gathering technique. To guarantee the validity and generalizability of study results, it is essential to comprehend and handle CMB (Gorrell et al., 2011).

Common Method Bias can also be caused by depending on a single source of information or simultaneously gathering data from participants (Jordan & Troth, 2020a; Keiser & Payne, 2019; Podsakoff et al., 2003b; Williams & Anderson, 1994). The effects of CMB may be widespread. Notably, it can result in an overestimation or underestimating of the true impacts of variables, making it difficult to accurately comprehend how different constructs are related. The validity of research findings may also be harmed by the possibility that the measurement technique, rather than the components under investigation, is primarily responsible for the variance in the study. These methodological traits could result in an inflated correlation between variables due to the common technique variance, leading to spurious correlations and inaccurate conclusions. (Podsakoff et al., 2003b). Furthermore, because the presence of CMB can alter associations between variables in a way that may not hold true in various contexts or with various data collection techniques, the restricted generalisability of findings raises concerns.(Podsakoff et al., 2003b).

There are also a few unusual situations in which a researcher can benefit from using CMB, according to (Jordan & Troth, 2020a). For instance, a researcher can cite CMB as a study's strength to claim that the method should have yielded stronger associations if they are doing a study in which they predict weak (or non-significant) associations between variables (as in the building of scales when examining discriminant validity). The use of statistical treatments was also acknowledged, but it was viewed as a last resort and as being less effective than ones based on methods. This supports the findings from Podsakoff et al., (2003) study that these statistical methods have significant shortcomings.

1.3 Causes of Common Method Bias:

Self-reporting: When information is acquired via self-report measures, such as questionnaires or surveys, respondents could unintentionally introduce bias by providing socially acceptable answers or by interpreting the questions differently (Gordon, 1987; Jakobsen & Jensen, 2015b; Jordan & Troth, 2020a; Kamakura, 2010a; Podsakoff et al., 2003b).

Single source of information: Due to common method variance, variables in a study may have an inflated correlation if all the data originated just from one source, such as a one respondent or a one technique (such as self-report) (Gordon, 1987; Jakobsen & Jensen, 2015b; Jordan & Troth, 2020a; Kamakura, 2010a; Podsakoff et al., 2003b).

Time proximity: When participant data are gathered concurrently, there is a higher likelihood of shared technique bias. This might occur if a participant's current mental state or a shared situational element affects how they react to different variables (Gordon, 1987; Jakobsen & Jensen, 2015b; Jordan & Troth, 2020a; Kamakura, 2010a; Podsakoff et al., 2003b).

1.4 Consequences of Common Method Bias:

False associations: One risk of CMB is the emergence of false associations between variables. The shared method's variance has the potential to artificially inflate or deflate the correlation coefficients across variables, leading to misleading or incorrect results (Gordon, 1987; Jakobsen & Jensen, 2015b; Jordan & Troth, 2020a; Kamakura, 2010a; Podsakoff et al., 2003b).

Effects may be over- or understated: Common technique bias can cause variables' actual effects to be over- or understated. This could lead to inaccurate conclusions and prevent a thorough knowledge of the relationships between various variables (Gordon, 1987; Jakobsen & Jensen, 2015b; Jordan & Troth, 2020a; Kamakura, 2010a; Podsakoff et al., 2003b).

Reduced validity: CMB may reduce the reliability of research results. When the variance in a study is mostly due to the measurement method rather than the variables being studied, it becomes difficult to draw meaningful and reliable inferences from the data (Gordon, 1987; Jakobsen & Jensen, 2015b; Jordan & Troth, 2020a; Kamakura, 2010a; Podsakoff et al., 2003b).

Limited generalizability: If there is common method bias, the generalizability of the results may be compromised. When employing different data collection methodologies or in different contexts, the bias may change the correlations between variables in such a way that the results may not hold true (Gordon, 1987; Jakobsen & Jensen, 2015b; Jordan & Troth, 2020a; Kamakura, 2010a; Podsakoff et al., 2003b).

1.5 Addressing Common Method Bias:

Researchers use a variety of techniques to lessen the possible effects of common method bias (Jordan & Troth, 2020a; Podsakoff et al., 2003b), including:

Utilise several methods: By utilising a range of data ***collection approaches***, such as objective measurements, archive data, or behavioural observations, researchers can reduce their reliance on self-report measures and avoid CMB (Jordan & Troth, 2020a; Podsakoff et al., 2003).

Statistical methods: To account for and mitigate the effects of CMB, researchers can employ statistical techniques like Harman's single factor test, minimising the impact of various method factors, partial correlation procedures created to regulate for method biases, also directly measurable latent methods factor, to name a few (Jordan & Troth, 2020a; Podsakoff et al., 2003). Utilising statistical control variables or latent variable modelling techniques, could aid in minimising CMB (Jordan & Troth, 2020a; Podsakoff et al., 2003).

Kock et al., (2021) acknowledge that only 86 papers across journals address common method bias in their investigation and that the applied controls are restricted to a small number of procedures that are also not state-of-the-art (Kock et al., 2021). Directly measured latent method factor and Unmeasured Latent Method Construct approaches receive little attention in (Kock et al., 2021) study. Ex ante approaches are used in a significant percentage of papers in the tourism sector, according to Kock et al., (2021). This raises the possibility of a widespread tendency across several businesses and supports Podsakoff et al., (2003) assertion that statistical approaches to CMB are rarely applied.

Due to the fact that it only makes reference to the standard level, (Gaskin, 2011) the work presented in a video on YouTube does not explain how he chooses what CMB level is considered acceptable. In order to reduce CMB, (Gaskin, 2011) strategy focuses on including a marker, or anything related to the survey dataset's design that is captured during data collection. (Gaskin, 2011) afterwards came to the realisation that his approach from the video was not the best one and discussed the flaw on this approach in the comments of the video. He contends that the common factor's pathways should not be all confined; rather, they should all be left uncontrolled. Additionally, one would need to look at how the latent factors and items' regression weights differ. This implies that the regression weights significantly alter when the common latent variable is added.

In a subsequent video rectifying the error, (Gaskin, 2012) attempted to fundamentally convey the methodology outlined by Podsakoff et al., 2003, but this does not demonstrate how to generate composite variables that can be used as a control variable. This method uses a confirmatory factor analysis marker technique, which is not what the current study is trying to address. The drawback of this approach is that CMB is only controlled at the level of the specific measurement item.

1.5.1. Addressing CMB using New Innovative Method:

With the use of the α parameter, the proposed model presents a novel mathematical framework that explicitly quantifies the degree of bias, allowing for accurate correction and a better understanding of CMB. The model provides a comprehensive answer by combining univariate and multivariate methods, which improves the precision and dependability of study findings. Because of its adaptability, it may be used in a variety of study settings and fields, which makes it a useful tool for a broad spectrum of researchers.

In addition, the model highlights the application of sophisticated multivariate analysis methods to reveal latent structures and correlations between data, including factor analysis and structural equation modelling. In contrast to conventional techniques, this strategy yields more trustworthy outcomes and deeper insights. The model's efficacy and practicality in real-world circumstances are ensured by iteratively refining the model and conducting pilot testing.

Conclusively, the suggested model constitutes a noteworthy addition to the CMB literature, providing an all-encompassing, adaptable, and useful resolution to a persistent quandary in behavioural science. This methodology has the potential to improve the rigor and validity of future research across different disciplines by filling in the gaps that have been discovered and expanding upon current methodologies.

1.6 Research problem, aims and objectives:

Research Problem: The literature has mentioned the difficulty of adequately addressing common method bias (CMB), but further investigation is needed. Despite extensive research into CMB, no definitive solution has been identified, particularly in terms of statistical methods. As a result, it is critical to provide a comprehensive review of existing literature, identify gaps in current knowledge, and propose next steps in addressing this persistent challenge in survey data research, with a primary focus on leveraging statistical methodologies.

Common method bias (CMB) frequently threatens the validity and reliability of survey-based research, distorting the relationships between variables and occasionally providing erroneous results.(Chin et al., 2012; Doty & Glick, 1998; Kamakura, 2010b) As a result, scholars use various techniques to address CMB, resulting in numerous inconsistencies in their findings. Although many studies recognize CMB and suggest different solutions, there remains a lacuna in the literature for a systematic review synthesising these techniques. (Fakhreddin, 2023; Jordan & Troth, 2020b; F. Kock et al., 2021b; Memon et al., 2023; Schwarz et al., 2017; Viswanathan & Kayande, 2012) Scholars face a disjointed terrain of methodological techniques, making it unclear which approach is best for addressing CMB. Also, while researchers acknowledge the challenges associated with CMB, the literature does not provide a comprehensive understanding of the various approaches that can be used to reduce the impact of CMB in survey datasets. (Fakhreddin, 2023; Jordan & Troth, 2020b; F. Kock et al., 2021b; Memon et al., 2023; Schwarz et al., 2017; Viswanathan & Kayande, 2012) Existing literature often focuses on specific disciplines and does not cover all approaches used across research domains (Fakhreddin, 2023; Jordan & Troth, 2020b; F. Kock et al., 2021b; Memon et al., 2023; Schwarz et al., 2017; Viswanathan & Kayande, 2012).

As a result, a comprehensive assessment of the literature is desperately needed in order to compile and assess the variety of methods used to address CMB in survey datasets from various academic disciplines. This research seeks to discuss the various techniques employed in the literature to address CMB. It further highlights the strengths and weaknesses of each technique and provide future research directions.

Scopus and Google Scholar were used for data collection, with a search period ranging from 1990 to 2023, and 20 studies have been screened and deemed appropriate for analysis.

Proposing A New Method

Despite the fact that CMB has been identified as a possible danger to authenticity, several research gaps must be filled in order to properly understand and mitigate its consequences. (Podsakoff et al., 2003b). The literature already in existence has drawn attention to the need for additional research into calculating and evaluating the magnitude of method variance, identifying the sources and mechanisms that contribute to its occurrence, examining the influence of CMB on research findings, exploring mitigation strategies, and conducting thorough meta-analytic studies to synthesise the overall effects of CMB.

Work done by (Podsakoff et al., 2003b) has identified research gaps in relation to Methodological Advancements where they outline that there is a need for further research to develop and evaluate new methodological advancements for addressing common method biases in behavioural research. This could involve exploring innovative measurement techniques, experimental designs, or statistical remedies to mitigate the potential bias. Furthermore, historically, (Williams & Anderson, 1994) presented an alternate strategy for dealing with method impacts, but there is a need for further research that directly compares the efficacy of latent-variable models with traditional approaches, such as common method bias techniques or covariance structure models. Comparative studies could shed light on the advantages and limitations of using latent-variable models in different research contexts.

This study proposes an innovate method that seeks to demonstrating how Common Method Bias (CMB) results from the mixing of average and latent data can be used to addressing deficiencies in current CMB methodologies in particular statistical approaches. This is based on a logic-based formulation that requires verification as part of further studies.

Research Purpose: The purpose of this study is to provide a thorough synthesis of existing literature, identify gaps and limitations in current knowledge, and propose concrete steps and strategies to move the field forward toward a more robust and reliable approach to mitigating common method bias in survey datasets. Finally, the study aims to contribute to the development of practical guidelines and recommendations that researchers can use to improve the validity and accuracy of survey research findings through the thoughtful application of statistical methodologies.

Objective: This work seeks to provide researchers with a way of dealing with CMB in a way that has not been assessed previously.

Research Hypothesis: The suggested mathematical approach for addressing common method bias (CMB) will improve the validity and dependability of study findings by providing a more exact and accurate estimation of latent constructs than typical univariate methods, holding all other factors constant.

1.7 Research Objectives

1.7.1 To investigate and evaluate existing literature on the phenomenon of common method bias (CMB) in survey data research.

1.7.2 To identify and delineate the gaps and limitations of the current body of literature regarding the removal of common method bias (CMB).

1.7.3 To propose a potentially new strategy for removing common method bias (CMB) using statistical methods in survey data research.

1.8 Delimitations of the study

Delimitations of the study define the specific boundaries and constraints imposed on the research. In the context of the proposed research on addressing common method bias (CMB) in survey data research using statistical methods, the following limitations are identified:

Time Frame: The study examine literature published between 1990 and 2023. This timeframe was chosen to account for recent advances in statistical methods and reflect the current state of research on common method bias. Due to a lack of extensive research on this topic, the research period has been extended to 24 years.

Methodological Focus: The primary focus is on statistical methods for overcoming common method bias. While other methodological approaches may be mentioned, the study will not delve deeply into non-statistical methodologies.

Publication Bias: The study acknowledges the possibility of publication bias, which occurs when positive or significant findings are more likely to be published. This may have an impact on the interpretation of findings and should be taken into account during the literature synthesis.

Language: The literature review only include articles published in English, limiting the analysis to studies carried out in English-speaking environments. This could result in a language bias, potentially excluding valuable insights from research published in other languages.

Publication Type: The study primarily examines peer-reviewed journal articles. While conference proceedings and other types of publications may provide useful information, the emphasis on journal articles ensures a thorough examination of established research.

Disciplinary Focus: The research primarily focuses on peer-reviewed journal articles. While conference proceedings and other forms of publication may provide useful information, the emphasis on journal articles ensures a thorough examination of established research.

Geographical Scope: The study does not explicitly account for regional or cultural differences in the prevalence or mitigation of common method bias. This limitation may affect the findings' applicability to specific cultural or regional contexts.

Technological Constraints: The study assumes access to standard electronic databases like Scopus, Google Scholar. Any technological constraints or limitations in accessing specific databases may have an impact on the scope of the literature review.

Justification for Search Engine: Two search engines were used in this study: Scopus, and Google Scholar. The final focus was primarily on two search engines: Scopus and Google Scholar. The justification for using these search engines is primarily because Scopus is reckoned to have a wider coverage and article search precision, is deemed to be better than other search engines such as Web of Science (WoS), PubMed, and Google Scholar.(Falagas et al., 2008) Scopus coverage is said to be 60% larger than WoS and PubMed. (Comerio & Strozzi, 2019; Falagas et al., 2008) Google Scholar is an open-source search engine that can be used to find publications in a variety of disciplines. The WoS search engine was not considered for this study due to difficulties in accessing it.

These boundaries are critical for maintaining the study's focus and feasibility while acknowledging the inherent limitations that may impact the interpretation and generalizability of the findings.

1.9. Significance of the Study

This review is an invaluable resource for researchers attempting to navigate the complexities of common method bias, emphasizing the importance of employing rigorous methodological and statistical approaches to ensure the integrity of empirical data.

The innovative technique proposed in this study improves researchers' understanding of Common Method Bias (CMB) by providing a systematic and parametric approach to assessing and mitigating methodological biases. The study emphasizes the importance of employing rigorous methodological and statistical techniques in order to ensure the integrity of empirical data. The innovative technique improves CMB results by providing a comprehensive tool that goes beyond traditional descriptive statistics and confirmatory factor analysis, allowing researchers to accurately identify and address biases across multiple datasets and research scenarios. This approach improves the validity and reliability of research findings, ultimately helping to advance knowledge in a variety of fields.

1.10 Structure of the study

Chapter 1: Introduction and Background

The first chapter discusses common method bias (CMB) and its role in empirical research. It discusses the problem of CMB, its potential impact on research validity, and the need for effective detection and mitigation methods. The first chapter also provides an overview of the thesis's research objectives, methodology, and structure.

Chapter 2: Preliminary Literature Review

Chapter two is a preliminary literature review that focuses on existing research on common method bias. It investigates key studies, theoretical frameworks, and empirical findings concerning CMB detection and mitigation techniques. This review provides a foundation for understanding the current state of knowledge in the field and highlights gaps or limitations in existing methodologies.

Chapter 3: Research Methodology

Chapter 3 delves deeply into the methodology for collecting and screening literature for analysis. This includes the criteria for identifying relevant studies, the search strategy used in databases such as Scopus and Google Scholar, and the screening and selection of literature using predefined criteria. The chapter also discusses potential biases in the literature selection process and how they can be addressed.

Chapter 4: Analysis of Literature

Chapter four delves into a detailed analysis of the literature gathered during the screening process outlined in Chapter 3. This analysis divides the techniques for detecting and mitigating common method bias (CMB) into methodological and statistical approaches. Each technique is evaluated for its applicability, strengths, weaknesses, and potential improvements, providing useful insights for researchers looking to address CMB in their studies. Furthermore, Chapter 4 provides a comparative analysis of the identified techniques, emphasizing their effectiveness and limitations in various research contexts. This thorough examination provides researchers with a better understanding of existing methodologies and the need for novel approaches to improve the validity of research findings.

Chapter 5: Proposed Innovative Technique

Chapter 5 describes an innovative technique for addressing common method bias (CMB) in empirical research. This chapter discusses the rationale for developing the new technique, its theoretical foundations, and the methodology for its implementation. The innovative technique is presented as a response to the limitations or gaps identified in existing methodologies, providing a novel approach to improving research validity and reliability.

Chapter Six: Conclusion and Recommendations

The final chapter summarizes the study's key findings, conclusions, and implications. It assesses the research's contributions to the field of CMB detection and mitigation, discusses its practical implications for empirical research, and identifies future research directions. Furthermore, chapter seven provides recommendations for researchers and practitioners looking to incorporate CMB into their studies, emphasizing the importance of methodological rigor and innovation in improving research validity and reliability.

CHAPTER 2: PRELIMINARY LITERATURE REVIEW

2.1. Theoretical Concepts & Operational Definitions

Alpha-Coefficient: The literature demonstrates that if the latent variable's average variance extracted (AVE) is thought to be larger than 50% (0.5) of the total variance explained by one component, indicates that your study demonstrates a common method bias. If the AVE is more than 0.5, the dataset used in either case is tainted by common method bias (N. Kock, 2021).

Bias Detection and Mitigation: Bias detection and mitigation refers to the techniques, methods, or approaches employed to identify, measure, quantify, or address CMB in the design, development, and deployment. It involves strategies to minimize the impact of CMB on the reliability and conclusions from studies (Bellamy et al., 2019).

Common Method Bias: In relation to this study, CMB relates to a systematic measurement error that arises due to the shared method of data collection or measurement in empirical studies. It arises when the measurement instrument or procedure used to gather data introduces a consistent bias that influences the observed association amongst variables in research (Podsakoff et al., 2003b).

Cross Sectional Data: Data that gathered over a brief period or at a exact moment in time is referred to as cross-sectional data. It gathers data from various people, things, or observations all at once, providing a "cross-section" or snapshot of the population or phenomenon of interest. Each observation in cross-sectional data represents a unique unit, such as a person, household, business, or area, and multiple variables of interest are measured concurrently for each unit. These variables, which are continual (e.g., income, age) alternatively categorical (e.g., occupation, gender), offer a multidimensional view of the population under study. In a variation of disciplines, including the social sciences, economics, public health, and market research, cross-sectional data is frequently employed. It enables researchers to investigate the traits, habits, or connections among other things (Zangirolami-raimundo & Leone, 2018).

Eigenvalues: An eigenvalue is a scalar value associated with matrices that describe the scaling effect of certain vectors when multiplied by the matrix. They provide valuable information about the transformation properties of the matrix and are widely used in various mathematical and scientific applications scalar value that represents a key property of a square matrix. Specifically, it is a value that, when multiplied by a corresponding eigenvector, yields the original vector multiplied by the matrix. In simpler terms, an eigenvalue tells us how a particular transformation affects the direction and magnitude of a vector. The magnitude of an eigenvalue indicates the scaling effect of the corresponding eigenvector. Larger eigenvalues correspond to more significant scaling effects, while smaller eigenvalues represent less pronounced transformations. Principal component analysis and other dimensionality reduction techniques are some examples of applications for eigenvalues (PCA), solving systems of linear equations, analysing the stability of dynamic systems, and understanding the principal components or factors in multivariate data analysis (Zangirolami-raimundo & Leone, 2018).

Latent Variables: Unobservable constructs or ideas known as latent variables are utilised in statistical modelling to shed light on the link between variables that can be observed. Because they cannot be directly detected or evaluated, these variables are frequently referred to as "hidden" or "latent." Latent variables are inferred from observable indications or measurements, as opposed to manifest variables, which are directly observed or measured. These measurements or indicators are employed to gauge or estimate the existence or properties of the underlying latent variables. Latent variables are frequently found in several disciplines, incorporating psychology, the social sciences, and market research. For instance, latent variables in psychological study include concepts like IQ, personality traits, and attitudes (Gorsuch, 2015).

Manifest Variables: In a research project, variables or information that can be quantified or directly observed are referred to as manifest variables. These factors are often collected by study participants through self-reporting, measurement, or direct observation. Manifest variables can take on several forms depending on the goal of the study and the measurements employed. Demographic details (such as gender, age and educational level), survey data, test results, bodily measurements (such as height and weight), behavioural observations, and documented behaviours or occurrences are examples of manifest variables. Manifest variables are readily available and do not need any further interpretation or inference, in contrast to latent variables, which are underlying or inferred variables. They are the tangible results or markers. (Bartholomew et al., 2011). In this work the manifest variables are comprised of two components, latent data, and averaged data.

Principal Component Analysis: A statistical method for reducing dimensionality and exploring data is Principal Component Analysis (PCA). It seeks to reduce a substantial set of correlated variables into a more manageable set of uncorrelated variables. PCA accomplishes this by identifying the directions in the data where there is the most variation and projecting the data onto these directions. The main steps involved in PCA are as follows: (i) Standardize the Data: PCA requires that the variables be standardised to have a standard deviation of one and a mean of zero. This step ensures that variables with larger scales do not dominate the analysis. (ii) Calculate the Covariance Matrix: To ascertain the correlations between variables, the covariance matrix is calculated. It provides information about how variables move together or in opposite directions. (iii) Calculate the Eigenvectors and Eigenvalues: The eigenvectors and eigenvalues of the covariance matrix are calculated. The major components are represented by eigenvectors, and the amount of variation explained by each component is shown by eigenvalues. The eigenvectors are orthogonal (uncorrelated) to each other. (iv) Select Principal Components: The principal components are ranked based on their corresponding eigenvalues. The components with larger eigenvalues explain more variance in the data. Typically, only the top components are retained to capture most of the variance. (v) Project the Data: To create a new collection of uncorrelated variables, the original data is projected onto the principal components that have been chosen. These new variables, known as scores, represent the transformed data. PCA is commonly used for various purposes: (i) Dimensionality Reduction: By selecting a smaller number of principal components, PCA enables data dimensionality reduction while maintaining the majority of the data's information. This can be useful when dealing with high-dimensional datasets or when visualizing data in lower-dimensional spaces. (ii) Data Exploration: PCA provides insights into the underlying structure and patterns in the data. It allows for identifying the most important variables contributing to the variation and understanding the relationships between variables. (iii) Data Preprocessing: PCA can be used as a preprocessing step before applying other statistical or machine learning algorithms. By reducing the dimensionality and removing correlated variables, it can improve the performance and interpretability of subsequent analyses. Overall, PCA is a powerful tool for data analysis and visualization, enabling researchers and analysts to gain a better understanding of complex datasets and extract key information (Mishra et al., 2017).

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

Through an extensive study of the literature, this chapter describes the systematic research approach used to overcome typical technique bias in survey datasets.

Conducting a systematic literature review on common method bias is essential for several reasons, namely:

The literature review approach used in this study is justified by its adherence to systematic principles that ensure comprehensiveness, bias minimization, evidence-based analysis, gap identification, findings synthesis, and contribution to knowledge development. A systematic literature review on common method bias from 1990 to 2023 provides researchers with insights into the historical context, coverage of relevant literature, emergence of methodological advances, changes in research practices, and policy/practice implications. This approach enables a thorough examination of the concept's evolution, methodological advances, and practical implications, ensuring a comprehensive understanding of common method bias and its impact on empirical research (Petticrew & Roberts, 2006; Higgins & Green, 2011; Sutton et al., 2011; Grant & Booth, 2009; H. M. Cooper, 1998; Gough et al., 2017; Tranfield et al., 2003; Podsakoff et al., 2003a; Richardson et al., 2009; Williams et al., 2010; Dillman et al., 2014; Krosnick, 1999; Armstrong & Overton, 1977; Conway & Lance, 2010b).

3.2 Database Selection

Google Scholar, PubMed, and Scopus are the main databases used in this study. Because they provide a wide range of scholarly material from different areas, these databases were selected.

3.3 Scopus

Scopus is a multidisciplinary abstract and citation database that provides comprehensive coverage of academic journals, conference proceedings, and patents.

Scopus' search strategy used relevant keywords like "common method bias," "survey research," and "methodology bias." The inclusion criteria looked at papers published between 1990 and 2023. The search was conducted on December 22, 2023, and resulted in 164 initially identified articles. The parameters and results obtained are illustrated in Figure 1 below.

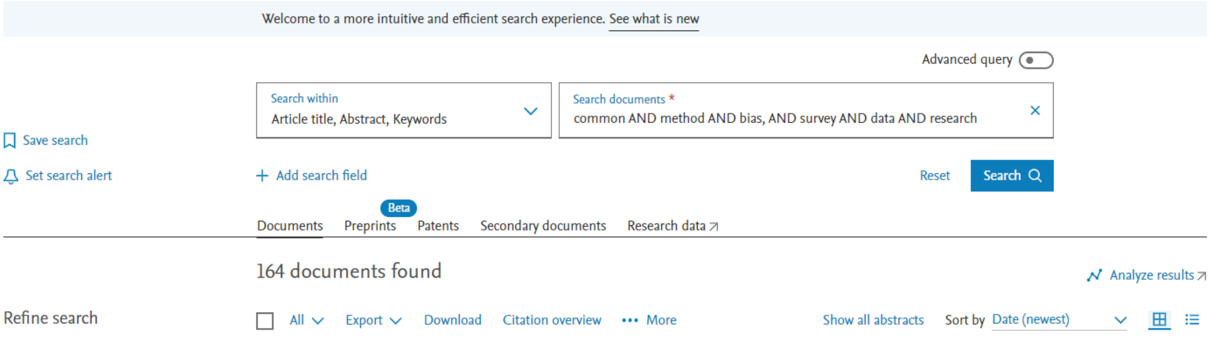

Figure 1: Scopus screenshot showing search conditions and outcome of 164 documents found.

3.4. Google Scholar

Google Scholar is an open-source search engine that indexes academic publications amid a variety of subjects. The Google Scholar search strategy was specific to the keywords "common method bias," which produced fewer results than Scopus. Papers published between 1990 and 2023 were also considered under the inclusion criteria. On 27 December 2023, the search produced 95 of the first found articles. Figure 2 below shows the parameters used and the retrieved results. Omitting survey research in the key words was done strategically in order to focus the search primarily on CMB related articles.

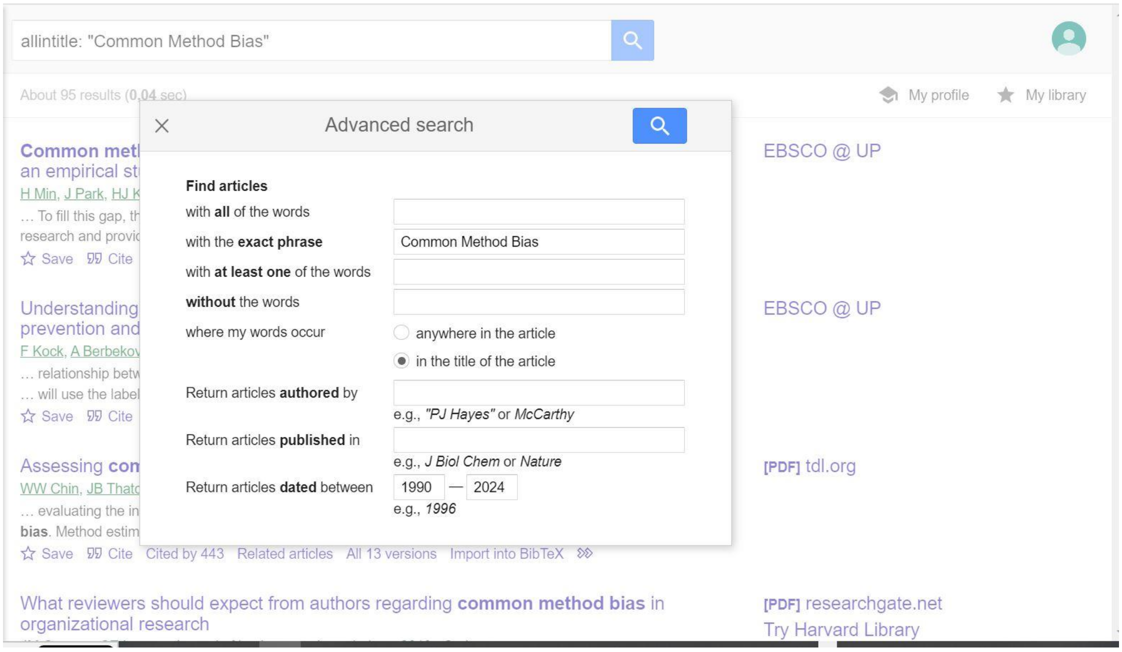

Figure 2: Google Scholar screenshot showing search conditions and outcome of 95 documents found.

3.5. PubMed

PubMed is a comprehensive database that focuses on biomedical literature and the life sciences. However, it also includes articles from a variety of fields. PubMed was searched with the previously listed keywords, and papers published between 1990 and 2024 were included. When the search was run on January 2, 2024, 90 items were found at first. The parameters and results obtained are shown in Figure 3 below. The keywords used included survey research to test whether the Google Scholar results were impacted by the use of the keywords 'survey research'. PubMed resulted in fewer hits than Google Scholar even though it included Survey Research as part of the search strategy. It should be noted that PubMed was not considered from this point on as it issued the same results as Google Scholar.

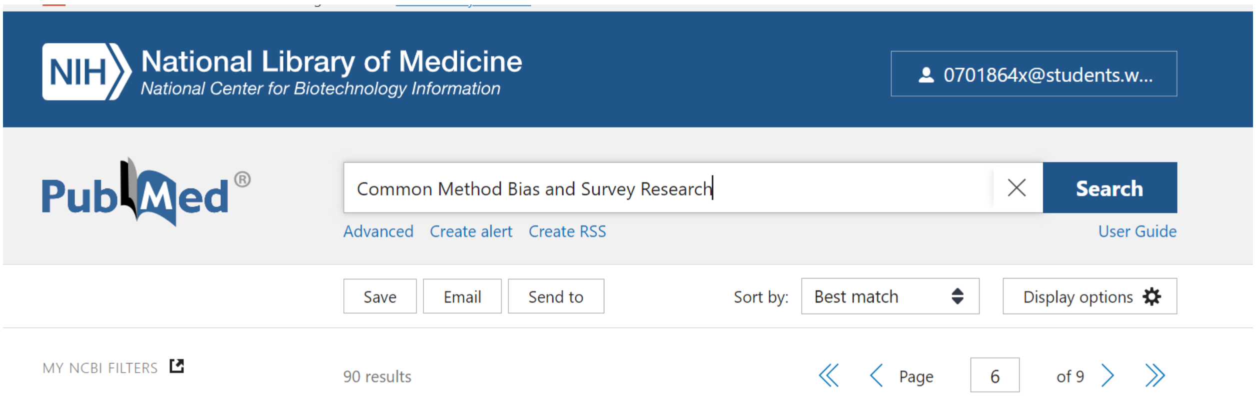

Figure 3: PubMed screenshot showing search conditions and outcome of 90 documents found.

3.6. Inclusion and Exclusion Criteria

This literature review included all English-language papers published between 1990 and 2023. Theoretical and conceptual frameworks, techniques, and empirical research addressing common method bias in survey datasets were discussed. Non-English articles, unrelated subjects, and papers that did not meet the research parameters were among the exclusion criteria. All articles that mentioned CMB in their methodology but did not conduct CMB-specific research were excluded.

The literature review on common method bias (CMB) includes English-language papers published between 1990 and 2024 for a variety of reasons:

Scope of Available Literature: English is the most widely used language in academic publishing, particularly in fields such as psychology, management, and social sciences, where research on common method bias is prevalent. The review is limited to English-language papers, ensuring access to a diverse pool of relevant literature (Bhat & Jagathyraj, 2020).

Theoretical and Conceptual Frameworks: The review's focus on theoretical and conceptual frameworks for common method bias ensures a thorough examination of the underlying principles and theoretical perspectives that shape research in this field. Understanding these frameworks is essential for contextualizing empirical data and methods (Conway & Lance, 2010b).

Techniques and Empirical Research: The review provides insights into methodological advancements as well as practical strategies for identifying and mitigating common method bias in survey datasets by discussing techniques and empirical research on the subject. This inclusion ensures that the review covers both theoretical discussions and empirical studies, increasing its comprehensiveness (Williams et al., 2010).

Exclusion Criteria: The exclusion of non-English articles, unrelated subjects, and papers that did not meet the research parameters helps to keep the literature review focused and relevant. By using clear exclusion criteria, the review ensures that only studies directly relevant to the topic of common method bias in survey datasets are included, increasing the quality and rigor of the synthesis (Moher et al., 2009).

Exclusion of Non-CMB Specific Research: Articles that only mention common method bias in their methodology but do not conduct CMB-specific research are excluded, ensuring that the review focuses on studies that directly investigate common method bias. This approach ensures that the literature review's findings and conclusions are based on studies specifically addressing the phenomenon of common method bias, rather than tangential mentions or references (Conway & Lance, 2010b).

In summary, the decision to include English-language papers published between 1990 and 2024 in the literature review on common method bias, while applying clear exclusion criteria, is justified by considerations of scope, historical perspective, theoretical relevance, methodological focus, and the need for rigor and relevance in synthesising research findings.

3.7. Search Strategy

The search strategy used a combination of Boolean operators, such as AND, OR, and NOT, to refine the search queries. The keywords were strategically combined to ensure a broad but focused retrieval of relevant literature (refer to subsections 3.3-3.5). Refer to the below subsections (3.8 & 3.9) relating to the summary of the outcomes of the search.

3.8. Data Analysis

The screening process focused primarily on articles with "CMB" in their titles and abstracts that explicitly addressed the concept of common method bias (CMB). The emphasis was on selecting studies whose abstracts demonstrated evidence of addressing CMB rather than empirical application. This approach ensured that only papers directly related to the topic of common method bias were included, regardless of the empirical context or discipline. Using this criterion, the screening process sought to identify articles that directly contributed to the understanding and discussion of common method bias in the literature.

3.9. Statistical Analysis of Search Results

Table 1 displays a statistical analysis of the search results from Scopus and Google Scholar. This includes the number of publications that were initially identified, the number that were screened for titles and abstracts, and the total number of articles included in the review.

Table 1: Table showing initial article count, article count post-screening and final inclusion per search engine, and finally the unique count articles applicable to this study.

DATABASE	INITIAL ARTICLES	AFTER SCREENING	FINAL INCLUSION	APPLICABLE ARTICLES – Unique Count
Scopus	164	40	16	**20 (not s sum of Scopus and Google Scholar articles – refer to below explanation)**
Google Scholar	95	35	9	

Scopus, the base search engine, returned 16 core articles that met the screening criteria. Google Scholar only returned four unique references that were not on Scopus. This is divided into two articles that appeared outside of the design period (1989 and 1986), as well as two other articles published in 1999 and 2002. This results in 16 Scopus articles (6 of which are also available on Google Scholar) and 4 unique Google Scholar articles, for a total of 20 unique count articles.

The articles on common method bias (CMB) that passed the screening are from a variety of fields, including psychology, management, sociology, education, marketing, economics, health sciences, communication, politics, and environmental science. These studies emphasize the significance of CMB in a variety of contexts, allowing for a better understanding of its prevalence, causes, and consequences.

3.9. Summary of research outcomes

This section described the methodology used for the literature review of common method bias in survey datasets. The systematic search and selection process was designed to ensure the inclusion of relevant articles from reputable databases. The statistical analysis sheds light on the screening process, and the recommended articles serve as the foundation for the subsequent discussion and analysis in the study.

Screening Criteria Summary

The key criteria in the screening that have led to a significant reduction in the qualifying articles related to the relevance are outlined in Table 2 below. The screening led to a split of the articles to either theoretical framework relevance or conceptual framework relevance. The theoretical framework relevance is mainly the seminal articles that defined the research foundation for CMB. The conceptual framework then relates to innovative applications of various methodological applications employed in addressing CMB. The screening was limited to conceptual and theoretical frameworks to ensure a focused examination of the conceptualization and theoretical underpinnings of common method bias (CMB) across different disciplines. By prioritizing articles that provide conceptual and theoretical insights into CMB, the study aimed to gain a deeper understanding of its nature, causes, and implications, laying the groundwork for subsequent empirical investigations. This approach allows for a comprehensive exploration of the conceptual landscape surrounding CMB, facilitating the development of robust research hypotheses and methodologies for future empirical studies.

Table 2: Shows the screening criteria and count per search engine of the relevant articles.

Count	Screening Criteria #1	Screening Criteria #2	Screening Criteria #3	Screening Criteria #4	Total
	Topic & Abstract Relevance	***Full Article Relevance***	***Theoretical Framework***	***Conceptual Framework***	
Count Scopus	40	15	6	10	**16**
Count Google Scholar	35	9	4 (4 articles are unique to Google Scholar and not on Scopus)	0	**4**
		Total	10	10	**20**

In total the articles that met the criteria totalled 24; however, 6 of these articles were available on both articles and thus factored into the Scopus count because Scopus analytics were more comprehensive. Furthermore, this overlap appears in articles that are part of the Conceptual Framework scope.

CHAPTER 4: POST-SCREENING RESULTS AND ANALYSIS

4.1. Literature Review Results

The following results are captured and analysed using the initial articles from two search engines (Scopus and Google Scholar). This is done to ensure that any bias caused by screening process selection does not limit the search results' reliability and repeatability. As outlined in the study's limitations, the screening process may have elements of subjectivity, so the results/analytics for the screened articles are not reported here.

4.2. Scopus Outcomes and Screening Logic

Based on the design period (1990-2023), Scopus shows that CMB publications have increased over time. Furthermore, it demonstrates that significant contributions in terms of article publication have gradually increased from 2010 to 2023, with peak years in 2012, 2020, and 2022-2023. Out of the screened articles, there were more CMB-related publications in 2020 than at any time since 1990. This suggests that researchers are very interested in the topic of CMB and that over time researchers recognize and appreciate the impact of CMB on the reliability of their studies hence more studies are surfacing over the years. Figure 4 below shows the number of articles published each year from 1990-2024 that have passed the screening applicable in this paper.

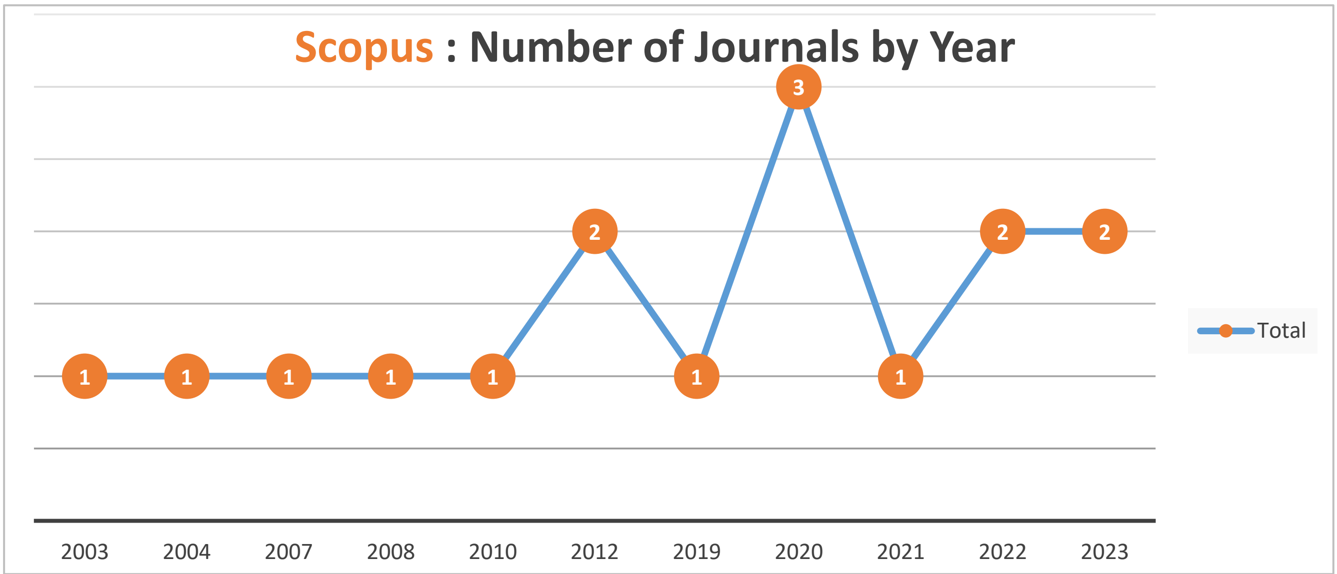

Figure 4: Showing Scopus trends of publications on CMB between 1990-2023 that have passed the screening process.

Figure 5 below shows that out of the articles that passed the screening, the following split by subject area was observed, 48.9% articles are from Business Management, 10.6% are decision science articles, 10.6% social science, 8.5% are computer science articles, 6.4% are articles from the economics discipline, only 6.4% are psychology-based articles, 4.3% are arts and humanities, 2.1% are linked to engineering, and 2.1% are mathematics based articles..

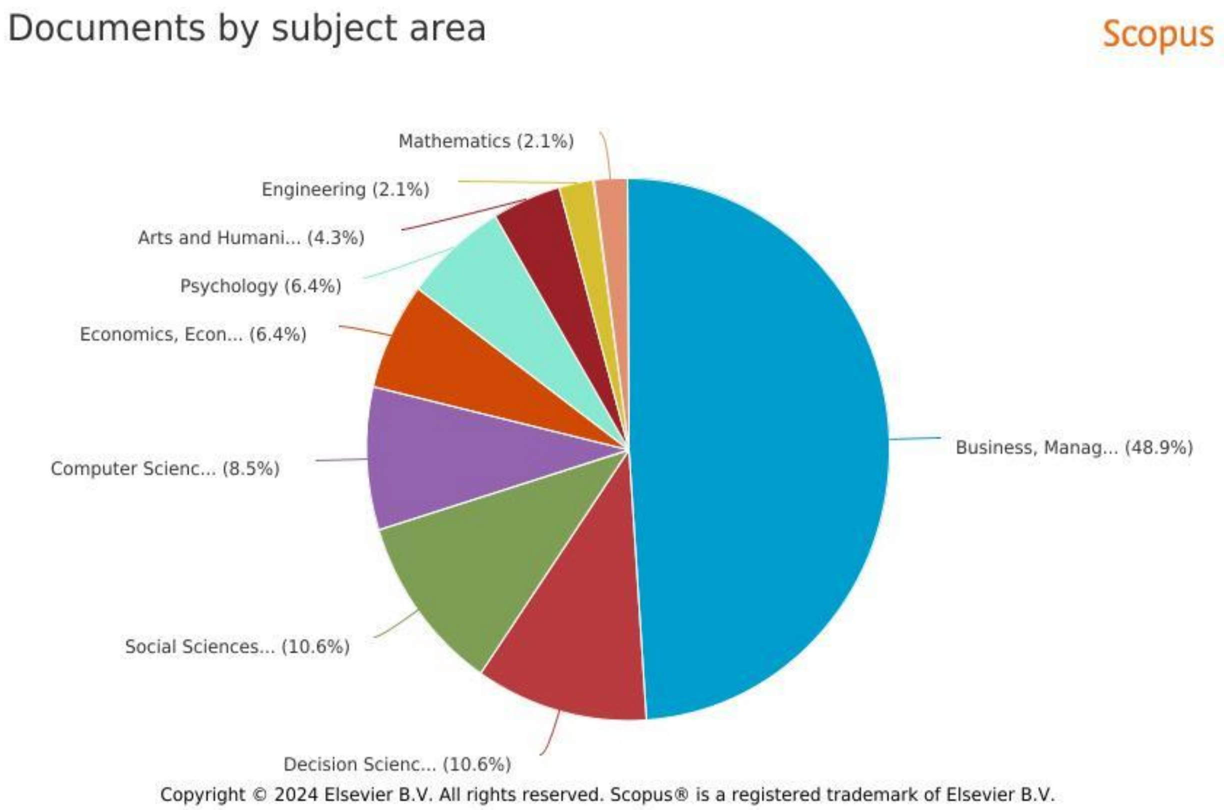

Figure 5: Showing Scopus split of documents by subject area for sources between 1990-2023

Furthermore, there was no discrimination based on the research affiliation, as shown in the Figure 6 below.

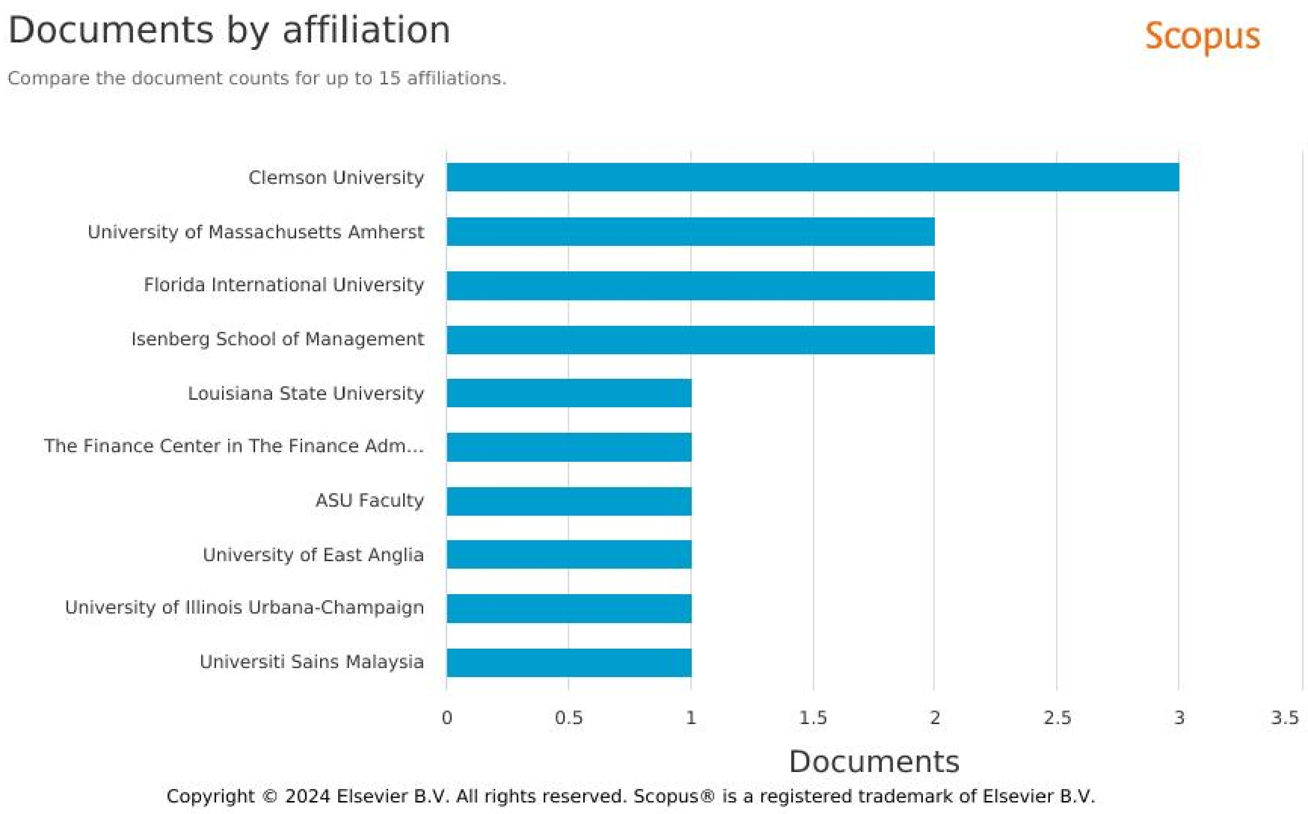

Figure 6: Showing Scopus split of documents by affiliation for sources between 1990-2023

4.3. Google Scholar

Unlike Scopus, Google scholar does not adequately capture the publication details and as such the results are not clear. The only meaningful result obtained from google scholar is the articles by year as shown in Figure 7 below.

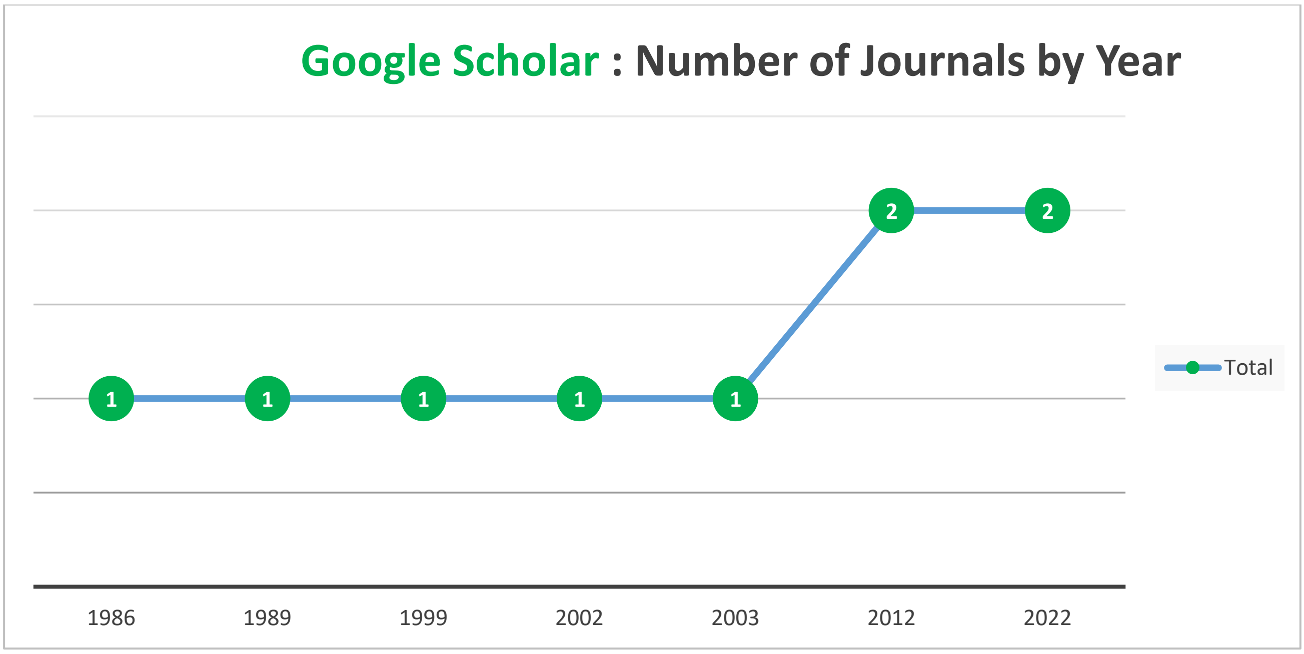

Figure 7: Showing Google Scholar split of documents by affiliation for sources between 1990-2023

4.4. Search Engine Summary

Despite the fact that Google Scholar data does not adequately provide year by source, document by subject area, and document by affiliation data, the results obtained for the document by year are reassuring because the trend is consistent with that observed on Scopus. This trend shows a flat period from 1990 to 2009. There are spikes in research output between 2009 and 2013, followed by an average positive trend from 2013 to 2021, with dips in between. A significant increase is observed during the 2021-2022 period. This suggests that, based on the similarities, Scopus data is reliable and can thus serve as a foundation for analysis. It should be noted that Google Scholar identified two critical articles published prior to the test design period (1990-2024); this could be due to a database glitch, but the articles were seminal in nature and thus could not be omitted.

4.5. Identified CMB Techniques

The critical literature review uncovered 30 techniques for detecting and mitigating common method bias (CMB), divided into two categories: methodological and statistical techniques. It should be noted that the articles and techniques are not in a 1:1 relationship. Some articles would cover/discuss several techniques.

In this section, we will go over each of these techniques in depth, including their definitions, applications, strengths, weaknesses, and suggestions for improvement. Furthermore, we will examine the frequency of use and trends in the adoption of these techniques over time to gain insight into their efficacy and applicability in research settings.

Methodological techniques: Shown in Table 3**,** fifteen methodological techniques were identified in the screened research papers from the period 1990 to 2024 on Scopus and Google Scholar.

Table 3: Methodological Techniques Identified in Scopus and Google Scholar Search

	#Ref	Technique	Technique Type
Methodological Techniques	1	Blinding Techniques	Methodological
	2	Randomized Response Technique	Methodological
	3	Counterbalancing	Methodological
	4	Procedural Remedies	Methodological
	5	Scale Anchoring	Methodological
	6	Triangulation of Data Sources	Methodological
	7	Longitudinal Designs	Methodological
	8	Control Variables	Methodological
	9	Multimethod Approach	Methodological
	10	Measurement Validation	Methodological
	11	Multiple Informant Approach	Methodological
	12	Item Order Randomization	Methodological
	13	Multitrait-Multimethod Matrix	Methodological
	14	Common Method Variance (CMV) Control Items	Methodological
	15	Cross-Cultural Validation	Methodological

These methodological techniques provide a variety of strategies for reducing biases in data collection procedures, improving research designs, and ensuring the validity of findings.

Statistical Techniques: As outlined in Table 4, fifteen statistical techniques were identified in the screened research papers from the period 1990 to 2024 on Scopus and Google Scholar.

Table 4: Statistical Techniques Identified in Scopus and Google Scholar Search

	#Ref	Technique	Technique Type
Statistical Techniques (15)	1	Sensitivity Analysis	Statistical
	2	Common Latent Factor Approach	Statistical
	3	Cross-Validation	Statistical
	4	Bayesian Methods	Statistical
	5	Bootstrapping	Statistical
	6	Nonlinear Structural Equation Modeling	Statistical
	7	Harman's Single-Factor Test	Statistical
	8	Marker Variable Technique	Statistical
	9	Partial Correlation Analysis	Statistical
	10	Correlation Analysis of Residuals	Statistical
	11	Multilevel Modeling	Statistical
	12	Multigroup Analysis	Statistical
	13	Latent Growth Curve Modeling	Statistical
	14	Structural Equation Modeling (SEM)	Statistical
	15	Confirmatory Factor Analysis (CFA)	Statistical

These statistical techniques offer sophisticated analytical frameworks for determining measurement validity, accounting for method variance, and examining complex relationships between variables.

4.5 Discussion: CMB Techniques

This comprehensive review and analysis examine techniques for detecting and mitigating common method bias, providing insights into their applicability, effectiveness, and practical implications in research settings. It emphasizes the importance of understanding the various techniques available for detecting and mitigating common method bias, as well as taking into account their applicability, effectiveness, and practical implications in research contexts.

4.5.1. Methodological Techniques

M.1. Blinding Technique:

Definition: Blinding techniques conceal specific information from participants, researchers, or both in order to reduce bias in data collection, analysis, or interpretation (Carlson & Perrewe, 1999; Jordan & Troth, 2020c; N. Kock, 2017). In research, blinding can be single-blind (participants are unaware of the treatment they receive), or double-blind (both participants and researchers are unaware) (MacKenzie & Podsakoff, 2012; Podsakoff et al., 2003c; Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007; Williams et al., 1989).

Application: Blinding is widely used in a variety of research disciplines, including clinical trials, psychology experiments, and surveys. For example, in a clinical trial evaluating the efficacy of a new medication, participants may be blinded to whether they are given the actual drug or a placebo, while researchers assessing the outcomes are unaware of the treatment assignments (MacKenzie & Podsakoff, 2012b, 2012a; Podsakoff et al., 2003c; Podsakoff & Organ, 1986). Blinding can also be used in observational studies, where researchers assessing subjective outcomes are not aware of the exposure status or intervention allocation (Carlson & Perrewe, 1999; Jordan & Troth, 2020c; N. Kock, 2017).

Strengths:

- **Reduces Bias:** Blinding reduces the risk of bias by preventing participants and researchers from influencing the results based on their own expectations or preferences (MacKenzie & Podsakoff, 2012; Podsakoff et al., 2003c; Podsakoff & Organ, 1986).

- **Enhances Validity:** Blinding improves the study's internal validity by reducing the influence of confounding variables and ensuring that observed effects are due to the intervention or exposure of interest (Carlson & Perrewe, 1999; Jordan & Troth, 2020c; N. Kock, 2017).
- **Increases Credibility:** Blinding improves the reliability and credibility of research findings by minimizing the possibility of systematic errors or manipulation (MacKenzie & Podsakoff, 2012b, 2012a; Podsakoff et al., 2003c; Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007).

Weaknesses:

- **Feasibility:** Implementing blinding may not always be feasible or practical, especially in studies where blinding procedures could jeopardize the intervention's integrity or the safety of participants (Carlson & Perrewe, 1999; Jordan & Troth, 2020c; Kock et al., 2021).
- **Ethical Considerations:** Blinding can raise ethical concerns, particularly in studies with significant risks or where participants have a right to know the nature of the intervention they receive (Carlson & Perrewe, 1999; Jordan & Troth, 2020c; Kock et al., 2021).
- **Complexity:** Blinding techniques can add complexity and cost to the research process, necessitating meticulous planning, training, and monitoring to ensure compliance (Schwarz et al., 2008; Sharma et al., 2007; Williams et al., 1989).

***Recommendations for Improvement*:**

- **Detailed Protocols:** Blinding procedures and criteria should be clearly defined in the study protocol to ensure consistency and transparency. (Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007; Williams et al., 1989)
- **Training:** Provide training to researchers, study personnel, and study participants to ensure they understand and follow blinding protocols (Kock et al., 2021c; MacKenzie & Podsakoff, 2012; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Schwarz et al., 2008).
- **Monitoring and Adherence Checks:** Implement monitoring mechanisms to ensure compliance with blinding protocols and detect any violations or

deviations (Carlson & Perrewe, 1999; Jordan & Troth, 2020c; F. Kock et al., 2021c; MacKenzie & Podsakoff, 2012; Podsakoff et al., 2003c; Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007; Williams et al., 1989).

- **Sensitivity Analysis:** Conduct sensitivity analyses to determine the impact of potential unblinding on study outcomes and conclusions, allowing researchers to assess the strength of their findings (Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007; Williams et al., 1989).
- **Ethical Review:** Obtain ethical approval and oversight from institutional review boards or ethics committees, which will ensure that blinding procedures are carried out ethically and responsibly (Schwarz et al., 2008; Sharma et al., 2007; Williams et al., 1989).

M.2. Randomized Response Technique:

Definition: The Randomized Response Technique (RRT) is a survey method that uses a randomized mechanism to elicit honest responses to sensitive or socially unacceptable questions. Warner developed it in 1965 (Carlson & Perrewe, 1999; Podsakoff et al., 2003c; Podsakoff & Organ, 1986; Williams et al., 1989).

Application: The RRT can be used in surveys or interviews where respondents are hesitant to give honest answers for fear of social desirability bias or repercussions. It is frequently used in research on sensitive issues such as substance abuse, illegal activities, and stigmatized behaviours. The RRT requires respondents to respond to a question with two possible answers: truthful and randomized. Only the respondent knows the probability of selecting the randomized response, which ensures confidentiality while allowing researchers to estimate the prevalence of sensitive behaviours (Carlson & Perrewe, 1999; Podsakoff et al., 2003c; Podsakoff & Organ, 1986; Williams et al., 1989).

Strengths:

- **Privacy Protection**: RRT protects respondent privacy and confidentiality by adding uncertainty to individual responses. Respondents can answer truthfully without fear of being identified or judged (Podsakoff et al., 2003; Podsakoff & Organ, 1986; Williams et al., 1989).
- **Increased Honesty:** RRT encourages greater honesty and disclosure than direct questioning methods, resulting in more accurate data on sensitive topics.

It reduces social desirability bias and enables researchers to make more precise estimates of sensitive behaviours (Podsakoff et al., 2003c; Podsakoff & Organ, 1986; Williams et al., 1989).

- **Estimation of Prevalence**: RRT enables researchers to estimate the prevalence of sensitive behaviours or attitudes without requiring participants to reveal potentially incriminating information (Podsakoff et al., 2003; Podsakoff & Organ, 1986). It is a useful tool for researching taboo topics or socially unacceptable behaviours (Carlson & Perrewe, 1999; Williams et al., 1989).

Weaknesses:

- **Complexity**: Implementing RRT necessitates careful design and administration to ensure the response mechanism's randomness and integrity (Podsakoff et al., 2003). Researchers must create appropriate randomization procedures and test their effectiveness (Carlson & Perrewe, 1999; Williams et al., 1989).
- **Sampling Bias**: RRT may introduce sampling bias if participants who agree to participate differ consistently from those who do not (Podsakoff & Organ, 1986; Williams et al., 1989). Researchers must consider the sample's representativeness and potential sources of selection bias (Podsakoff & Organ, 1986; Williams et al., 1989).
- **Interpretation Challenges**: RRT results can be difficult to interpret because the relationship between observed responses and true behaviors or attitudes is determined by the randomization process's accuracy. When analyzing and interpreting RRT data, researchers must consider potential biases and limitations (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Williams et al., 1989).

Recommendations for Improvement:

- **Pilot Testing**: Pilots test the RRT procedure in the target population to determine its feasibility, acceptability, and effectiveness. Before you begin the main study, identify and address any implementation challenges or concerns (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Williams et al., 1989).
- **Clear Instructions**: Provide participants with clear instructions and explanations about how and why randomization is used (Carlson & Perrewe, 1999; Podsakoff et al., 2003). Ensure that respondents understand their options,

as well as the study's goal of encouraging cooperation and honesty (Podsakoff et al., 2003c; Podsakoff & Organ, 1986; Williams et al., 1989).

- **Validation Studies:** Validate RRT results by comparing them to data from alternative sources or validation studies. Assess the reliability and validity of the RRT in capturing sensitive behaviours or attitudes (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Williams et al., 1989).
- **Complementary Techniques**: Consider using complementary techniques, such as indirect questioning or behavioural observations, to back up RRT findings and improve their validity. Use multiple methods to triangulate results and reduce the impact of potential biases (Podsakoff et al., 2003; Podsakoff & Organ, 1986; Williams et al., 1989).

M.3. Counterbalancing Technique:

Definition: Counterbalancing is a methodological technique used in experimental designs to account for order effects, which occur when the order of conditions or treatments influences participants' responses Lance et al., 2002; MacKenzie & Podsakoff, 2012). Counterbalancing is the process of systematically varying the order in which experimental conditions are presented to participants in order to reduce the impact of order effects on study outcomes (MacKenzie & Podsakoff, 2012; Podsakoff et al., 2003; Zhang et al., 2022).

Application**:** Counterbalancing is a common technique used in experimental research across a variety of disciplines, including psychology, medicine, and education (Lance et al., 2002; Zhang et al., 2022). It is especially useful in studies with repeated measures or within-subject designs, in which participants are subjected to multiple conditions or treatments. Counterbalancing attempts to distribute potential order effects evenly across experimental conditions by systematically changing the sequence of conditions, ensuring that any observed differences are due to the treatments rather than the order of presentation (Lance et al., 2002; MacKenzie & Podsakoff, 2012;; Zhang et al., 2022).

Strengths:

- **Minimizes Order Effects:** Counterbalancing reduces the impact of order effects on study results by systematically varying the sequence of conditions across participants. This helps to control for potential biases introduced by the order of presentation, thereby improving the study's internal validity (MacKenzie & Podsakoff, 2012; Podsakoff et al., 2003).

- **Enhances Control:** Counterbalancing enables researchers to have more control over potential sources of bias, such as practice effects or carryover effects, which can complicate the interpretation of experimental data. (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Zhang et al., 2022) Counterbalancing strengthens the experimental design by equating order's influence across conditions (Podsakoff et al., 2003; Zhang et al., 2022).
- **Increases Precision:** Counterbalancing improves the accuracy and reliability of study results by reducing the variability caused by order effects. (Lance et al., 2002; Zhang et al., 2022) Counterbalancing improves statistical power and effect estimates by ensuring that each condition is presented an equal number of times in each possible order (MacKenzie & Podsakoff, 2012; Podsakoff et al., 2003; Zhang et al., 2022).

Weaknesses:

- **Complexity:** Implementing counterbalancing can be difficult, particularly in studies with multiple conditions or factors (Lance et al., 2002; MacKenzie & Podsakoff, 2012). Researchers must carefully plan the counterbalancing scheme, randomize the order of presentation, and ensure that all possible sequences are adequately represented (Podsakoff et al., 2003; Zhang et al., 2022).
- **Participant Fatigue**: Counterbalancing may increase participant burden and fatigue, especially in studies involving lengthy or repetitive procedures (Lance et al., 2002; MacKenzie & Podsakoff, 2012). Participants may become disengaged or less motivated to perform accurately as the study progresses, potentially skewing the results (MacKenzie & Podsakoff, 2012; Podsakoff et al., 2003; Zhang et al., 2022).
- **Order Carryover Effects:** Despite counterbalancing efforts, residual order effects may still occur, especially if the interval between conditions is too short to eliminate carryover effects. Researchers must consider the timing and spacing of conditions in order to reduce the likelihood of order effects persisting (Lance et al., 2002; MacKenzie & Podsakoff, 2012b; Podsakoff et al., 2003c; Zhang et al., 2022).

Recommendations for Improvement:

- **Randomization:** Use randomization procedures to assign participants to different counterbalanced sequences, ensuring that each participant has an equal chance of encountering each condition order (MacKenzie & Podsakoff, 2012b; Podsakoff et al., 2003c; Zhang et al., 2022).
- **Pilot Testing:** Pilot test the counterbalancing procedure to determine its feasibility and effectiveness in controlling for order effects. Identify and address any practical challenges or implementation issues before beginning the main study (Lance et al., 2002; Zhang et al., 2022).
- **Monitoring and Adherence Checks:** Monitor participant compliance with the counterbalancing protocol and perform adherence checks to ensure that participants correctly follow the assigned sequence of conditions (Lance et al., 2002; Podsakoff et al., 2003).
- **Sensitive Analysis:** Conduct sensitivity analyses to determine the resiliency of study findings to various counterbalancing schemes or potential order effects. Investigate alternative counterbalancing strategies and evaluate their impact on study results (MacKenzie & Podsakoff, 2012; Podsakoff et al., 2003; Zhang et al., 2022).
- **Reporting Guidelines:** In research publications, clearly report the counterbalancing procedures and results, including details of the counterbalancing scheme, randomization methods, and any deviations from the planned protocol (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Podsakoff et al., 2003; Zhang et al., 2022).

M.4. Procedural Technique:

Definition: Procedural remedies are a set of methodological techniques used during the design and administration of surveys or experiments to reduce common method bias (CMB) (MacKenzie & Podsakoff, 2012; Podsakoff et al., 2003; Williams et al., 1989). These remedies are intended to reduce the likelihood of systematic errors caused by methodological factors such as design, administration procedures, and respondent characteristics (Memon et al., 2023; Podsakoff et al., 2003c; Williams et al., 1989).

Application:

Procedural remedies are useful in a variety of research contexts, including psychology, organizational behaviour, marketing, and social sciences (MacKenzie & Podsakoff, 2012;

Williams et al., 1989). They are frequently used in studies that use self-report measures or surveys to collect data on constructs susceptible to CMB, such as attitudes, behaviours, and perceptions (MacKenzie & Podsakoff, 2012; Williams et al., 1989). By implementing procedural remedies, researchers hope to improve the validity and reliability of their findings by reducing the impact of common method bias on study outcomes (MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003; Williams et al., 1989).

Strengths:

- **Reduces Systematic Bias:** Procedural remedies can help to reduce systematic biases caused by common method bias, improving the accuracy and validity of study results. Researchers can increase the credibility of their findings and reduce potential threats to internal validity by implementing methodological safeguards (MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003c; Williams et al., 1989).
- **Enhances Data Quality:** By addressing methodological sources of bias, procedural remedies improve the overall quality of survey or experiment data collection. Researchers can obtain more reliable and precise measurements of the constructs being studied by optimizing survey design, administration procedures, and respondent instructions (Memon et al., 2023; Podsakoff et al., 2003c; Williams et al., 1989).
- **Increases Confidence in Results:** The effective implementation of procedural remedies increases confidence in the interpretability and generalizability of study results. Researchers can improve the credibility of their research by demonstrating rigor and attention to methodological detail (Podsakoff et al., 2003; Williams et al., 1989).

Weaknesses:

- **Implementation Challenges:** Implementing procedural remedies may necessitate additional resources, time, and expertise, especially in large-scale research projects or studies involving complex survey designs (MacKenzie & Podsakoff, 2012b; Memon et al., 2023; Podsakoff et al., 2003; Williams et al., 1989).

- Researchers must carefully plan and implement these remedies to ensure their efficacy without unduly burdening participants or jeopardizing study validity (Memon et al., 2023; Podsakoff et al., 2003c; Williams et al., 1989).
- **Potential Trade-Offs:** Some procedural remedies, such as increasing survey length or incorporating validation measures, may compromise participant burden or response rate. Researchers must weigh the advantages of avoiding common method bias against the potential drawbacks in terms of participant engagement, data quality, and practical feasibility (MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003; Williams et al., 1989).
- **Limited Effectiveness:** While procedural remedies can help reduce common method bias, they may not eliminate it entirely (Memon et al., 2023; Podsakoff et al., 2003; Williams et al., 1989). Certain biases, such as social desirability and acquiescence bias, may persist despite methodological safeguards. Researchers must recognize the limitations of procedural remedies and interpret study results accordingly (MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003; Williams et al., 1989).

Recommendations for Improvement:

- **Pretest Procedures:** Conduct pretests or pilot studies to assess the efficacy of procedural remedies in the specific research context. Pretesting enables researchers to identify and address potential methodological issues before beginning the main study, increasing the reliability and validity of the data collected (MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003c; Williams et al., 1989).
- **Continuous Monitoring:** Continuously monitor survey administration procedures and respondent behaviour throughout the data collection process. Regular checks for data quality, completeness, and consistency can help detect and correct deviations from the intended protocol, reducing the risk of common method bias (Memon et al., 2023; Podsakoff et al., 2003; Williams et al., 1989).
- **Methodological Transparency**: Transparently report the use of procedural remedies in research publications, including survey design details, administration protocols, and any steps taken to reduce common method biases. By documenting the study's methodological rigor, researchers increase the credibility and reproducibility of their findings’ approaches can help confirm

the reliability and generalizability of the results (MacKenzie & Podsakoff, 2012; Memon et al., 2023).

Researchers can reduce the impact of common method bias on study results by carefully implementing and documenting procedural remedies, which improves the validity, reliability, and credibility of their research findings.

M.5. Scale Anchoring Technique:

Definition: Scale anchoring is a methodological technique that reduces common method bias (CMB) in surveys by giving respondents clear and explicit anchors or reference points when rating items on a scale (Carlson & Perrewe, 1999; Podsakoff et al., 2003c; Podsakoff & Organ, 1986). This technique aims to standardize respondent interpretations of scale endpoints while reducing response biases caused by subjective or idiosyncratic interpretations of scale labels (Podsakoff & Organ, 1986; Vieluf et al., 2009).

Application: Scale anchoring is a common technique used in survey research across many disciplines, including psychology, marketing, and organizational behaviour (Podsakoff & Organ, 1986; Vieluf et al., 2009). It is especially useful in studies that employ Likert-type scales or other rating formats to assess constructs such as attitudes, opinions, or perceptions. By providing specific anchors or descriptors for scale endpoints, researchers hope to improve the consistency and comparability of responses across respondents, lowering the possibility of common method bias (Carlson & Perrewe, 1999; Podsakoff et al., 2003).

Strengths:

- **Standardizes Interpretations:** Scale anchoring standardises respondent interpretations of scale endpoints by providing clear and unambiguous reference points (Podsakoff et al., 2003). By specifying the meaning of scale anchors (for example, "strongly disagree" to "strongly agree"), researchers ensure that respondents interpret scale items consistently, reducing response variability and bias (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Vieluf et al., 2009).
- **Minimizes Response Variance**: Anchoring scale endpoints reduces response variance due to differences in respondent understanding or interpretation of

scale labels (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Podsakoff & Organ, 1986). This improves the reliability and validity of survey data by reducing the impact of irrelevant or idiosyncratic factors on respondent ratings (Podsakoff & Organ, 1986; Vieluf et al., 2009).

- **Enhances Cross-Study Comparability:** Scale anchoring makes survey results more comparable across studies or populations by aligning scale interpretations with pre-established norms or standards (Carlson & Perrewe, 1999; Podsakoff et al., 2003). The consistent use of anchored scales enables researchers to meaningfully compare responses over time or across different samples, improving the generalizability and external validity of their findings (Podsakoff et al., 2003; Podsakoff & Organ, 1986; Vieluf et al., 2009).

Weaknesses:

- **Limited Flexibility**: Scale anchoring may limit respondents' ability to express nuanced or contextually relevant attitudes or opinions. By limiting responses to predefined scale endpoints, researchers risk overlooking subtleties or differences in respondents' perspectives that could provide valuable insights (Podsakoff & Organ, 1986; Vieluf et al., 2009).
- **Potential Anchoring Effects:** While scale anchoring is intended to reduce response bias, it may unintentionally introduce anchoring effects, in which respondents' ratings are influenced by the provided anchors. To avoid biasing respondents' perceptions or judgments, researchers must carefully select and validate scale anchors (Carlson & Perrewe, 1999; Podsakoff et al., 2003).
- **Difficulty in Implementation:** Designing effective scale anchors necessitates careful consideration of the construct being measured, the target population, and the precise wording of scale labels (Podsakoff et al., 2003; Podsakoff & Organ, 1986; Vieluf et al., 2009). Creating clear and meaningful anchors that resonate with respondents while avoiding ambiguity or confusion can be difficult (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Vieluf et al., 2009).

Recommendations for Improvement:

- **Pilot Testing:** Pilot-test scale anchors with a representative sample of respondents to determine their clarity, comprehensibility, and efficacy in standardizing answers (Podsakoff & Organ, 1986; Vieluf et al., 2009). Solicit feedback from participants to identify any ambiguities or misinterpretations, and then refine the scale anchors accordingly (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Vieluf et al., 2009).

- **Iterative Refinement:** Iteratively refine scale anchors based on pilot testing results and ongoing data collection (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Podsakoff & Organ, 1986). Continuously assess the impact of scale anchoring on response consistency and validity, making changes as needed to improve the clarity and relevance of scale labels (Podsakoff et al., 2003; Podsakoff & Organ, 1986; Vieluf et al., 2009).
- **Sensitivity Analysis:** Conduct sensitivity analyses to determine the survey findings' robustness to variations in scale anchoring. Compare responses obtained with various anchor formats or wording to assess the stability and reliability of results across conditions (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Vieluf et al., 2009).
- **Transparent Reporting**: Transparently report the use of scale anchoring techniques in research publications, including information about the scale labels, anchors, and any validation procedures used. Explain the rationale for selecting scale anchors and how they may affect study results (Carlson & Perrewe, 1999; Podsakoff et al., 2003).

Researchers can improve the consistency, reliability, and validity of survey data while reducing the risk of common method bias by using scale anchoring techniques in a thoughtful and transparent manner.

M.6. Triangulation of Data Sources Technique:

Definition: Triangulation of data sources is a methodological approach for mitigating common method bias (CMB) by collecting data from multiple independent sources or methods to confirm findings (MacKenzie & Podsakoff, 2012, Memon et al., 2023). This technique entails combining data from various sources or measurement approaches to improve the reliability, validity, and robustness of study findings (MacKenzie & Podsakoff, 2012; Memon et al., 2023).

Application: Triangulation of data sources is widely used in multidisciplinary research contexts such as social sciences, education, healthcare, and management. This technique is used by researchers to triangulate information collected from a variety of sources, including self-reports, observational data, archival records, interviews, and secondary sources. By combining multiple data streams, researchers hope to overcome the limitations of any single method and gain a more complete understanding of the phenomena under investigation (MacKenzie & Podsakoff, 2012; Memon et al., 2023).

Strengths:

- **Enhanced Validity:** Triangulating data from multiple sources improves the validity of study results by reducing reliance on a single measurement method or informant. Researchers gain confidence in the accuracy and trustworthiness of study results by correlating data from various perspectives or sources (MacKenzie & Podsakoff, 2012; Memon et al., 2023).
- **Reduction of Bias:** Triangulation helps to mitigate common method bias by reducing the impact of systematic errors inherent in any single data collection method. By cross-validating findings from multiple independent sources, researchers reduce the risk of method-specific biases and strengthen study conclusions (MacKenzie & Podsakoff, 2012; Memon et al., 2023).
- **Comprehensive Insights:** Triangulation enables researchers to gain a more comprehensive and nuanced understanding of complex phenomena by combining multiple perspectives and datasets (Memon et al., 2023). Researchers can uncover hidden insights into the research topic by combining subjective and objective measures or triangulating qualitative and quantitative data (MacKenzie & Podsakoff, 2012; Memon et al., 2023).

Weaknesses:

- **Increased Complexity**: Triangulating data from multiple sources complicates research design, collection, and analysis. Coordinating various data collection methods, ensuring consistency across sources, and integrating diverse datasets necessitates meticulous planning, resources, and expertise (MacKenzie & Podsakoff, 2012; Memon et al., 2023).
- **Potential Conflicts:** Triangulation may produce contradictory or incongruent findings across data sources, complicating interpretation and synthesis. Conflicting evidence can arise as a result of methodological differences, measurement error, or inherent variability between sources, requiring

researchers to carefully reconcile disparate results (MacKenzie & Podsakoff, 2012; Memon et al., 2023).

- **Resource Intensiveness**: Conducting triangulated research can be resource-intensive, necessitating more time, funding, and logistical support than studies that rely on a single data source. Researchers must strike a careful balance between the advantages of triangulation and the practical constraints and limitations of available resources (MacKenzie & Podsakoff, 2012; Memon et al., 2023).

Recommendations for Improvement:

- **Methodological Integration:** Integrate data collection and analysis procedures from multiple sources to ensure that the findings are consistent and comparable. Create clear protocols for data collection, coding, and analysis to aid in cross-source validation and integration (MacKenzie & Podsakoff, 2012; Memon et al., 2023).
- **Mixed-Methods Approach:** To triangulate findings, use a mixed-methods research design that includes both qualitative and quantitative data collection methods. Researchers can improve their understanding of complex phenomena by combining survey data with qualitative interviews, observations, or archival records (MacKenzie & Podsakoff, 2012; Memon et al., 2023).
- **Participant Validation:** Validate findings with participants or stakeholders to confirm research findings and ensure interpretations are accurate and relevant. Solicit feedback on research findings, interpretations, and conclusions to increase the study's credibility and trustworthiness (MacKenzie & Podsakoff, 2012; Memon et al., 2023).
- **Transparent Reporting:** Transparently report the use of triangulation techniques in research publications, including information on data sources, methods, and procedures used. Provide a rationale for choosing triangulation methods and explain how they contribute to the validity and reliability of study findings (MacKenzie & Podsakoff, 2012; Memon et al., 2023).

Researchers can improve the rigor, credibility, and validity of their research findings by effectively and transparently triangulating data sources, thereby mitigating common method bias and producing more robust and meaningful insights into the phenomena under investigation.

M.7. Longitudinal Designs Technique

Definition: Longitudinal designs are research methodologies that examine changes or trends in variables over time, usually involving repeated measurements of the same individuals or units (Memon et al., 2023; Podsakoff et al., 2023; Podsakoff & Organ, 1986). In terms of mitigating common method bias (CMB), longitudinal designs are an effective method for assessing temporal relationships between variables, allowing researchers to control for potential biases caused by common methods and unobserved confounders (MacKenzie & Podsakoff, 2012; Podsakoff et al., 2023; Podsakoff & Organ, 1986).

Application: Longitudinal designs are commonly used in a variety of disciplines, including psychology, sociology, epidemiology, and organizational research. (Podsakoff et al., 2023; Podsakoff & Organ, 1986) Longitudinal studies allow researchers to investigate developmental trajectories, causal relationships, and the long-term effects of interventions or treatments. In terms of addressing common method bias, longitudinal designs allow researchers to track changes in constructs of interest while accounting for stable individual differences and common method effects (MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2023; Podsakoff & Organ, 1986).

Strengths:

- ***Temporal Ordering***: Longitudinal designs enable researchers to establish temporal precedence between variables, which aids causal inference and reduces the possibility of spurious associations. By measuring variables at multiple time points, researchers can track changes in constructs over time and identify causal patterns (MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2023; Podsakoff & Organ, 1986).
- **Control for Time-Varying Confounders**: Longitudinal studies allow researchers to account for time-varying confounders that can affect both predictor and outcome variables. By tracking individuals over time, researchers can account for individual differences and other factors that may confound cross-sectional associations, improving the internal validity of study findings

(MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2023; Podsakoff & Organ, 1986).

- **Detection of Change Mechanisms**: Longitudinal designs shed light on the mechanisms driving changes in variables over time, allowing researchers to identify mediating processes, moderators, and individual differences in trajectories (Memon et al., 2023; Podsakoff et al., 2023). Researchers can better understand the drivers of change and inform intervention strategies by examining within-person changes and variability (MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2023; Podsakoff & Organ, 1986).

Weaknesses:

- **Resource Intensive:** Longitudinal studies are frequently resource-intensive, necessitating long-term commitment, significant funding, and logistical assistance for data collection, participant retention, and follow-up assessments. Attrition rates may rise over time, resulting in sample loss and potential bias if not addressed adequately (Memon et al., 2023; Podsakoff et al., 2023). Longitudinal studies are frequently resource-intensive, necessitating long-term commitment, significant funding, and logistical assistance for data collection, participant retention, and follow-up assessments. Attrition rates may rise over time, resulting in sample loss and potential bias if not addressed adequately (MacKenzie & Podsakoff, 2012; Podsakoff et al., 2023).
- **Time Constraints:** Longitudinal designs necessitate long periods of data collection and analysis, making it difficult to address research questions with immediate practical implications. Researchers must weigh the advantages of longitudinal data against time and resource limitations (MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2023; Podsakoff & Organ, 1986).
- **Potential Attrition Bias**: Longitudinal studies are prone to attrition bias, in which participants who drop out of the study differ systematically from those who stay, resulting in biased estimates and reduced generalizability of findings. Researchers must implement strategies to reduce attrition and assess the impact on study outcomes (MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2023; Podsakoff & Organ, 1986).

Recommendations for Improvement:

- **Robust Retention Strategies:** Implement effective retention strategies to reduce attrition and increase participant retention throughout the study. To keep participants interested and committed, engage them with regular communication, incentives, and personalized feedback (MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2023; Podsakoff & Organ, 1986).
- **Flexible Study Designs:** Consider alternative study designs, such as accelerated longitudinal or sequential cohort designs, to balance data collection time and sample representativeness. Flexible designs enable researchers to capture long-term trends while adapting to shifting research priorities and resource constraints (MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2023; Podsakoff & Organ, 1986).
- **Statistical Techniques:** To effectively analyse longitudinal data, use advanced statistical techniques such as growth curve modelling, latent growth modelling, and multilevel modelling. These methods allow researchers to model individual trajectories, account for nested data structures, and investigate time-varying effects while avoiding common method bias (MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2023; Podsakoff & Organ, 1986).
- **Sensitivity Analyses:** Conduct sensitivity analyses to determine whether longitudinal findings are robust to potential biases and missing data. Use imputation techniques, sensitivity tests, and propensity score matching to reduce attrition bias and assess the impact of missing data on study conclusions (MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2023; Podsakoff & Organ, 1986).

Researchers can improve the validity, reliability, and generalizability of their findings by effectively leveraging longitudinal designs and proactively addressing potential limitations while minimizing common method bias and advancing our understanding of complex phenomena over time.

M.8. Control Variables Technique:

Definition: Control variables, also known as covariates or confounders, are variables used by researchers in analyses to account for alternative explanations or sources of bias (Memon et al., 2023; Podsakoff et al., 2003,; Zhang et al., 2022). Control variables are used to statistically control for extraneous factors that may influence both the predictor and the outcome variables, lowering the possibility of false associations (Cruz, 2022;

MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003; Zhang et al., 2022).

Application: The control variables technique is widely used in many research fields, including psychology, sociology, economics, and epidemiology. Researchers use this technique to isolate the relationship between the independent and dependent variables of interest while taking into account the effects of other variables that may confound the association (Cruz, 2022; Memon et al., 2023; Podsakoff et al., 2003; Zhang et al., 2022). To address common method bias, statistical models include control variables to account for method-specific variance and unobserved confounders that could inflate or distort study results (Cruz, 2022; Memon et al., 2023).

Strengths:

- **Minimization of Confounding Effects**: Control variables help to reduce confounding effects by statistically adjusting for potential alternative explanations or sources of bias that may affect the predictor-outcome relationship. Researchers can improve the internal validity of study results by including relevant covariates in the analysis (Cruz, 2022; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003; Zhang et al., 2022).
- **Enhanced Precision:** Controlling for extraneous variables by including control variables improves statistical estimates' precision and accuracy, reducing the likelihood of Type I and II errors. By accounting for additional sources of variance, researchers can obtain more reliable and trustworthy estimates of the relationship between variables (Cruz, 2022; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003; Zhang et al., 2022).
- **Robustness of Findings:** Control variables improve study findings by accounting for method-specific biases and unmeasured confounders that could undermine the validity of research conclusions. Controlling for common method bias and other potential sources of error enables researchers to boost the credibility and generalizability of their findings (Cruz, 2022; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003; Zhang et al., 2022).

Weaknesses:

- **Selection of Control Variables:** Choosing appropriate control variables requires careful consideration of theoretical relevance, empirical evidence, and statistical criteria. The inclusion of irrelevant or poorly measured control variables may introduce noise or bias into the analysis, jeopardizing the study's validity (Cruz, 2022; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003; Zhang et al., 2022).
- **Assumptions of Linearity and Independence:** The effectiveness of control variables is based on the assumption that the covariates and variables of interest are linear and independent. Violations of these assumptions may cause biased estimates or misinterpretation of results, emphasizing the importance of diagnostic tests and sensitivity analyses (Cruz, 2022; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003; Zhang et al., 2022).
- **Potential Overcontrol:** Overcontrolling occurs when researchers include control variables that act as mediators or colliders in the causal pathway linking predictors and outcomes. Overcontrol can distort estimates, mask true effects, or introduce spurious relationships, underscoring the importance of careful model specification and theoretical justification (Cruz, 2022; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003; Zhang et al., 2022).

Recommendations for Improvement:

- **Theoretical Justification:** Control variables are chosen based on theoretical grounds and prior empirical evidence to ensure their relevance and validity in the context of the research question. Examine the study's conceptual framework for potential confounders that could affect the hypothesized relationships (Cruz, 2022; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003; Zhang et al., 2022).
- **Sensitivity Analyses:** Conduct sensitivity analyses to see how resilient the study's findings are to changes in control variable specification. Alternative model specifications, variable transformations, and subgroup analyses can be used to assess the stability of results and identify potential sources of bias (Cruz, 2022; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003; Zhang et al., 2022).

- **Measurement Validation**: Implement stringent measurement validation protocols to ensure the reliability and validity of the control variables. To improve measurement accuracy, use established measurement scales, psychometric testing, or pilot studies (Cruz, 2022; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003; Zhang et al., 2022).
- **Transparency and Reporting:** In research publications, explain why control variables were included, how they were operationalized and measured, and any potential limitations. Provide detailed descriptions of model specifications, statistical assumptions, and sensitivity analyses to improve the study's transparency and reproducibility (Cruz, 2022; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003; Zhang et al., 2022).

Researchers can enhance the internal validity, reliability, and credibility of their research findings by employing control variables in an effective and transparent manner.

M.9. Multimethod Approach Technique:

Definition: The multimethod approach involves investigating the same phenomenon using multiple research methods or data collection techniques. The multimethod approach, when used to mitigate common method bias (CMB), seeks to triangulate findings from various sources or methodologies in order to improve the validity, reliability, and generalizability of research conclusions (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003). Researchers can overcome the limitations of any single method by using a variety of techniques to gain a more comprehensive understanding of the phenomenon under investigation (Lance et al., 2002; MacKenzie & Podsakoff, 2012).

Application: The multimethod approach is applicable in a variety of research fields, including psychology, sociology, education, and management. This technique enables researchers to investigate complex phenomena from multiple perspectives by combining quantitative and qualitative methods, self-report measures, observational data, and experimental designs (MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003). In terms of addressing common method bias, the multimethod approach enables researchers to corroborate findings across multiple data sources, reducing reliance on any single method while controlling for method-specific biases. (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003)

Strengths:

- **Convergence of Evidence:** The multimethod approach makes it easier to combine evidence from different sources or methodologies, which improves the validity and reliability of research findings. Triangulating results from multiple methods allows researchers to identify consistent patterns, corroborate conclusions, and mitigate the impact of method-specific biases or measurement errors (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).
- **Complementarity of Methods:** Different methods have distinct strengths and weaknesses, allowing researchers to complement each other's limitations while increasing the depth and breadth of data collection. Combining quantitative and qualitative approaches allows researchers to capture both the breadth of relationships and the richness of contextual insights, resulting in a more nuanced understanding of the research phenomenon (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).
- **Enhanced Validity:** Using multiple methods improves the internal and external validity of study findings by lowering the possibility of spurious associations, confounding variables, or common method bias. Researchers can strengthen causal inference, control for alternative explanations, and improve the robustness of research conclusions by triangulating data from multiple sources (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).

Weaknesses:

- **Resource Intensive:** Implementing a multimethod approach necessitates significant resources, including time, funding, expertise, and logistical assistance for data collection, analysis, and integration. Multiple studies or diverse methodologies may present challenges in terms of coordination, data harmonization, and participant burden, especially in interdisciplinary research contexts (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).

- **Complexity of Integration:** Integrating results from various methods or datasets can be complicated and difficult, necessitating careful consideration of methodological congruence, data compatibility, and analytical strategies. Researchers must deal with potential inconsistencies, discrepancies, or methodological conflicts while synthesizing various sources of evidence and drawing coherent conclusions (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).
- **Interpretive Challenges:** Combining qualitative and quantitative data can be difficult to interpret, especially when reconciling contradictory findings or dealing with methodological triangulation issues. Researchers must critically evaluate each method's strengths and limitations, take into account researcher biases or preconceptions, and provide transparent accounts of methodological decisions and analytical processes (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).

Recommendations for Improvement:

- **Methodological Triangulation:** Use methodological triangulation to integrate results from multiple methods or datasets in a systematic way. Use complementary methods to look into different aspects of the research phenomenon, cross-validate your findings, and identify convergent or divergent patterns across data sets (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).
- **Interdisciplinary Collaboration:** Encourage interdisciplinary collaboration and expertise to capitalize on the strengths of various research traditions, methodologies, and perspectives. Engage researchers from various disciplines or methodological backgrounds to enrich the research process, test assumptions, and encourage novel approaches to data collection and analysis (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).
- **Transparent Reporting:** Provide a clear rationale for using a multimethod approach, as well as detailed descriptions of methodological procedures, data integration strategies, and interpretive frameworks. Provide detailed explanations of how various methods complement one another, address research objectives, and contribute to the overall validity and reliability of study

findings (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).

- **Methodological Flexibility:** Maintain methodological flexibility and reflexivity throughout the research process, allowing for iterative adjustments, methodological refinements, and evidence triangulation as required by new insights or unexpected findings. Change research designs, data collection instruments, or analytical techniques to reflect shifting research priorities, participant needs, or contextual dynamics (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).

By adopting a multimethod approach and implementing these recommendations, researchers can improve the rigor, credibility, and impact of their research while reducing the influence of common method bias and advancing our understanding of complex phenomena from various perspectives.

M.10. Measurement Validation Technique:

Definition: Measurement validation entails examining the validity and reliability of research instruments to ensure that they accurately measure the constructs of interest. In order to address common method bias (CMB), measurement validation techniques focus on verifying the psychometric properties of measurement tools used in data collection (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003). By validating measures, researchers can increase the trustworthiness and credibility of their findings while reducing the possibility of method-related biases (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003).

Application: Measurement validation techniques are useful in a wide range of research disciplines, including psychology, sociology, marketing, and management. These techniques are used by researchers to assess the validity, reliability, and dimensionality of survey instruments, questionnaires, scales, or indices that measure latent constructs such as attitudes, behaviours, or perceptions (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023). To reduce common method bias, measurement validation involves conducting psychometric analyses such as factor analysis, reliability testing, and criterion validation to ensure that measurement tools produce accurate and consistent results across different samples, settings, and time periods (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).

Strengths:

- **Enhanced Construct Validity**: Measurement validation techniques provide evidence for research instruments' construct validity by evaluating their ability to accurately and meaningfully measure the intended constructs. By examining the relationships between items and underlying constructs, researchers can show that measurement tools capture the theoretical domains of interest and have convergent and discriminatory validity (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).
- **Increased Reliability:** Validating measures improves reliability by evaluating internal consistency, test-retest reliability, and inter-rater agreement. By examining the consistency of responses across items or raters, researchers can identify sources of measurement error, random variability, or response bias and take corrective actions to improve measurement tool stability and precision (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).
- **Identification of Measurement Biases**: Researchers use measurement validation techniques to identify and mitigate potential sources of measurement bias, such as common method bias, response bias, and social desirability bias. By examining the factorial structure of measurement models, researchers can determine how much method-related variance contaminates observed variable relationships and implement statistical controls or procedural remedies to address bias (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).

Weaknesses:

- **Complexity of Psychometric Analysis**: Measurement validation necessitates knowledge of psychometric theory, statistical methods, and measurement modelling, which can be difficult for researchers with little specialized training or experience. Factor analysis, item response theory, and structural equation modelling are all examples of complex and computationally intensive psychometric analyses that necessitate careful consideration of model assumptions, estimation techniques, and result interpretation (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).

- **Limited Generalizability:** Measurement validation studies may have limited generalizability due to sample-specific characteristics, measurement contexts, or cultural variations. Findings from validation studies in one population or setting may not be generalizable to other contexts, necessitating cross-validation studies or cultural adaptation of measurement instruments to ensure their applicability and robustness across diverse populations (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).
- **Potential for Bias in Validation Procedures:** If the validation process is not rigorous and transparent, it can introduce biases or errors. Researchers must avoid methodological biases such as researcher allegiance effects, confirmation bias, and selection bias by adhering to standardized procedures, pre-registering analysis plans, and transparently reporting methodological decisions and findings (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).

Recommendations for Improvement:

- **Pretesting and Pilot Testing**: Before conducting formal validation studies, pretest and pilot test measurement instruments to identify any potential flaws, ambiguities, or comprehension issues. Solicit feedback from target respondents, expert reviewers, or focus groups to improve item wording, response options, or scale formats, as well as ensure measurement items are clear, relevant, and comprehensible (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).
- **Criterion Validation:** Validate measurement instruments against external criteria or gold standard measures to ensure their concurrent, predictive, or discriminant validity. Compare the proposed measurement tool's scores to those obtained from established measures or objective indicators to determine the degree of agreement, prediction accuracy, or divergence between measures and to support their validity claims (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).
- **Cross-Cultural Validation:** Conduct cross-cultural validation studies to determine the equivalence, invariance, and measurement properties of

instruments from various cultural or linguistic backgrounds. Use rigorous cross-cultural validation techniques, such as multigroup confirmatory factor analysis or differential item functioning analysis, to assess measurement model comparability and ensure measurement instruments' validity and fairness across diverse populations (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).

- **Transparency and Reproducibility:** Ensure that the validation process is transparent and reproducible by thoroughly documenting all methodological procedures, analytical steps, and validation results. Provide clear rationales for measurement decisions, describe sample characteristics and data collection procedures, and distribute analysis scripts, syntax files, or measurement validation protocols to allow for independent verification and replication of results (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).

Researchers can improve the validity, reliability, and cross-cultural applicability of their measurement instruments by implementing rigorous measurement validation techniques and following these recommendations, reducing the influence of common method bias and increasing the trustworthiness and credibility of their research findings.

M.11. Multiple Informant Approach Technique:

Definition: The multiple-informant approach entails collecting data from multiple sources or informants to evaluate the same constructs or variables of interest (Podsakoff et al., 2003, 2023). In the context of addressing common method bias (CMB), this technique aims to reduce reliance on single-source data while also improving the validity and reliability of research findings by triangulating information from various perspectives, sources, or methods (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023).

Application: The multiple-informant approach is widely used in many research fields, including psychology, organizational behaviour, sociology, and education. Researchers use this technique to collect data from multiple sources, such as self-reports, supervisor ratings, peer assessments, or archival records, in order to measure constructs such as personality traits, job performance, leadership behaviours, or organizational climate (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023). Researchers can gain a more comprehensive and accurate understanding of the phenomena under investigation by incorporating diverse perspectives and complementary sources of information, while minimizing the impact of common method bias and response distortions found in single-source data (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023)***.***

Strengths:

- **Enhanced Validity and Reliability:** The multiple informant approach improves the validity and reliability of research findings by reducing methodological biases and strengthening measurement instruments. By triangulating data from multiple sources, researchers can cross-validate measurement constructs, identify converging or diverging patterns of results, and assess the consistency and stability of findings across different informants or measurement events (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023).
- **Comprehensive Assessment:** This method enables a more comprehensive evaluation of complex constructs or phenomena by capturing multiple perspectives, viewpoints, or contextual factors. Researchers can obtain richer, more nuanced data that reflect the multidimensional nature of the constructs under study by soliciting feedback from a variety of stakeholders or observers, thereby improving the ecological validity and generalizability of research findings (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023).
- **Mitigation of Common Method Bias**: The multiple informant approach reduces common method bias by diversifying data collection sources and relying less on self-reported measures. By combining self-reports with other reports or objective indicators, researchers can distinguish between method-specific and true score variance, control for shared method variance, and provide more accurate estimates of construct validity and effect sizes (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023).

Weaknesses:

- **Inter-Rater Variability:** The multiple-informant approach may result in variability or disagreement among informants due to differences in perspectives, perceptions, or biases. Discrepancies in ratings or evaluations among informants can complicate data interpretation and make it difficult to reach consensus or reconcile opposing viewpoints, necessitating the use of statistical procedures (e.g., inter-rater agreement indices) or qualitative analyses (e.g., content analysis of discrepancies) to address discordance (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023).
- **Practical Constraints:** Collecting data from multiple informants can be logistically difficult, time-consuming, and resource-intensive, especially in large-scale or longitudinal studies. To overcome logistical barriers and maintain data quality, it may be necessary to carefully plan, communicate, and negotiate in order to recruit and coordinate multiple informants, ensure their willingness to participate, and manage data collection procedures across different settings or organizations (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023).
- **Potential Bias in Informant Reports:** Subjective biases, perceptual filters, and situational factors can all influence informant ratings or assessments, resulting in systematic errors or inaccuracies in data collection. Social desirability bias, halo effects, and interpersonal dynamics can all have an impact on the reliability and validity of informant reports, emphasizing the importance of training informants, providing clear rating instructions, and putting in place quality control measures to reduce bias (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023).

Recommendations for Improvement:

- **Training and Calibration:** Provide informants with training sessions or guidelines to help them better understand rating criteria, evaluation standards, and data collection procedures. Provide calibration exercises, practice trials, or feedback mechanisms to improve inter-rater agreement, reduce rating discrepancies, and standardize data collection protocols among informants (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023).

- **Anonymous Reporting:** Maintain confidentiality and anonymity in informant reporting to encourage honest and unbiased feedback. Use anonymous survey methods or confidential data collection procedures to reduce social desirability bias, alleviate concerns about reprisal or judgment, and encourage informants to provide candid responses, especially in sensitive or high-stakes situations (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023).
- **Combination of Objective Measures:** Supplement informant reports with objective measures or behavioural indicators to back up findings and improve data interpretation validity. Combining qualitative insights from informant interviews or focus groups with quantitative ratings or observational data allows you to triangulate information, validate measurement constructs, and gain a more nuanced understanding of the phenomenon under investigation (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023).
- **Cross-Validation and Sensitivity Analysis:** Conduct cross-validation or sensitivity analyses to determine the robustness and generalizability of findings across informants, measurement methods, and sampling frames. Compare results from self-reports, other reports, and archival data sources to identify sources of variability, systematic biases, or measurement errors, as well as assess the consistency and stability of research conclusions (Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023).

By following these recommendations and leveraging the multiple-informant approach's strengths, researchers can improve the validity, reliability, and comprehensiveness of their research findings while minimizing the impact of common method bias and informant-related biases.

M.12. Item Order Randomization Technique:

Definition: Item order randomization entails changing the order in which survey items or questionnaire prompts are presented to participants across multiple survey administrations (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Williams et al., 1989). In terms of addressing common method bias (CMB), this technique seeks to reduce response biases or order effects caused by the systematic arrangement of survey items, thereby improving the reliability and validity of self-reported data (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Williams et al., 1989).

Application: The item order randomization technique is widely used in survey research across disciplines such as psychology, marketing, and social sciences. Researchers use this technique to reduce response biases such as primacy or recency effects, which cause participants to favourably or unfavourably endorse items presented earlier or later in the survey, regardless of their true attitudes or behaviours (Carlson & Perrewe, 1999; Williams et al., 1989). Researchers can reduce the impact of order effects on response patterns by randomly shuffling the order of survey items for each participant or survey wave, preventing participants from anticipating or habituating to item sequences, and obtaining more unbiased and accurate results (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Williams et al., 1989).

Strengths:

- **Minimization of Order Effects**: Item order randomization reduces order effects by evenly distributing the influence of item placement among participants or measurement occasions. Researchers can disrupt systematic response patterns, eliminate biases associated with item position, and ensure that participants' responses reflect genuine attitudes, opinions, or experiences rather than transient contextual factors by randomizing the sequence of survey items (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Williams et al., 1989).
- **Enhanced Data Quality**: This technique improves the quality and reliability of self-reported data by lowering response biases and increasing the internal validity of survey instruments. By reducing the impact of response order on participants' ratings or evaluations, researchers can obtain more consistent, accurate, and representative measurements of the constructs under investigation, resulting in stronger research findings and conclusions (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Williams et al., 1989).
- **Flexibility and Adaptability:** Item order randomization provides flexibility and adaptability in survey design, allowing researchers to test different item sequences, rotation schemes, and randomization algorithms to improve data collection procedures. Researchers can tailor item orders to specific research

objectives, participant characteristics, or experimental conditions, ensuring that survey instruments capture the desired constructs while minimizing methodological artifacts (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Williams et al., 1989).

Weaknesses:

- **Increased Survey Length:** Randomizing item order may result in longer survey completion times or increased respondent burden, especially if participants encounter unfamiliar or unexpected item combinations. Long surveys can cause respondent fatigue, decreased attention or engagement, and higher attrition rates, making data collection difficult and compromising overall response quality (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Williams et al., 1989).
- **Potential Confounding Factors:** Despite randomization efforts, factors such as item content, question-wording, or cognitive complexity may continue to influence participants' responses regardless of item order. Confounding variables or contextual cues embedded in survey items may interact with response order effects, making it difficult to separate each factor's individual contributions to response variability or bias (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Williams et al., 1989).
- **Limited Generalizability:** The efficacy of item order randomization may differ depending on the survey items' specific characteristics, respondent population, or research context. Findings from randomized surveys may not be applicable to all survey designs or measurement scenarios, as certain constructs or response patterns may be more susceptible to order effects than others, necessitating caution in interpreting results and drawing conclusions (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Williams et al., 1989).

Recommendations for Improvement:

- **Pilot Testing and Validation:** Conduct pilot studies or pretests to assess the efficacy of various item order randomization strategies in reducing response bias and improving data quality. Assess participants' perceptions of item sequences using cognitive interviewing techniques, think-aloud protocols, or debriefing sessions, identify potential sources of confusion or fatigue, and refine survey designs as needed (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Williams et al., 1989).

- **Balancing Survey Length and Complexity:** Strike a balance between survey length and complexity to reduce respondent burden while maximizing the effectiveness of item order randomization. To streamline survey administration and maintain participant engagement, prioritize essential survey items or key constructs for randomization while reducing redundant or extraneous content (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Williams et al., 1989).
- **Monitoring and Quality Control:** Implement monitoring and quality control procedures to ensure that item order randomization remains accurate and consistent across survey administrations (Podsakoff et al., 2003; Podsakoff & Organ, 1986; Williams et al., 1989). Use survey software platforms or scripting tools to automate randomization processes, track item sequences, and detect deviations or errors in survey execution (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Williams et al., 1989). Monitor survey completion rates, item response distributions, and participant feedback on a regular basis to identify potential issues and troubleshoot them in real time (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Williams et al., 1989).

Researchers can optimize survey design, reduce response biases, and improve the reliability and validity of self-reported data by implementing these recommendations and leveraging the strengths of the item order randomization technique while addressing common method bias.

M.13. Multitrait-Multimethod Technique:

Definition: The Multitrait-Multimethod (MTMM) matrix technique is a methodological approach for determining the convergent and discriminant validity of measures by examining the patterns of correlations between multiple traits measured by multiple methods (Lance et al., 2002). This technique involves collecting data on several constructs (traits) using multiple measurement methods and analysing the resulting correlation matrix to evaluate the extent to which measures of the same construct (convergent validity) correlate more strongly with each other than with measures of other constructs (discriminant validity) (Lance et al., 2002).

Application: The MTMM technique is frequently used in psychometrics, social sciences, and organizational research to assess the validity of measurement instruments, especially when common method bias (CMB) is a concern (Lance et al., 2002; Memon et al., 2023). This technique is used by researchers to distinguish between the effects of method variance and true trait variance, providing empirical evidence for the distinctiveness and accuracy of their measures (Memon et al., 2023; Podsakoff et al., 2003). Researchers can rigorously evaluate the degree to which measures behave as expected in terms of theoretical considerations by systematically varying both the traits being measured and the methods used to assess them (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003).

Strengths:

- **Assessment of Validity:** The MTMM technique provides a comprehensive framework for evaluating measurement instrument validity, taking into account both convergent and discriminant validity. By systematically manipulating traits and methods, researchers can gain a more nuanced understanding of how well their measures capture the intended constructs and distinguish them from unrelated constructs (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003).
- **Control for Common Method Bias:** By incorporating multiple data collection methods (e.g., self-report, observer ratings, behavioural observations), the MTMM technique assists researchers in controlling for common method bias. Researchers can identify and correct for method-specific biases that may inflate or distort variable relationships by comparing their correlation patterns across different methods (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003).
- **Enhanced Construct Clarity:** The MTMM technique encourages clarity and precision in construct definition and operationalization. Researchers can better align their construct conceptualizations and measurement models with theoretical frameworks by specifying a priori hypotheses about the expected pattern of correlations within and across methods (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003).

Weaknesses:

- **Complexity of Design:** Because of its complexity, the MTMM technique must be carefully planned and executed. Designing studies with multiple traits and methods requires significant resources, including time, expertise, and participant recruitment. Researchers must also ensure that the methods used are sufficiently diverse and valid for the constructs being studied (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003).
- **Data Interpretation Challenges:** Analysing MTMM data can be difficult, especially when dealing with complex correlation matrices containing numerous variables and method combinations. Researchers may struggle to identify meaningful patterns of correlations, distinguish between trait variance and method variance, and draw valid conclusions about the validity of their measurements (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003).
- **Sensitivity to Assumptions:** The MTMM technique is based on several assumptions, including the orthogonality of trait and method factors, the absence of method-specific effects, and the comparability of measurement scales between methods. Violations of these assumptions can jeopardize the validity of MTMM analyses, resulting in biased estimates of construct validity (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003).

Recommendations for Improvement:

- **Careful Method Selection:** To increase the discriminant validity of the MTMM design, choose methods that are conceptually and methodologically distinct from one another. Consider using a combination of self-report measures, observer ratings, behavioural observations, and physiological indicators to capture various aspects of the constructs being studied (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003).
- **Transparent Reporting:** The rationale for method and trait selection, as well as the specific procedures used to implement the MTMM design, should be reported transparently. Provide detailed descriptions of measurement instruments, administration protocols, and data analysis procedures to improve finding reproducibility and interpretability (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003).
- **Sensitivity Analyses:** Conduct sensitivity analyses to determine the robustness of MTMM results under various model specifications, estimation

methods, and assumptions. Examine different model configurations, such as correlated trait-correlated method models or higher-order factor models, to determine the stability and generalizability of validity estimates (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003).

Addressing these concerns and leveraging the strengths of the MTMM technique allows researchers to improve the validity and reliability of their measurement instruments, as well as provide more robust evidence for the validity of their research findings while mitigating the potential biases introduced by common method variance.

M.15. Cross-Cultural Technique:

Definition: The Cross-Cultural Validation technique entails adapting and validating measurement instruments in different cultural contexts in order to ensure their reliability and validity across diverse populations (Memon et al., 2023; Podsakoff et al., 2023). It seeks to determine whether the constructs under investigation are understood and measured consistently across cultural groups, thereby addressing potential sources of bias, such as common method bias (CMB) caused by cultural differences in response styles, language, and survey item interpretation (Cooper et al., 2020; Jordan & Troth, 2020; Memon et al., 2023; Podsakoff et al., 2003, 2023).

Application: Cross-cultural validation is critical in fields like psychology, sociology, and organizational behaviour, where researchers frequently seek to generalize their findings across different populations (Cooper et al., 2020; Podsakoff et al., 2003, 2023). This method entails a systematic process of translating, back-translating, and testing measurement instruments to ensure linguistic equivalence and cultural appropriateness (Cooper et al., 2020; Jordan & Troth, 2020; Memon et al., 2023; Podsakoff et al., 2003, 2023). Researchers collect data from a variety of cultural groups and conduct analyses to assess measurement model comparability, measurement invariance, and cultural differences in construct conceptualization and operationalization (Cooper et al., 2020; Jordan & Troth, 2020; Memon et al., 2023; Podsakoff et al., 2003, 2023).

Strengths:

- **Enhanced Generalizability:** Cross-cultural validation improves the generalizability and external validity of research findings by demonstrating the reliability of measurement instruments in various cultural contexts. By validating measures in multiple cultural groups, researchers can determine whether their findings are consistent across diverse populations, improving the reliability and validity of their conclusions (Cooper et al., 2020; Jordan & Troth, 2020; Memon et al., 2023; Podsakoff et al., 2003, 2023).

- **Cultural Sensitivity:** This technique encourages cultural sensitivity and inclusivity in research by recognizing and accommodating differences in language, values, and norms. By including members of the target cultural groups in the adaptation and validation process, researchers can ensure that measurement instruments are culturally appropriate and reflect participants' lived experiences (Cooper et al., 2020; Jordan & Troth, 2020; Memon et al., 2023; Podsakoff et al., 2003, 2023).
- **Identification of Cultural Biases**: Cross-cultural validation allows researchers to identify and mitigate potential sources of bias, such as common method bias, which stems from cultural differences in response styles, social desirability, and communication norms. Researchers can determine whether observed differences in responses are the result of true cultural variations or measurement artifacts by comparing measurement models across cultures. (Cooper et al., 2020; Jordan & Troth, 2020; Memon et al., 2023; Podsakoff et al., 2003, 2023).

Weaknesses:

- ***Resource Intensive:*** Cross-cultural validation can be resource-intensive and time-consuming because it requires translation, back-translation, piloting, and data collection from multiple cultural groups. Researchers must devote adequate resources to linguistic and cultural adaptation processes, such as hiring bilingual translators, conducting cognitive interviews, and recruiting diverse samples (Cooper et al., 2020; Jordan & Troth, 2020; Memon et al., 2023; Podsakoff et al., 2003, 2023).
- ***Measurement Invariance Assumptions:*** Cross-cultural validation is based on the assumption of measurement invariance, which holds that measurement instruments perform similarly across cultural groups. Violations of measurement invariance can result in biased comparisons and undermine the validity of cross-cultural results. Researchers must rigorously test for

measurement invariance using techniques such as multigroup confirmatory factor analysis (MGCFA) to ensure measurement model comparability (Cooper et al., 2020; Jordan & Troth, 2020; Memon et al., 2023; Podsakoff et al., 2003, 2023).

- **Cultural Bias in Measurement**: Despite efforts to adapt and validate measurement instruments, cultural biases may persist, especially in items that are deeply embedded in specific cultural contexts or linguistic nuances. Researchers must exercise caution when interpreting cross-cultural findings, taking into account potential cultural biases that may influence respondents' interpretations and responses (Cooper et al., 2020; Jordan & Troth, 2020; Memon et al., 2023; Podsakoff et al., 2003, 2023).

Recommendations for Improvement:

- **Collaborative Research Partnerships:** Encourage collaborative research partnerships with scholars and practitioners from various cultural backgrounds to aid in the adaptation and validation of measurement tools. Local experts and community members should be involved in the translation, piloting, and refinement of survey items to ensure linguistic accuracy and cultural relevance (Cooper et al., 2020; Jordan & Troth, 2020; Memon et al., 2023; Podsakoff et al., 2003, 2023).
- **Mixed-Methods Approaches:** To gain a better understanding of cultural differences in response patterns and survey item interpretation, supplement quantitative analyses with qualitative methods like focus groups, interviews, and cultural probes. Qualitative data can help contextualize quantitative findings and identify culturally relevant nuances that may affect measurement validity (Cooper et al., 2020; Jordan & Troth, 2020; Memon et al., 2023; Podsakoff et al., 2003, 2023).
- **Robust Validation Procedures:** To ensure the validity and comparability of measurement instruments across cultural groups, use robust validation procedures such as measurement invariance tests, factorial equivalence tests, and differential item functioning. Use advanced statistical techniques, such as MGCFA and item response theory (IRT), to rigorously assess the psychometric properties of measures in various cultural contexts (Cooper et al., 2020; Jordan & Troth, 2020; Memon et al., 2023; Podsakoff et al., 2003, 2023).

By following these recommendations and leveraging the cross-cultural validation technique's strengths, researchers can improve the validity, reliability, and cultural sensitivity of their measurement instruments, allowing for cross-cultural comparisons and furthering our understanding of human behaviour across diverse populations.

4.5.2. Statistical Techniques

S.1. Sensitivity Analysis Technique:

Definition: Sensitivity analysis is a statistical technique used to evaluate the robustness and reliability of research findings by examining how changes in key parameters or assumptions affect the study's outcomes (Zhonglin & Tang, 2020; Zhou & Long, 2004). In the context of addressing common method bias (CMB), sensitivity analysis entails systematically varying method-related factors such as item wording, response format, and data collection procedures in order to assess their impact on study results and conclusions (MacKenzie & Podsakoff, 2012; M. Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).

Application: Researchers use sensitivity analysis to identify and quantify the potential impact of common method biases on study findings. This technique enables researchers to investigate alternative scenarios and assess the stability of findings under various methodological conditions (MacKenzie & Podsakoff, 2012; M. Memon et al., 2023; Podsakoff et al., 2003, 2023). By manipulating method-related variables systematically, researchers can assess the sensitivity of results to changes in measurement procedures and ensure the robustness of their conclusions in the presence of common method bias (MacKenzie & Podsakoff, 2012; M. Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).

Strengths:

- **Comprehensive Assessment:** Sensitivity analysis provides a comprehensive assessment of the robustness of research findings by taking into account various methodological factors that could introduce bias or error into the study. By testing the sensitivity of results to changes in key parameters, researchers can identify potential sources of bias and determine how much methodological considerations influence study conclusions (MacKenzie & Podsakoff, 2012; M. Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).

- **Transparent Reporting:** Sensitivity analysis promotes research transparency and rigor by encouraging researchers to document and disclose the potential impact of common method bias on study outcomes. By explicitly reporting the results of sensitivity analyses, researchers increase the credibility and trustworthiness of their findings, allowing readers to assess the reliability and validity of study conclusions (MacKenzie & Podsakoff, 2012; M. Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Evidence-Based Decision Making:** Sensitivity analysis allows researchers to make evidence-based decisions by providing valuable insights into the strength of study findings and the relative importance of method-related factors. By quantifying the sensitivity of results to changes in measurement procedures, researchers can make more informed decisions about the suitability of analytical techniques, data collection methods, and measurement tools (MacKenzie & Podsakoff, 2012; M. Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).

Weaknesses:

- **Assumption Sensitivity:** Sensitivity analysis is based on certain assumptions about the relationship between method-related factors and study outcomes, which may not always be accurate in practice. Researchers must carefully consider the validity of underlying assumptions, as well as the possibility of interactions or confounding variables that could influence the results of sensitivity analyses (MacKenzie & Podsakoff, 2012; M. Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Complexity and Interpretation:** Conducting sensitivity analysis can be complicated and difficult, especially when evaluating the simultaneous impact of multiple method-related factors on study results. Interpreting sensitivity analysis results necessitates careful consideration of the magnitude and direction of observed changes in study outcomes, as well as the underlying mechanisms causing sensitivity to methodological variations (MacKenzie & Podsakoff, 2012; M. Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Resource Intensive:** Sensitivity analysis may necessitate significant computational resources and statistical expertise to be implemented

successfully, particularly when conducting simulation-based analyses or investigating nonlinear relationships between variables. Researchers must set aside adequate time and resources to conduct sensitivity analyses and accurately interpret the results (MacKenzie & Podsakoff, 2012; M. Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).

Recommendations for Improvement:

- **Scenario-Based Analyses:** Conduct scenario-based sensitivity analyses to investigate a variety of plausible scenarios and assess the strength of study findings under various methodological conditions. By systematically varying key parameters and assumptions, researchers can identify the most influential factors that contribute to bias and prioritize strategies for reducing common method bias (MacKenzie & Podsakoff, 2012; M. Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Monte Carlo Simulation:** Use Monte Carlo simulation techniques to simulate data under various conditions and determine the sensitivity of study results to changes in method-related variables. Monte Carlo simulations enable researchers to quantify the uncertainty associated with parameter estimates as well as evaluate the stability of statistical inference in the presence of common method bias (MacKenzie & Podsakoff, 2012; M. Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Sensitivity Plots:** Visualize the results of sensitivity analyses with sensitivity plots or tornado diagrams to show the relative importance of various method-related factors and their effect on study outcomes. Visual representations of sensitivity analyses help researchers and stakeholders communicate and interpret results more effectively, allowing them to identify priority areas for methodological improvement (MacKenzie & Podsakoff, 2012; M. Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).

Researchers can improve the reliability, validity, and transparency of their research findings by incorporating these recommendations and leveraging the strengths of sensitivity analysis, advancing our understanding of the phenomena under investigation while mitigating the impact of common method bias.

S.2. Common Latent Factor Approach Technique:

Definition: The Common Latent Factor Approach (CLFA) is a statistical technique for accounting for common method bias (CMB) by introducing a latent variable that represents the method effect shared by multiple variables (Memon et al., 2023; Podsakoff et al., 2003, 2023). In this approach, researchers incorporate a common latent factor into their measurement model to capture systematic variance due to methodological factors such as response biases or measurement errors, thereby distinguishing method-related variance from true score variance in the observed variables (Zhonglin & Tang, 2020; Zhou & Long, 2004).

Application: Researchers use the Common Latent Factor Approach to reduce the impact of common method bias on study results, particularly in structural equation modeling (SEM) or confirmatory factor analysis (CFA) frameworks (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004). Researchers can use a latent method factor in the measurement model to statistically control for method-related variance and obtain more accurate estimates of the relationships between constructs of interest (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).

Strengths:

- **Statistical Control:** The Common Latent Factor Approach allows researchers to statistically control for common method bias by explicitly modelling the shared variance due to methodological factors. By including a latent method factor in the measurement model, researchers can isolate and account for method-related variance, improving the accuracy and validity of parameter estimates for the focal constructs (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Model Flexibility:** This approach provides flexibility in modelling the structure and relationships between variables, allowing researchers to incorporate the common latent factor into a variety of SEM or CFA models. Researchers can tailor the measurement model to the unique characteristics of their data and research objectives, while effectively addressing common method bias (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Interpretation Clarity**: By distinguishing between method-related and true score variance, the Common Latent Factor Approach allows for a clearer interpretation of study findings and improves the substantive meaning of

observed relationships between constructs. Researchers can confidently attribute observed effects to underlying constructs rather than methodological artifacts, increasing the validity and credibility of their findings (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).

Weaknesses:

- **Assumption Dependence:** The Common Latent Factor Approach's effectiveness is based on the assumption that the latent method factor accounts for all method-related variance. However, this assumption may not be true in practice, particularly if methodological biases are not adequately represented by the latent factor or if other sources of bias go unaccounted for (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Model Misspecification:** Mis-specifying the measurement model or the relationships between variables can result in biased parameter estimates and incorrect conclusions. Researchers must carefully design and validate their measurement model to ensure that the common latent factor accurately captures method-related variance while not confounding true score variance (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Complexity and Interpretation:** Incorporating a common latent factor complicates the measurement model and may necessitate advanced statistical methods for model estimation and interpretation. To successfully implement this approach and accurately interpret the results, researchers must have expertise in SEM or CFA methodologies (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).

Recommendations for Improvement:

- **Model Sensitivity Analysis:** Conduct sensitivity analyses to determine the robustness of model estimates and the consistency of results across model specifications. Researchers can investigate alternative measurement models, factor structures, or variable inclusion/exclusion to assess the sensitivity of findings to modelling decisions (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).

- **Model Fit Assessment**: Use goodness-of-fit indices and model comparison techniques to determine the measurement model's adequacy and whether the common latent factor adequately captures method-related variance. Researchers should strive for acceptable model fit statistics to ensure that their measurement model accurately represents the data (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Measurement Development:** Invest in rigorous measurement development and validation procedures to ensure the reliability and validity of the observed variables used in the measurement model. Researchers can improve parameter estimates and reduce the impact of measurement error on study results by employing well-validated measures and carefully designing survey instruments (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).

By taking these factors into account and leveraging the Common Latent Factor Approach's strengths, researchers can effectively control for common method bias and produce more valid and reliable findings in their research.

S.3. Cross-Validation Technique:

Definition: Cross-validation is a statistical technique for evaluating predictive models' performance and generalization ability. It involves partitioning the dataset into multiple subsets, training the model on one subset, and evaluating it on the complementary subset (Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020). The process is repeated iteratively, with each subset serving as both training and testing data, allowing researchers to predict how well the model will perform on previously unseen data (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).

Application: Cross-validation can be used to assess the robustness of models designed to detect or control for method-related variance. Researchers divide the dataset into multiple folds, ensuring that each fold contains a representative sample of observations (Memon et al., 2023; Zhou & Long, 2004). They then train the model on a subset of folds and use the remaining fold(s) for validation. Researchers obtain multiple performance metrics, such as accuracy, precision, and recall, by iteratively rotating the validation set across all folds. This provides insights into the model's effectiveness in mitigating common method bias (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).

Strengths:

- **Generalization Assessment:** Cross-validation allows researchers to objectively assess the generalization ability of models for detecting and controlling common method bias. Researchers gain insights into how well the model can generalize to previously unseen data by evaluating model performance on independent datasets that were not used during model training, boosting confidence in its effectiveness (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Bias Reduction:** Cross-validation reduces the risk of overfitting by systematically partitioning the dataset and iteratively training and testing the model on different subsets. This occurs when the model learns noise or idiosyncrasies in the training data. This reduces the likelihood of spurious relationships or inflated performance metrics caused by data fluctuations (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Model Selection:** Cross-validation makes it easier to compare multiple models or techniques for addressing common method bias, allowing researchers to determine the most effective approach based on performance metrics like accuracy, sensitivity, and specificity. Researchers can iteratively refine their models to find the optimal configuration that minimizes bias while increasing predictive accuracy (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).

Weaknesses:

- **Data Dependency:** Cross-effectiveness validation is determined by the dataset's representativeness and quality. Biased or unrepresentative data can produce overly optimistic or pessimistic estimates of model performance, undermining the validity of cross-validation results. To obtain reliable results, researchers must ensure that the dataset adequately captures the underlying phenomenon's variability and complexity (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).

- **Computational Complexity:** Cross-validation entails repeated iterations of model training and testing, which can be computationally expensive, particularly for large datasets or complex models. This may require significant computational resources and time, especially when using techniques like k-fold cross-validation with a large number of folds (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Evaluation Metric Selection**: The evaluation metrics used to assess model performance in cross-validation can have an impact on the results' interpretation and model selection. Researchers must carefully choose appropriate metrics that are consistent with the research objectives while also taking into account the dataset's and modelling task's specific characteristics (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).

Recommendations for Improvement:

- **Stratified Sampling:** Use stratified sampling techniques to ensure that each fold of the cross-validation process has the same class distribution as the original dataset. This reduces biases caused by uneven class representation and ensures that the model is exposed to all relevant data patterns (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Nested Cross-Validation:** Use nested cross-validation, which uses an inner loop to tune model hyperparameters and an outer loop to evaluate model performance. When compared to traditional cross-validation, this approach provides more reliable estimates of model performance while lowering the risk of overfitting (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Ensemble Techniques**: Consider ensemble techniques, such as bagging or boosting, to improve model robustness and stability. Ensemble methods, which aggregate predictions from multiple models trained on different subsets of the data, can reduce the impact of data variability while improving overall predictive performance (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020; Zhou & Long, 2004).

By addressing these concerns and leveraging cross-strengths, validation researchers can effectively assess and mitigate common method bias, improving the validity and reliability of their research findings.

S.4. Bayesian Technique:

Definition: Bayesian methods are statistical techniques that incorporate prior knowledge or beliefs about parameters into the analysis, which are then updated based on observed data to produce posterior distributions (Carlson & Perrewe, 1999; Lance et al., 2002; Williams et al., 1989). Bayesian techniques, when used to address common method bias (CMB), provide a framework for modelling uncertainty and estimating parameters while explicitly accounting for prior information (Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007).

Application: Bayesian techniques can be used for a variety of CMB detection and mitigation tasks, such as modelling latent constructs, estimating regression coefficients, and determining the presence of method-related variance. Researchers define prior distributions for model parameters based on their prior knowledge or beliefs about the phenomenon under investigation (Lance et al., 2002; Podsakoff et al., 2003; Schwarz et al., 2008; Williams et al., 1989;). They then update these priors with observed data, resulting in posterior distributions that reflect updated parameter estimates and associated uncertainty. Bayesian methods enable researchers to quantify uncertainty, incorporate prior information, and make probabilistic statements about model parameters, resulting in a versatile and principled approach to CMB analysis (Vieluf et al., 2009; Williams et al., 1989; Zhonglin & Tang, 2020; Zhou & Long, 2004).

Strengths:

- **Incorporation of Prior Information**: Bayesian techniques enable researchers to incorporate prior knowledge, expert opinions, and empirical evidence about model parameters into their analyses. By explicitly specifying prior distributions, researchers can use existing information to inform parameter estimation and improve model inference accuracy, especially when data is limited or noisy (Carlson & Perrewe, 1999; Lance et al., 2002; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Williams et al., 1989; Zhonglin & Tang, 2020; Zhou & Long, 2004).

- **Uncertainty Quantification:** Bayesian inference is a principled approach to quantifying uncertainty in parameter estimates and model predictions. Obtaining posterior distributions allows researchers to gain insight into the range of plausible values for model parameters and assess the robustness of conclusions to various sources of uncertainty, such as measurement error and sampling variability (Carlson & Perrewe, 1999; Lance et al., 2002; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Williams et al., 1989; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Flexibility in Model Specification:** Bayesian methods provide flexibility in model specification, allowing researchers to incorporate complex relationships, hierarchical structures, and prior knowledge into their analyses (Williams et al., 1989; Zhonglin & Tang, 2020; Zhou & Long, 2004). This allows for the creation of custom models that are tailored to the specific characteristics of the data and research question, while also accommodating the nonlinearities, interactions, and latent constructs inherent in CMB analysis (Carlson & Perrewe, 1999; Lance et al., 2002; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007).

Weaknesses:

- **Computational Complexity:** Bayesian inference frequently necessitates numerical methods, such as Markov chain Monte Carlo (MCMC) algorithms, which can be computationally demanding and time-consuming, especially for high-dimensional or complex models (Zhonglin & Tang, 2020; Zhou & Long, 2004). Analysing large datasets or fitting complex Bayesian models may require significant computational resources as well as algorithm implementation and tuning expertise (Vieluf et al., 2009; Williams et al., 1989; Zhou & Long, 2004).
- **Subjectivity in Prior Specification:** Prior distributions can influence posterior inference and model outcomes, adding subjectivity to the analysis. Researchers must carefully justify their prior choices and assess the sensitivity of results to various prior specifications to ensure that conclusions are robust to changes in prior assumptions and beliefs (Carlson & Perrewe, 1999; Lance et al., 2002; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Williams et al., 1989; Zhonglin & Tang, 2020; Zhou & Long, 2004).

- **Interpretability Challenges:** Bayesian models frequently involve complex mathematical formulations and probabilistic reasoning, which can make it difficult to interpret and communicate results, particularly to non-specialist audiences. Researchers must strike a balance between model complexity and interpretability, transparently communicating uncertainty and model assumptions to promote understanding and trust in the findings (Carlson & Perrewe, 1999; Lance et al., 2002; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Williams et al., 1989; Zhonglin & Tang, 2020; Zhou & Long, 2004).

Recommendations for Improvement:

- **Sensitivity Analyses:** Conduct sensitivity analyses to assess the Bayesian models' robustness to various prior specifications and modelling assumptions. By systematically varying priors and assessing their impact on posterior inference and model outcomes, researchers can identify influential priors, reduce subjectivity, and improve the credibility of results (Carlson & Perrewe, 1999; Lance et al., 2002; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Williams et al., 1989; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Model Validation**: Bayesian models should be validated using techniques such as posterior predictive checks or cross-validation to assess their predictive performance and fit. Validating models against independent datasets or simulated data ensures that they accurately capture the underlying data-generation process and provide reliable inference and predictions (Carlson & Perrewe, 1999; Lance et al., 2002; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Williams et al., 1989; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Transparent Reporting:** Transparently report the Bayesian analysis pipeline, which includes prior specifications, model assumptions, inference procedures, and sensitivity analyses. Providing detailed documentation and code facilitates reproducibility, allows for peer review, and increases the credibility and trustworthiness of research findings (Carlson & Perrewe, 1999; Lance et al., 2002; Podsakoff et al., 2003c; Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Williams et al., 1989; Zhonglin & Tang, 2020; Zhou & Long, 2004).

By addressing these concerns and leveraging the strengths of Bayesian techniques, researchers can effectively model and mitigate common method bias, resulting in robust and interpretable insights into the phenomena under investigation.

S.5. Bootstrapping Technique:

Definition: Bootstrapping is a resampling technique that uses observed data to estimate a statistic's sampling distribution (Sharma et al., 2007; Zhonglin & Tang, 2020; Zhou & Long, 2004). In the context of common method bias (CMB), bootstrapping can be used to evaluate the robustness of statistical estimates such as regression coefficients or factor loadings, as well as to quantify uncertainty in parameter estimates (Carlson & Perrewe, 1999; Lance et al., 2002; Podsakoff et al., 2003; Schwarz et al., 2008; Sharma et al., 2007).

Application: Bootstrapping can be used at multiple stages of CMB analysis, such as model estimation, hypothesis testing, and model validation (Sharma et al., 2007; Zhonglin & Tang, 2020; Zhou & Long, 2004). In regression analysis, bootstrapping enables researchers to estimate confidence intervals for regression coefficients, assess the significance of indirect effects, and evaluate model fit statistics, such as the root mean square error of approximation (RMSEA) or comparative fit index (CFI), by repeatedly resampling from observed data (Lance et al., 2002; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Schwarz et al., 2008; Williams et al., 1989; Zhonglin & Tang, 2020; Zhou & Long, 2004).

Strengths:

- **Non-parametric Estimation:** Bootstrapping does not require strict distributional assumptions about the data, making it ideal for non-normal or skewed distributions commonly encountered in CMB analysis. Bootstrapping generates an empirical sampling distribution of the statistic of interest by resampling from observed data, allowing for robust estimation and inference without relying on specific parametric distribution assumptions (Schwarz et al., 2008; Sharma et al., 2007; Williams et al., 1989; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Estimation of Standard Errors:** Bootstrapping is a simple method for estimating standard errors and confidence intervals for parameter estimates,

even when analytical methods are unavailable or unreliable due to distributional assumption violations or small sample sizes (Carlson & Perrewe, 1999; Lance et al., 2002; Podsakoff et al., 2003). Bootstrapping captures the variability inherent in the sample by sampling it repeatedly, resulting in accurate estimates of uncertainty around parameter estimates (Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Williams et al., 1989; Zhou & Long, 2004).

- **Flexible Application:** Bootstrapping can be used with a variety of statistical techniques, such as regression analysis, structural equation modelling (SEM), and mediation analysis, to assess the stability and generalizability of results across different resampling iterations (Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009). Bootstrapping can also handle more complex modelling scenarios, such as multilevel or longitudinal data structures, increasing its versatility and applicability in CMB research (Carlson & Perrewe, 1999; Lance et al., 2002; Podsakoff et al., 2003; Williams et al., 1989; Zhonglin & Tang, 2020; Zhou & Long, 2004).

Weaknesses:

- **Computational Intensity:** Bootstrapping entails repeated resampling of observed data, which can be computationally expensive, particularly for large datasets or complex models (Podsakoff et al., 2003; Williams et al., 1989; Zhonglin & Tang, 2020; Zhou & Long, 2004). Creating a large number of bootstrap samples can take a significant amount of computational resources and time, especially when using iterative resampling procedures or combining them with other estimation techniques (Carlson & Perrewe, 1999; Lance et al., 2002; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Schwarz et al., 2008).
- **Dependency on Sample Size:** The effectiveness of bootstrapping is determined by the size of the original sample; smaller sample sizes may result in less reliable estimates of the sampling distribution. When the sample size is small, bootstrapping can produce unstable or biased estimates of standard errors, jeopardizing the accuracy of inferential results (Williams et al., 1989; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Assumption of Exchangeability:** Bootstrapping assumes that the observed data are interchangeable, and that each observation is drawn independently and identically from the underlying population distribution (Williams et al., 1989;

Zhonglin & Tang, 2020; Zhou & Long, 2004). Violations of these assumptions, such as dependence between observations or non-random sampling mechanisms, may result in biased estimates or incorrect conclusions based on bootstrapped results (Carlson & Perrewe, 1999; Lance et al., 2002; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007).

Recommendations for Improvement:

- **Consider Alternative Resampling Methods:** Investigate alternative resampling techniques, such as parametric bootstrap or wild bootstrap, which may provide better performance in certain modelling scenarios or data conditions (Carlson & Perrewe, 1999; Lance et al., 2002; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Schwarz et al., 2008). Researchers can reduce potential biases and improve the reliability of bootstrapped results by tailoring the resampling procedure to the data's characteristics and the research question (Vieluf et al., 2009; Williams et al., 1989; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Assess Sensitivity to Assumptions:** Conduct sensitivity analyses to determine the robustness of bootstrapped results to changes in resampling parameters, such as the number of bootstrap samples or the resampling technique(Podsakoff et al., 2003; Podsakoff & Organ, 1986; Schwarz et al., 2008). By systematically varying these parameters and assessing their impact on inference, researchers can identify potential sources of bias or instability in bootstrapped estimates and adjust the analysis (Carlson & Perrewe, 1999; Lance et al., 2002; Podsakoff et al., 2003; Zhonglin & Tang, 2020; Zhou & Long, 2004).
- **Validate Bootstrapped Results:** Validate bootstrapped results with external validation datasets or simulation studies to ensure the accuracy and validity of inferential conclusions (Zhonglin & Tang, 2020; Zhou & Long, 2004). Comparing bootstrapped estimates to analytically derived results or known population parameters ensures that bootstrapped inferences are reliable and generalizable in CMB analysis (Sharma et al., 2007; Vieluf et al., 2009; Williams et al., 1989; Zhonglin & Tang, 2020; Zhou & Long, 2004).

Researchers can use bootstrapping effectively to assess common method bias and improve the validity of statistical inference in empirical research by leveraging its strengths while addressing its limitations, such as sample size, computational constraints, and underlying assumptions.

S.6. Nonlinear Structural Equation Model Technique:

Definition: Nonlinear structural equation modelling (SEM) is an extension of traditional SEM that allows for the representation of nonlinear relationships between variables (Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Zhou & Long, 2004). It accommodates complex relationships, such as curvilinear or interaction effects, that linear models cannot adequately capture. Nonlinear SEM techniques allow researchers to explore and account for nonlinear relationships between variables while assessing the presence and impact of method bias (Carlson & Perrewe, 1999; Cooper et al., 2020; Lance et al., 2002).

Application: Nonlinear SEM can be used in CMB research to investigate the non-linear relationships between latent constructs and observable indicators, as well as to test for interaction effects or non-linear mediation pathways (Podsakoff et al., 2003; Schwarz et al., 2008; Sharma et al., 2007; Zhou & Long, 2004). To capture the complexity of relationships between variables, researchers can specify nonlinear structural equations with polynomial terms, spline functions, or interaction terms. By incorporating non-linear specifications into SEM frameworks, researchers can improve model estimates' accuracy and validity while also better understanding the underlying mechanisms driving observed data patterns (Carlson & Perrewe, 1999; Cooper et al., 2020; Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003c).

Strengths:

- **Flexibility in Modelling Complex Relationships**: Nonlinear SEM techniques provide greater flexibility in modelling complex relationships that linear models cannot adequately capture (Cooper et al., 2020; Lance et al., 2002; Memon et al., 2023). Researchers can gain a better understanding of the underlying data-generating process by allowing them to specify non-linear structural equations that account for curvilinear, threshold, or interaction effects between variables (Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Zhou & Long, 2004).
- **Improved Model Fit and Interpretability**: Nonlinear SEM can improve model fit by detecting nonlinearities in data that linear models may miss, resulting in more accurate parameter estimates and better-fitting models (Memon et al., 2023; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Schwarz et al., 2008).

Furthermore, non-linear specifications improve the interpretability of SEM results by providing information about the shape and direction of relationships between variables, allowing researchers to identify critical points, inflection points, and threshold effects in the data (Memon et al., 2023; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007).

- **Enhanced Discriminant Validity:** Nonlinear SEM improves discriminant validity by allowing researchers to distinguish between genuine relationships and spurious associations caused by method bias (Carlson & Perrewe, 1999; Cooper et al., 2020; Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003) Researchers can improve the validity of study conclusions by specifying non-linear models that account for the data's underlying structure (Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Zhou & Long, 2004).

Weaknesses:

- **Increased Model Complexity:** Nonlinear SEM models are frequently more complex than their linear counterparts, necessitating additional parameters and assumptions to accurately capture nonlinear relationships (Carlson & Perrewe, 1999; Cooper et al., 2020; Lance et al., 2002) As a result, estimating non-linear SEM models can be computationally demanding and prone to issues like local optima or convergence problems, especially when dealing with large or high-dimensional data (Cooper et al., 2020; Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003; Sharma et al., 2007; Vieluf et al., 2009; Zhou & Long, 2004).
- **Greater Data Requirements:** Nonlinear SEM techniques may necessitate larger sample sizes to achieve stable parameter estimates and a reliable model fit, particularly when estimating complex nonlinear relationships or interactions. Inadequate sample sizes can result in overfitting or unreliable model estimates, jeopardizing the validity and generalizability of study results (Carlson & Perrewe, 1999; Cooper et al., 2020; Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Zhou & Long, 2004).
- **Challenges in Model Identification and Interpretation:** Identifying and interpreting non-linear effects in SEM models can be difficult, especially when specifying complex functional forms or interaction terms (Carlson & Perrewe, 1999; Cooper et al., 2020; Lance et al., 2002). Researchers must carefully consider

the theoretical justification for nonlinear specifications and ensure that model interpretations are in line with theoretical expectations and empirical evidence (Sharma et al., 2007; Vieluf et al., 2009; Zhou & Long, 2004).

Recommendations for Improvement:

- **Theoretical Grounding**: Ensure that nonlinear specifications in SEM models are theoretically justified and empirically supported (Podsakoff et al., 2003; Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Zhou & Long, 2004). Researchers should carefully consider the nature of the relationships between variables and choose non-linear functions or transformations that are consistent with theoretical expectations and previous research findings (Cooper et al., 2020; Lance et al., 2002; M. Memon et al., 2023; Podsakoff et al., 2003; Podsakoff & Organ, 1986).
- **Sample Size Considerations:** Conduct power analyses or simulation studies to determine the smallest sample size needed to detect non-linear effects of interest with sufficient statistical power (Podsakoff et al., 2003; Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Zhou & Long, 2004). When estimating nonlinear SEM models, researchers should prioritize larger sample sizes in order to obtain robust estimates and reliable model fit (Memon et al., 2023; Podsakoff et al., 2003; Sharma et al., 2007; Vieluf et al., 2009; Zhou & Long, 2004).
- **Model Selection and Comparison**: Compare different model specifications, including linear and non-linear models, to determine the relative fit and interpretability of various model formulations (Podsakoff et al., 2003; Schwarz et al., 2008; Sharma et al., 2007; Zhou & Long, 2004). Researchers should use model selection criteria like information criteria (e.g., AIC, BIC) or fit indices (e.g., RMSEA, CFI) to find the most parsimonious and well-fitting model that adequately captures the underlying data structure (Cooper et al., 2020; Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003; Zhou & Long, 2004).
- **Sensitivity Analyses:** Conduct sensitivity analyses to determine the robustness of nonlinear SEM results to changes in model specifications or estimation techniques. (Cooper et al., 2020; Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003; Zhou & Long, 2004) To ensure the reliability and validity of study findings, researchers can assess the stability of parameter estimates,

model fit indices, and substantive conclusions using various modelling approaches (Podsakoff et al., 2003; Schwarz et al., 2008; Sharma et al., 2007; Zhou & Long, 2004).

Researchers can effectively use nonlinear SEM to investigate common method bias and advance methodologically rigorous empirical research by leveraging the flexibility of these techniques while addressing their inherent challenges through careful theoretical justification, adequate sample size considerations, and rigorous model evaluation.

S.7. Nonlinear Structural Equation Model Technique

Definition: Nonlinear structural equation modelling (SEM) is a sophisticated statistical technique used in social science research to investigate complex relationships between variables that are not adequately captured by linear models. (Lance et al., 2002; M. Memon et al., 2023; Podsakoff et al., 2003; Podsakoff & Organ, 1986) It allows you to model non-linear relationships between latent constructs and observed indicators, such as curvilinear, threshold, or interaction effects. Nonlinear SEM builds on traditional linear SEM frameworks by incorporating non-linear structural equation specifications, allowing researchers to investigate intricate patterns of association and gain a better understanding of the underlying mechanisms driving observed data (Memon et al., 2023; Podsakoff et al., 2003; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Zhou & Long, 2004).

Application: Nonlinear SEM is used in a variety of research contexts, including common method bias (CMB) detection and mitigation. Nonlinear SEM techniques in CMB research allow researchers to evaluate and account for non-linear relationships between latent constructs, observed measures, and potential method bias indicators (Memon et al., 2023; Podsakoff et al., 2003; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Zhou & Long, 2004). Non-linear structural equations within SEM frameworks allow researchers to assess the presence and impact of method bias while controlling for confounding variables and alternative explanations (Cooper et al., 2020; Lance et al., 2002; M. Memon et al., 2023; Podsakoff et al., 2003; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Zhou & Long, 2004) Nonlinear SEM enables the simultaneous testing of multiple hypotheses as well as the investigation of complex mediation or moderation effects, resulting in a more comprehensive understanding of the relationships between variables in CMB studies (Cooper et al., 2020; Lance et al., 2002; M. Memon et al., 2023; Podsakoff et al., 2003; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Zhou & Long, 2004).

Strengths:

- **Flexibility in Modelling:** Nonlinear SEM provides greater flexibility in modelling complex relationships that linear models cannot adequately capture (Memon et al., 2023; Podsakoff et al., 2003; Zhou & Long, 2004) It enables researchers to specify non-linear functional forms, such as quadratic, logarithmic, or interaction terms, in order to better represent the data structure (Podsakoff et al., 2003; Sharma et al., 2007; Vieluf et al., 2009).
- **Accommodation of Non-Linear Effects:** Nonlinear SEM techniques can account for nonlinear effects such as curvilinear relationships, threshold effects, and interaction effects, resulting in a more accurate representation of variable relationships (Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Zhou & Long, 2004).
- **Enhanced Model Fit:** Nonlinear SEM, by incorporating nonlinear specifications, frequently improves model fit when compared to linear models, resulting in more accurate parameter estimates and models that fit better (Cooper et al., 2020; Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003; Schwarz et al., 2008; Sharma et al., 2007; Zhou & Long, 2004).
- **Comprehensive Analysis:** Nonlinear SEM enables researchers to conduct comprehensive analyses of complex data patterns by examining multiple nonlinear relationships simultaneously within a single model (Carlson & Perrewe, 1999; Podsakoff et al., 2003;; Sharma et al., 2007; Zhou & Long, 2004).

Weaknesses:

- **Complexity:** Nonlinear SEM models are frequently more complex than linear models, necessitating precise specification of nonlinear terms and additional model parameters (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003; Zhou & Long, 2004).
- . As a result, estimating and interpreting nonlinear SEM models may prove more difficult and computationally demanding (Carlson & Perrewe, 1999; Podsakoff et al., 2003; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Zhou & Long, 2004).

- **Sample Size Requirements:** Nonlinear SEM techniques may necessitate larger sample sizes to achieve stable parameter estimates and a reliable model fit, especially when estimating complex nonlinear relationships or interactions (Memon et al., 2023; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007).
- **Model Identification Challenges:** Identifying appropriate non-linear specifications and interpreting the resulting model estimates can be difficult, especially when dealing with complex data patterns or ambiguous theoretical predictions (Carlson & Perrewe, 1999; Cooper et al., 2020; Zhou & Long, 2004).

Recommendations for Improvement:

- **Theoretical Justification:** Ensure that non-linear specifications in SEM models are theoretically sound and supported by empirical data (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003; Zhou & Long, 2004). Researchers should carefully consider the nature of the variables' relationships and choose appropriate non-linear functional forms that are consistent with theoretical expectations and prior research findings (Carlson & Perrewe, 1999; Schwarz et al., 2008; Sharma et al., 2007; Zhou & Long, 2004).
- **Sample Size Considerations**: Conduct power analyses or simulation studies to determine the smallest sample size required to detect nonlinear effects with sufficient statistical power. When estimating nonlinear SEM models, researchers should prioritize larger sample sizes in order to obtain robust estimates and reliable model fit (Carlson & Perrewe, 1999; Podsakoff et al., 2003c; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009).
- **Model Evaluation:** Compare different model specifications, including linear and non-linear models, to determine the relative fit and interpretability of various model formulations. Researchers should use model selection criteria and diagnostic tests to determine the most appropriate model for capturing the underlying data structure (Lance et al., 2002; M. Memon et al., 2023; Podsakoff et al., 2003c; Schwarz et al., 2008; Sharma et al., 2007; Zhou & Long, 2004).
- **Sensitivity Analyses:** Conduct sensitivity analyses to determine the robustness of nonlinear SEM results to changes in model specifications or estimation techniques. To ensure the reliability and validity of study findings, researchers can assess the stability of parameter estimates, model fit indices,

and substantive conclusions using various modelling approaches (Podsakoff et al., 2003; Schwarz et al., 2008; Sharma et al., 2007).

Researchers can effectively use nonlinear SEM to investigate common method bias and advance methodologically rigorous empirical research by leveraging the flexibility of these techniques while addressing their inherent challenges through careful theoretical justification, adequate sample size considerations, and rigorous model evaluation.

S.8. Harman's Single-Factor Test Technique

Definition: Harman's Single-Factor Test is a methodological technique that detects common method bias (CMB) in survey research by looking for a single dominant factor in the data. It is based on Frederick Harman's work from the 1960s and assumes that if CMB is prevalent, a single general factor will account for a significant portion of the variation in responses across different survey items (Carlson & Perrewe, 1999; Memon et al., 2023; Podsakoff et al., 2003).

Application: Harman's Single-Factor Test is widely used in organizational and social science research to determine the potential impact of common method bias on study results. Typically, researchers use a principal components analysis (PCA) or exploratory factor analysis (EFA) on the survey items to determine the proportion of variance explained by the first factor. If a single factor accounts for a significant portion of the variance, it indicates the presence of common method bias rather than genuine variability in the constructs being measured (Carlson & Perrewe, 1999; Cooper et al., 2020; Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003).

Strengths:

- **Simplicity:** Harman's Single-Factor Test is simple to implement, making it accessible to researchers with little statistical experience. (Carlson & Perrewe, 1999; Memon et al., 2023; Podsakoff et al., 2003)
- **Quick Screening:** It performs a quick initial screening for common method bias, allowing researchers to identify potential problems early in the research process (Carlson & Perrewe, 1999; Cooper et al., 2020; Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009).

- **Low Cost:** Conducting a PCA or EFA to perform Harman's Single-Factor Test is less expensive than other more sophisticated techniques, making it ideal for studies with limited resources (Carlson & Perrewe, 1999; Cooper et al., 2020; Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003).
- **Diagnostic Tool:** While there is no conclusive evidence of common method bias, a significant single factor warrants further investigation into potential methodological issues and alternative explanations (Carlson & Perrewe, 1999; Cooper et al., 2020; Lance et al., 2002; Memon et al., 2023).

Weaknesses:

- **Limited Diagnostic Power:** Harman's Single-Factor Test has been criticized for having limited diagnostic power and failing to definitively confirm the presence or absence of common method bias. Other factors, such as construct overlap or substantive relationships between variables, may contribute to the emergence of a single dominant factor (Cooper et al., 2020; Lance et al., 2002; Podsakoff et al., 2003; Schwarz et al., 2008; Sharma et al., 2007).
- **Interpretation Challenges:** The results of Harman's Single-Factor Test should be interpreted with caution, as the presence of a dominant factor does not always imply common method bias. Researchers must consider alternative explanations and conduct additional analyses to rule out other potential sources of variation (Cooper et al., 2020; Memon et al., 2023; Podsakoff et al., 2003; Zhou & Long, 2004).
- **Methodological Criticisms:** Some scholars argue that Harman's Single-Factor Test oversimplifies the complexities of common method bias and fails to account for construct multidimensionality and measurement error (Cooper et al., 2020; Memon et al., 2023).

Recommendations for Improvement:

- **Use in Conjunction with Other Techniques**: Researchers should supplement Harman's Single-Factor Test with other CMB detection techniques, such as procedural remedies, a multi-trait multi-method matrix, or structural equation modelling. Integrating multiple methods allows for a more comprehensive assessment of common method bias (Cooper et al., 2020; Lance et al., 2002; Memon et al., 2023).

- **Replication and Validation:** Replicate Harman's Single-Factor Test findings in independent samples or studies to improve the reliability and validity of the outcomes. Cross-validation confirms the stability of the observed factor structure and reduces the possibility of spurious results (Carlson & Perrewe, 1999; Memon et al., 2023; Podsakoff et al., 2003; Zhou & Long, 2004).
- **Contextual Understanding:** When interpreting the results of Harman's Single-Factor Test, keep in mind the research setting's specific context and characteristics. Factors such as sample composition, survey design, and data collection procedures can all influence the presence and magnitude of common method bias (Cooper et al., 2020; Memon et al., 2023; Podsakoff et al., 2003).
- **Sensitivity Analysis:** Conduct sensitivity analyses to determine whether Harman's Single-Factor Test results are robust to changes in model specifications or data preprocessing techniques. Sensitivity analyses help to assess the stability of the findings and alleviate concerns about methodological artifacts (Carlson & Perrewe, 1999; Cooper et al., 2020; Memon et al., 2023; Podsakoff et al., 2003; Sharma et al., 2007; Zhou & Long, 2004).

Overall, while Harman's Single-Factor Test is a useful initial screening tool for detecting potential common method bias in survey data, researchers should use caution when interpreting it and combine it with other complementary techniques to strengthen the validity of their findings.

S.9. Partial Correlation Analysis Technique

Definition: Partial correlation analysis is a statistical technique that evaluates the relationships between variables while accounting for the influence of other variables. It allows researchers to examine the unique relationship between two variables by removing the linear effect of one or more additional variables, thus mitigating the impact of common method bias (CMB) (Carlson & Perrewe, 1999; Chin et al., 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989).

Application: Partial correlation analysis is commonly used in social science, psychology, and other fields to investigate the relationships between variables while controlling for potential confounding factors (Chin et al., 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhou & Long, 2004). In the context of CMB detection, researchers use partial correlation analysis to determine whether the associations between variables are still significant after accounting for shared method variance (Carlson & Perrewe, 1999; Williams et al., 1989; Zhou & Long, 2004).

Strengths:

- **Control for Confounding Variables:** Partial correlation analysis allows researchers to isolate the relationship between two variables while accounting for the influence of other variables. By removing the effects of potential confounders, it aids in distinguishing genuine associations from spurious relationships caused by common method bias (Chin et al., 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023).
- **Quantification of Unique Associations:** This technique quantifies the strength and direction of the relationship between two variables after controlling for the effects of other variables (Chin et al., 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023) It sheds light on the specific contribution of each variable to the relationship, allowing researchers to better understand the underlying mechanisms (Memon et al., 2023; Podsakoff et al., 2003, 2023; Podsakoff & Organ, 1986; Vieluf et al., 2009).
- **Flexibility:** Partial correlation analysis can accommodate multiple independent variables while controlling for their simultaneous influence on the dependent variable. It provides flexibility in modelling complex relationships between variables, making it appropriate for a wide range of research designs and analytical scenarios (Carlson & Perrewe, 1999; Chin et al., 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023).

Weaknesses:

- **Assumption of Linearity**: Partial correlation analysis assumes linear relationships between variables, which may not always be valid in real-world data. This technique may fail to capture nonlinear associations adequately, resulting in biased estimates (Carlson & Perrewe, 1999; Chin et al., 2012; Memon et al., 2023; Williams et al., 1989; Zhou & Long, 2004).
- **Potential for Mis-specification:** The results of a partial correlation analysis may be skewed if the variables used are not comprehensive or if relevant confounding variables are left out. Mis-specification of the model can skew

estimates of the associations of interest (Podsakoff et al., 2003, 2023; Vieluf et al., 2009; Williams et al., 1989; Zhou & Long, 2004).

- **Data Requirements:** To produce reliable estimates from partial correlation analysis, a large sample size is required, especially when controlling for multiple variables. Small sample sizes may result in unreliable estimates and inflated Type I error rates (Chin et al., 2012; Memon et al., 2023; Zhou & Long, 2004).

Recommendations for Improvement:

- **Model Sensitivity Analyses:** Conduct sensitivity analyses to determine the robustness of the results to changes in model specifications, such as the addition of new control variables or functional forms. Sensitivity analyses assist in identifying potential sources of bias and ensuring the reliability of the findings (Vieluf et al., 2009; Williams et al., 1989; Zhou & Long, 2004).
- **Consider Nonlinear Relationships:** Investigate the possibility of nonlinear relationships between variables using different analytical techniques, such as polynomial regression or nonparametric methods. Supplementing partial correlation analysis with nonlinear modelling techniques can provide a more complete understanding of the data (Carlson & Perrewe, 1999; Vieluf et al., 2009; Williams et al., 1989; Zhou & Long, 2004).
- **Validation Studies:** Validate the results of partial correlation analysis in independent samples or via replication studies. Confirming the robustness of the results across different datasets improves the generalizability and reliability of the findings (Carlson & Perrewe, 1999; Vieluf et al., 2009; Williams et al., 1989; Zhou & Long, 2004).
- **Account for Measurement Error**: Include measures to account for measurement errors in the variables used in the analysis. Using reliable and valid measures lowers the risk of bias and increases the validity of the results (Carlson & Perrewe, 1999; Vieluf et al., 2009; Williams et al., 1989; Zhou & Long, 2004).

To summarize, partial correlation analysis is an effective tool for investigating relationships between variables while controlling for confounding factors such as common method bias. However, researchers should be aware of its assumptions and limitations, and use complementary methods to ensure the robustness and validity of their results (Carlson & Perrewe, 1999; Chin et al., 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023; Podsakoff & Organ, 1986; Vieluf et al., 2009; Williams et al., 1989; Zhou & Long, 2004).

S.10. Correlation Analysis of Residuals Technique

Definition: The correlation analysis of residuals is a statistical technique used to detect common method bias (CMB) by examining the correlations between variable residuals after accounting for the effects of other variables in a regression model. (Carlson & Perrewe, 1999; Chin et al., 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023; Vieluf et al., 2009; Zhou & Long, 2004). This technique seeks to identify systematic patterns of residual correlations, which could indicate the presence of shared method variance (Williams et al., 1989; Zhou & Long, 2004).

Application: In research settings where common method bias is a concern, correlation analysis of residuals can be used to determine whether residual correlations exist above what would be expected by chance. (Carlson & Perrewe, 1999; Chin et al., 2012; Memon et al., 2023) By regressing variables of interest on control variables or other relevant factors and then examining the residual correlations, researchers can determine whether method-related factors are influencing the observed relationships (Podsakoff & Organ, 1986; Vieluf et al., 2009; Williams et al., 1989; Zhou & Long, 2004).

Strengths:

- **Direct Assessment of Common Method Bias:** The correlation analysis of residuals examines the residual correlations between variables after controlling for other factors, providing a specific assessment of the potential influence of common method bias on the relationships of interest. (Vieluf et al., 2009; Williams et al., 1989; Zhou & Long, 2004)
- **Utilizes Existing Regression Models**: This technique makes use of commonly used regression models in research, allowing researchers to leverage existing data and analyses without requiring any additional experimental manipulations (Chin et al., 2012; Memon et al., 2023; Podsakoff et al., 2003c, 2023; Podsakoff & Organ, 1986; Vieluf et al., 2009; Zhou & Long, 2004).
- **Flexible and Interpretable:** Correlation analysis of residuals is simple to implement and interpret, making it accessible to researchers from many disciplines. It provides flexibility in modelling complex relationships and can

handle multiple variables at the same time (Carlson & Perrewe, 1999; Chin et al., 2012; M. Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhou & Long, 2004).

Weaknesses:

- **Assumption of Linearity and Independence:** Correlation analysis of residuals, like other regression-based techniques, assumes that variables have linear relationships and that residuals are independent. Violations of these assumptions may jeopardize the validity of the findings (Vieluf et al., 2009; Williams et al., 1989; Zhou & Long, 2004).
- **Limited to Linear Associations:** This technique may fail to capture nonlinear associations between variables, potentially missing important relationships that could be influenced by common method bias (Carlson & Perrewe, 1999; Chin et al., 2012; Memon et al., 2023; Podsakoff et al., 2003).
- **Dependence on Model Specification:** The results of residual correlation analysis can vary depending on the control variables and regression specifications used. Inadequate control for relevant factors may result in biased residual correlation estimates (Chin et al., 2012; Memon et al., 2023; Podsakoff et al., 2003; Zhou & Long, 2004).

Recommendations for Improvement:

- **Sensitivity Analyses:** Conduct sensitivity analyses to determine the robustness of the results to changes in model specifications, such as the addition of new control variables or functional forms. Sensitivity analyses assist in identifying potential sources of bias and ensuring the reliability of the findings (Chin et al., 2012; Memon et al., 2023; Podsakoff et al., 2003; Zhou & Long, 2004).
- **Consider Nonlinear Relationships:** Investigate the possibility of nonlinear relationships between variables using different analytical techniques, such as polynomial regression or nonparametric methods. Combining correlation analysis of residuals with nonlinear modelling approaches can provide a more comprehensive understanding of the data (Chin et al., 2012; Memon et al., 2023; Podsakoff et al., 2003; Zhou & Long, 2004).
- **Validation Studies:** Validate the results of residual correlation analysis using independent samples or replication studies. Confirming the robustness of the

results across different datasets improves the generalizability and reliability of the findings (Carlson & Perrewe, 1999; Chin et al., 2012; Memon et al., 2023).

- **Account for Measurement Error:** Include measures to account for measurement errors in the variables used in the analysis. Using reliable and valid measures lowers the risk of bias and increases the validity of the results (Carlson & Perrewe, 1999; Chin et al., 2012; Memon et al., 2023).

To summarize, residual correlation analysis is an effective technique for detecting common method bias in regression-based analyses. While it provides a simple and interpretable method for detecting potential sources of bias, researchers should be aware of its assumptions and limitations, and use complementary methods to ensure the robustness and validity of their findings.

S.11. Multilevel Modelling Technique

Definition: Multilevel modelling (MLM), also known as hierarchical linear modelling (HLM) or mixed-effects modelling, is a statistical technique used to analyse data with nested structures, where individuals are grouped within higher-level units (e.g., students within schools, employees within organizations) (Carlson & Perrewe, 1999; Chin et al., 2012; Memon et al., 2023; Podsakoff et al., 2023). MLM allows for the examination of both within-group (individual) and between-group (contextual) effects in common method bias (CMB) research while accounting for the data's hierarchical structure (Carlson & Perrewe, 1999; Chin et al., 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023; Podsakoff & Organ, 1986).

Application: Multilevel modelling is especially useful in research contexts where common method bias can occur due to the nested nature of the data. MLM allows researchers to disentangle within-group and between-group variance, resulting in a more nuanced understanding of the underlying processes. MLM can be used in CMB research to assess how method-related factors influence both individual-level outcomes and higher-level constructs (Carlson & Perrewe, 1999; Chin et al., 2012; Memon et al., 2023; Williams et al., 1989).

Strengths:

- **Hierarchical Structure**: MLM recognizes the data's hierarchical nature, allowing for the investigation of effects at multiple levels of analysis. This method is ideal for studying CMB in nested datasets, in which individuals are nested within higher-level units (Carlson & Perrewe, 1999; Chin et al., 2012; Memon et al., 2023; Podsakoff et al., 2023; Vieluf et al., 2009).

- **Partitioning Variance:** MLM divides the total variance in the outcome variable into within-group and between-group components, allowing for the identification of both individual and contextual influences. This variance partitioning helps to distinguish between genuine effects and method-related biases (Carlson & Perrewe, 1999; Chin et al., 2012; Memon et al., 2023; Podsakoff et al., 2023).
- **Accounting for Nesting:** By explicitly modelling the data's nesting structure, MLM accounts for the non-independence of observations within groups, lowering the risk of biased estimates and inflated Type I error rates (Chin et al., 2012; M. Memon et al., 2023; Podsakoff et al., 2023).
- **Flexibility in Model Specification:** MLM enables the use of random effects to capture heterogeneity across groups, as well as fixed effects to investigate the effects of predictors at various levels. This flexibility allows researchers to create complex models that account for multiple sources of variation (Carlson & Perrewe, 1999; Memon et al., 2023; Podsakoff et al., 2023; Zhou & Long, 2004).

Weaknesses:

- **Complexity:** MLM can be conceptually and computationally challenging, particularly when dealing with large and nested datasets. Researchers may need specialized training and software to correctly implement and interpret multilevel models (Carlson & Perrewe, 1999; Memon et al., 2023; Podsakoff et al., 2003c, 2023; Zhou & Long, 2004).
- **Sample Size Requirements:** MLM requires larger sample sizes than traditional regression models, especially when estimating random effects at multiple levels. Inadequate sample sizes can result in unstable parameter estimates and reduced statistical power (Chin et al., 2012; M. Memon et al., 2023; Podsakoff et al., 2003, 2023; Podsakoff & Organ, 1986).
- **Assumptions:** MLM, like any other statistical technique, is predicated on certain assumptions, such as linearity, normality, and residual homoscedasticity. Violations of these assumptions can have an impact on the estimates' validity and reliability (Carlson & Perrewe, 1999; Chin et al., 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023).

Recommendations for Improvement:

- **Sample Size Considerations:** Prioritize obtaining adequate sample sizes, especially at the higher levels, to ensure the findings' reliability and generalizability. Conduct power analyses to determine the minimum sample size needed to detect significant effects (Carlson & Perrewe, 1999; Chin et al., 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023).
- **Model Simplification:** Given the complexity of MLM, consider simplifying the model structure by beginning with a simpler model and gradually increasing complexity based on theoretical considerations and model fit indices (Carlson & Perrewe, 1999; Chin et al., 2012; Memon et al., 2023).
- **Robust Estimation Techniques:** Investigate robust estimation techniques, such as Bayesian estimation or robust standard errors, to reduce the impact of distributional assumption violations and outliers (Podsakoff et al., 2003, 2023; Podsakoff & Organ, 1986; Zhou & Long, 2004).
- **Sensitivity Analyses:** Conduct sensitivity analyses to determine how robust the results are to various model specifications and assumptions. Examine the stability of parameter estimates and model fit under different specifications (Memon et al., 2023; Podsakoff et al., 2003, 2023).

Multilevel modelling is a powerful technique for investigating common method bias in nested datasets, allowing researchers to disentangle within-group and between-group effects while accounting for the data's hierarchical structure. While it has many benefits, researchers should be aware of its complexities and assumptions, and take steps to ensure the validity and reliability of their findings.

S.12. Multigroup Analysis Technique

Definition: Multigroup analysis is a statistical technique that compares structural models in multiple groups of a dataset. It enables researchers to determine whether the relationships between variables differ significantly across subgroups such as gender, age, and cultural background. In the context of common method bias (CMB) research, multigroup analysis can help determine whether the strength or nature of relationships between constructs varies across different methodological conditions or respondent groups (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020).

Application: Multigroup analysis is frequently used in CMB research to determine whether the presence of common method bias affects the relationships between variables differently for different subgroups. For example, researchers could look into whether the strength of the relationship between predictor and outcome variables differs between groups with high and low method bias. Multigroup analysis sheds light on the findings' robustness and generalizability by comparing model fit indices and parameter estimates across groups. (Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020)

Strengths:

- **Detection of Bias:** Multigroup analysis enables researchers to detect and quantify common method bias by comparing structural model fit across groups with and without methodological manipulations. Significant differences in model fit indices (such as the chi-square difference test and RMSEA) between unconstrained and constrained models may indicate bias (Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020). **Assessment of Invariance:** Multigroup analysis makes it easier to assess measurement and structural invariance across groups, ensuring that variable relationships remain consistent across subgroups. This contributes to the validity and generalizability of the research findings (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989).
- **Identification of Moderators:** Multigroup analysis allows researchers to identify potential moderators who influence the strength or direction of relationships between constructs. By examining subgroup differences, researchers can uncover important nuances in data that may have gone unnoticed in aggregate analyses (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020).

Weaknesses:

- **Assumption of Equivalence:** Multigroup analysis is based on the assumption of measurement invariance between groups, which may not always be true in practice. Violations of this assumption can result in biased parameter estimates and incorrect conclusions about group differences (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).

- **Complexity of Interpretation:** Multigroup analysis results can be difficult to interpret, especially when multiple groups and model constraints are being examined at the same time. Researchers must carefully interpret model fit indices and parameter estimates before drawing meaningful conclusions about subgroup differences (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2023; Zhonglin & Tang, 2020).
- **Sample Size Considerations:** To ensure the reliability and stability of the estimates in multigroup analysis, sample sizes in each subgroup must be large enough. Small sample sizes within specific groups may result in unreliable parameter estimates and low statistical power (Memon et al., 2023; Podsakoff et al., 2003c, 2023; Zhonglin & Tang, 2020).

Recommendations for Improvement:

- **Robust Measurement Development:** Prioritize the creation of reliable measurement instruments that show measurement invariance across groups or methodological conditions. Conduct pre-tests and pilot studies to ensure that the measures are valid and reliable (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020).
- **Sensitivity Analyses:** Conduct sensitivity analyses to determine the results' robustness to various model specifications and assumptions. Investigate alternative model constraints and compare the fit of unconstrained and constrained models to assess the stability of the results (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).
- **Careful Interpretation**: When interpreting multigroup analysis results, proceed with caution, paying close attention to model fit indices, parameter estimates, and substantive implications. Consider performing post-hoc analyses or supplementary tests to investigate significant subgroup differences (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989).
- **Replication and Validation:** Validate multigroup analysis findings by conducting replication studies with independent samples or in different contexts. Replicating the results in different settings improves the generalizability and reliability of the findings (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020).

Multigroup analysis is a useful technique for investigating common method bias in CMB research because it compares structural models across different subgroups. While this approach has several advantages for detecting bias and identifying moderators, researchers must carefully consider the assumptions, complexities, and sample size requirements to ensure the validity and reliability of their findings (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020).

S.13. Latent Growth Curve Modelling Technique

Definition: Latent growth curve modelling (LGCM) is a statistical technique for analysing longitudinal data that simulates individual change trajectories over time. In the context of common method bias (CMB) research, LGCM enables researchers to investigate how constructs of interest evolve or change over multiple measurement occasions while accounting for measurement error and bias (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).

Application: LGCM is used in CMB research to assess the stability and change in constructs of interest over time while accounting for common method bias. Researchers can simulate the growth trajectories of latent variables over multiple waves of data collection and see if the observed patterns differ systematically across methodological conditions or groups (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020).

Strengths:

- **Longitudinal Analysis:** LGCM enables researchers to analyse longitudinal data by capturing intra-individual changes over time. Modelling growth trajectories allows researchers to identify patterns of change, such as linear or nonlinear growth, and determine whether these patterns are influenced by common method bias (Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020).
- **Accounting for Measurement Error:** LGCM accounts for measurement error by modelling latent variables that represent the true underlying constructs of interest. LGCM provides more accurate estimates of the relationships between constructs while also reducing the impact of common method bias on the results (Lance et al., 2002; Memon et al., 2023; Zhonglin & Tang, 2020).
- **Identification of Change Mechanisms:** LGCM allows researchers to identify potential mechanisms driving changes in constructs over time. By investigating

the effects of predictors on growth parameters (e.g., intercept, slope), researchers can identify factors that contribute to changes in constructs and investigate how methodological factors may influence these mechanisms (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023).

Weaknesses:

- **Complexity of Analysis:** LGCM requires complex modelling procedures, especially when analysing data from multiple measurement waves and investigating construct interactions. Researchers may need advanced statistical knowledge and software to accurately specify and estimate models (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020).
- **Data Requirements:** To accurately model growth trajectories, LGCM requires longitudinal data collected at multiple time points. Inadequate data points or uneven spacing between measurements may limit the ability to capture meaningful patterns of change and estimate accurate growth parameters (Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020).
- **Assumptions of Linearity:** LGCM assumes that latent variable growth trajectories are linear or can be accurately approximated by linear functions. Linear models may fail to accurately capture nonlinear patterns of change, resulting in biased parameter estimates and misinterpretation of results (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020).

Recommendations for Improvement:

- **Robust Model Specification:** Ensure that LGCMs are properly specified in order to capture the complexity of longitudinal data and the dynamics of change in the constructs of interest. Consider alternative model specifications, such as piecewise or quadratic growth models, to account for nonlinear patterns of change (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020).
- **Sensitivity Analyses:** Conduct sensitivity analyses to determine the results' robustness to various model specifications and assumptions. Investigate alternative model constraints and compare the fit of competing models to

assess the stability of the results (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023).

- **Data Quality Assurance:** Implement rigorous data collection procedures to reduce measurement errors and ensure longitudinal data reliability. To increase the validity of the findings, collect data using validated measurement instruments and standardised protocols (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003c, 2023).
- **Sample Size Considerations:** Ensure that the sample size is large enough to accurately estimate the parameters of interest while maintaining adequate statistical power. Conduct power analyses to determine the minimum sample size needed to detect meaningful effects and account for potential attrition in longitudinal studies (Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).

Latent growth curve modelling is an effective technique for analysing longitudinal data and investigating changes in constructs of interest over time in CMB research. While it has several advantages in terms of capturing longitudinal dynamics and controlling for measurement error, researchers must carefully consider the analysis's complexity, data requirements, and model assumptions to ensure valid and reliable results.

S.14. Structural Equation Modelling Technique

Definition: Structural Equation Modeling (SEM) is a comprehensive statistical approach that tests and estimates complex relationships between latent (unobserved) and observed variables (Memon et al., 2023; Podsakoff et al., 2003, 2023). In the context of common method bias (CMB) research, SEM enables researchers to evaluate both the measurement model (relationships between observed indicators and latent constructs) and the structural model (relationships among latent constructs) while controlling for measurement error and potential bias (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003c, 2023).

Application: SEM is used in CMB research to evaluate the validity of measurement instruments, determine the extent of common method bias, and assess the relationships between constructs of interest. Researchers create a measurement model to represent the relationships between observed indicators and latent constructs, as well as a structural model to test hypotheses about latent construct relationships. By combining measurement and structural models, SEM allows researchers to investigate the underlying processes that drive observed relationships and identify sources of bias (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).

Strengths:

- **Integration of Measurement and Structural Models:** SEM enables the simultaneous estimation of measurement and structural models, resulting in a comprehensive assessment of both construct validity and structural relationships. This integration allows researchers to investigate how common method bias affects the relationships between constructs while accounting for measurement error (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020).
- **Accounting for Measurement Error:** SEM accounts for measurement error by modelling latent constructs, which represent the actual underlying variables of interest. By distinguishing between latent constructs and observed indicators, SEM enables researchers to obtain more accurate estimates of construct relationships while reducing the impact of measurement error on results (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003; 2023; Williams et al., 1989; Zhonglin & Tang, 2020).
- **Flexibility in Model Specification:** SEM provides flexibility in defining complex models with multiple latent constructs and observed indicators. To investigate the underlying mechanisms and nuances of construct relationships, researchers can test a variety of hypotheses and model specifications, such as mediation, moderation, and latent variable interactions (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).
- **Assessment of Model Fit:** SEM uses rigorous statistical tests and fit indices to determine the adequacy of hypothesized models. Researchers can evaluate how well the specified models fit the observed data and then make informed decisions about model refinement and modification to improve model fit (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).

- **Handling Missing Data:** SEM frameworks, such as Full Information Maximum Likelihood (FIML) estimation, can include cases with missing data, maximizing the use of available information and reducing potential biases caused by data loss (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020).

Weaknesses:

- **Complexity of Analysis:** SEM involves complex modelling procedures that necessitate advanced statistical knowledge as well as expertise in model specification and interpretation. Misinterpretation of SEM results or misspecification of models can result in biased parameter estimates and incorrect conclusions (Lance et al., 2002; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020).
- **Sample Size Requirements:** SEM typically necessitates larger sample sizes in order to accurately estimate parameters and achieve adequate statistical power, especially for models with numerous parameters or complex structures. Insufficient sample sizes can result in underpowered analyses, unstable estimates, and inaccurate model fit evaluations (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020).
- **Assumptions of Normality:** SEM assumes multivariate normality of observed variables and residuals, which may not be applicable to all datasets. Violations of this assumption may affect parameter estimates, standard errors, and model fit indices, potentially biasing the analysis's results and conclusions (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989).

Recommendations for Improvement:

- **Model Sensitivity Analyses:** Conduct sensitivity analyses to determine the robustness of SEM results under various model specifications and assumptions. Examine alternative model constraints, measurement configurations, or estimation methods to determine the stability of the findings (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989).
- **Advanced Training and Consultation:** Seek advanced training in SEM methodologies or consult with industry experts to ensure proper model

specification, estimation, and interpretation. Collaboration with methodological experts can help reduce errors and improve the rigor of SEM analyses (Memon et al., 2023; Podsakoff et al., 2003, 2023).

- **Data Quality Assurance:** Implement stringent data collection and preprocessing procedures to reduce measurement error and ensure the accuracy of the observed indicators. Conduct validity and reliability tests on measurement instruments to confirm their suitability for SEM analysis (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).
- **Sample Size Considerations:** SEM analyses should be adequately powered by ensuring sufficient sample sizes based on model complexity and desired statistical power level. Conduct power analyses to determine the minimum sample size needed to detect meaningful effects while accounting for potential model complexity (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).
- **Model Refinement and Modification:** Use model fit indices and diagnostic tests to pinpoint areas of model misfit or parameter instability. Consider refining the model iteratively, such as adding or removing paths, covariances, or latent variables, to improve the SEM's overall fit and interpretability (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).

Structural Equation Modelling (SEM) is an effective and versatile technique for investigating complex relationships between latent constructs and observed variables in CMB research. While SEM has numerous advantages in terms of integrating measurement and structural models and providing comprehensive insights into underlying processes, researchers must carefully consider the complexity of the analysis, sample size requirements, and model assumptions in order to ensure valid and reliable results.

S.15. Confirmatory Factor Analysis Technique

Definition: Confirmatory Factor Analysis (CFA) is a statistical technique used to test and validate the underlying structure of a set of observed variables (indicators). It confirms the presence of hypothesized latent constructs (factors). In common method bias (CMB) research, CFA is used to evaluate the convergent and discriminant validity of measurement instruments as well as to identify potential sources of bias (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020).

Application: CFA is used in CMB research to assess how well-observed variables measure the intended latent constructs and how these constructs differ from other related constructs. Researchers formulate a priori hypotheses about the measurement model's factor structure and then test whether the observed data fit the hypotheses. CFA allows researchers to assess the reliability and validity of measurement instruments while also detecting potential method effects by estimating factor loadings, latent factor variances, covariances, and error variances (Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989).

Strengths:

- **Evaluation of Measurement Model:** CFA enables researchers to assess the goodness-of-fit between observed data and hypothesized measurement models. Fit indices such as the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA) can be used to assess how well the specified model reproduces the observed covariance matrix and identify areas of model misfit (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).
- **Assessment of Convergent and Discriminant Validity:** CFA aids in the evaluation of convergent validity by examining the strength and significance of factor loadings, which represent the relationships between observed indicators and latent variables. Furthermore, researchers can evaluate discriminant validity by comparing the squared correlations between latent factors and their confidence intervals (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).
- **Identification of Model Misspecification:** CFA enables researchers to identify and correct potential model misspecifications, such as omitted paths, correlated errors, and factor indeterminacy. Researchers can refine the measurement model and improve its fit to the data by iteratively modifying it in response to modification indices and theoretical considerations (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).

- **Control for Common Method Bias:** CFA offers a framework for addressing common method bias by explicitly modelling method effects or including method-related variables as covariates in the measurement model. Researchers can isolate and reduce the impact of common method bias on results by distinguishing between method-related variance and variance due to the constructs of interest (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).
- **Incorporation of Multigroup Analysis:** CFA supports multigroup analysis, which enables researchers to compare the measurement model across various subgroups (e.g., demographic groups, cultural contexts). By testing for measurement invariance, researchers can determine whether the factor structure and item loadings are consistent across groups, improving the measurement model's generalizability and validity (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).

Weaknesses:

- **Assumption of Linearity:** CFA assumes linear relationships between observed indicators and latent constructs, which may not be valid for all datasets or constructs. Violations of this assumption can result in biased parameter estimates and inaccurate assessments of model fit, especially when nonlinear relationships exist (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).
- **Sensitivity to Model Specification:** CFA results may be sensitive to measurement model specification, such as indicator selection, factor rotation method, and model constraints (Memon et al., 2023; Podsakoff et al., 2003, 2023). Inappropriate model specifications or constraints can result in poor model fit, misinterpretation of factor loadings, and incorrect conclusions about construct validity (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023).
- **Limited Causal Inference:** CFA is primarily a confirmatory technique used to validate the measurement model and assess construct validity. While CFA can identify associations between observed variables and latent constructs, it lacks direct evidence of causality or temporal precedence, making it ineffective for making causal inferences or testing causal hypotheses (Lance et al., 2002;

Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).

- **Sample Size Requirements:** CFA typically necessitates larger sample sizes to achieve stable parameter estimates and adequate statistical power, especially for models with multiple indicators or factors. Insufficient sample sizes can lead to underpowered analyses, inflated standard errors, and unreliable model fit estimates (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).
- **Potential for Misspecification Bias:** Despite its confirmatory nature, CFA is subject to misspecification bias if the hypothesized measurement model does not accurately reflect the data's underlying structure. Misspecification of factor loadings, correlated errors, or omitted factors can result in biased parameter estimates and construct validity assessments (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).

Recommendations for Improvement:

- **Model Sensitivity Testing:** Conduct sensitivity analyses to determine the robustness of CFA results under various model specifications, such as alternative factor structures, indicator sets, and estimation methods. Compare the fit of competing models and assess the consistency of parameter estimates across model configurations (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989).
- **Theory-Driven Model Specification:** Measurement model specifications should be based on relevant theory, prior research, and conceptual considerations. Ensure that the indicators chosen adequately to represent the latent constructs of interest and avoid overfitting the model by including unnecessary or redundant variables (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Zhonglin & Tang, 2020).
- **Sample Size Planning**: Ensure sufficient sample sizes based on the model's complexity and desired statistical power when conducting CFA analyses. Perform power analyses to determine the minimum sample size required to detect meaningful effects while accounting for model complexity (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).

- **Model Modification Procedures:** Use diagnostic tools like modification indices, standardized residuals, and fit indices to pinpoint areas of model misfit and potential sources of bias. Consider iteratively modifying the model in response to empirical evidence and theoretical insights to improve the CFA's overall fit and interpretability (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023; Williams et al., 1989; Zhonglin & Tang, 2020).
- **Validation Strategies:** To corroborate the CFA findings, use validation strategies such as cross-validation, replication studies, and convergent/divergent validity assessments. Compare CFA results to alternative measurement models or independent measures to increase confidence in the measurement instruments' validity and reliability (Lance et al., 2002; Memon et al., 2023; Podsakoff et al., 2003, 2023).

Confirmatory Factor Analysis (CFA) is an effective method for assessing the validity and reliability of measurement instruments in CMB research. Despite its limitations and challenges, CFA provides a systematic method for assessing construct validity, controlling common method bias, and improving the rigor of measurement model testing. Researchers can use CFA's strengths to advance understanding in their respective fields by carefully considering model specifications, performing sensitivity analyses, and implementing validation strategies.

Summary CMB Techniques

Following a discussion of various methodological and statistical techniques for detecting and mitigating common method bias (CMB), it is clear that no single technique is universally applicable or superior in all research contexts. Instead, researchers should take a comprehensive and nuanced approach that incorporates multiple techniques to address the multifaceted nature of CMB. The following is a summary of the key methodologies and statistical techniques discussed, as well as recommendations on how to choose the most appropriate technique:

Methodological Techniques:

- **Blinding Techniques**: To reduce response bias, implement procedures that blind participants or raters to the study hypotheses and conditions.
- **Randomized Response Technique:** To protect respondents' privacy and reduce social desirability bias, use indirect questioning methods.

- **Counterbalancing:** To account for sequence effects, use counterbalancing procedures to systematically vary the order of presentation of items or conditions across participants.
- **Procedural Remedies:** To reduce participant response bias, implement procedural safeguards such as anonymity, confidentiality, and informed consent.
- **Scale Anchoring**: To standardize response options and reduce response bias, use fixed-scale endpoints or anchor points.
- **Triangulation of Data Sources:** To cross-validate findings and reduce method bias, use multiple data sources (for example, self-report, observer ratings, and archival records).
- **Longitudinal Designs:** Collect data at multiple time points to assess response changes and account for common method bias caused by single-point measurements.
- **Control Variables:** Control variables should be included in statistical analyses to account for potential confounding factors and reduce bias.
- **Multimethod Approach:** Use multiple measurement methods (e.g., self-report, behavioural observation) to evaluate constructs from various perspectives and reduce method bias.
- **Measurement Validation**: Validate measurement instruments against established criteria (e.g., reliability, validity) to ensure accurate and reliable construct measurement.

Statistical Techniques:

- **Confirmatory Factor Analysis (CFA):** Use CFA to validate the factor structure of measurement instruments and to assess construct validity.
- **Multiple Informant Approach:** To triangulate findings and reduce method bias, collect data from multiple sources (for example, self-reports and peer ratings).
- **Item Order Randomization:** Randomize the order of survey items to account for order effects and reduce response bias.
- **Multitrait-Multimethod Matrix:** Use the MTMM method to assess the convergent and discriminant validity of measurement instruments.

- **Common Latent Factor Approach:** In structural equation models, use a common latent factor to account for shared method variance.
- **Cross-validation:** Validate measurement models on multiple samples or datasets to determine their generalizability and replicability.
- **Bayesian Techniques:** Apply Bayesian methods to estimate parameters and evaluate model fit while accounting for uncertainty.
- **Bootstrapping:** To estimate sampling distributions and confidence intervals for model parameters, apply bootstrapping techniques.
- **Nonlinear Structural Equation Modelling:** Use nonlinear SEM to model complex relationships while accounting for nonlinear effects.
- **Latent Growth Curve Modelling:** LGCM is used to analyse longitudinal data and examine growth trajectories while controlling for method bias.

Recommendations for Selecting Techniques:

- **Understand the Research Context:** When selecting techniques, keep in mind your specific research objectives, constructs of interest, and methodological constraints. Aligning technique selection with specific research objectives, constructs, and methodological constraints is critical for ensuring methodological alignment with research goals (Hair et al., 2010).
- **Triangulate Evidence:** Combine multiple techniques (methodological and statistical) to corroborate findings and improve the validity of results. Using methodological and statistical techniques to triangulate evidence improves the credibility and robustness of findings, a practice widely advocated in research methodology (Memon et al., 2023).
- **Evaluate Trade-offs**: Evaluate each technique's strengths, weaknesses, and practical implications in light of the research context and goals. Considering the strengths, weaknesses, and practical implications of each technique assists in making informed decisions about their application, a principle emphasized in the literature on research methodology (MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).
- **Consult Existing Literature:** Examine previous research in the field to identify commonly used techniques and best practices for dealing with CMB. Drawing on previous research in the field provides valuable insights into commonly used

techniques and best practices for dealing with CMB, supporting evidence-based decision-making in research methodology (Memon et al., 2023).

- **Pilot Testing:** Before implementing selected techniques on a larger scale, conduct pilot studies or pretests to assess their feasibility and effectiveness. Pilot testing enables researchers to assess the feasibility and effectiveness of chosen techniques before full implementation, minimizing errors and refining procedures, as advocated in the literature (Podsakoff et al., 2003; Podsakoff & Organ, 1986; Williams et al., 1989).
- **Iterative Approach:** Iterate between data collection, analysis, and technique refinement to ensure that results are valid and reliable. Using an iterative approach that involves refining techniques based on ongoing data collection and analysis ensures the validity and reliability of results, aligning with the principles of continuous improvement in research methodology (Lance et al., 2002; Mackenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003).

Researchers can detect and mitigate common method bias in their studies by taking a systematic and integrative approach that combines methodological rigor and statistical sophistication. It is critical to tailor the technique selection to the specific needs of each research context, as well as to critically evaluate each approach's strengths and limitations. Collaboration among methodologists, statisticians, and domain experts can improve the robustness and validity of research findings in addressing common method biases (Cruz, 2022; Jordan & Troth, 2020c; Kock et al., 2021c; Kock, 2017; Lance et al., 2002; MacKenzie & Podsakoff, 2012; Memon et al., 2023; Podsakoff et al., 2003, 2023; Podsakoff & Organ, 1986; Schwarz et al., 2008; Sharma et al., 2007; Vieluf et al., 2009; Williams et al., 1989; Zhang et al., 2022; Zhonglin & Tang, 2020; Zhou & Long, 2004).

4.5.3. CMB Technique - Unique Gap

Expanding the literature scope to include empirical research that does not meet the initial screening criteria is critical for ensuring a thorough examination of common method bias (CMB) and its implications. Previous research has emphasized the significance of thorough literature reviews in understanding the complexities of CMB (e.g., Podsakoff et al., 2003; Lindell & Whitney, 2001). According to scholars like Tranfield et al., (2003) and Grant & Booth., (2009), by considering a broader range of empirical studies, researchers can identify gaps, contradictions, and emerging trends in the literature. Furthermore, incorporating diverse empirical research allows for a deeper exploration of the practical implications and real-world applications of addressing CMB, aligning with Gough et al., (2017) recommendations for evidence-based analysis. Overall, this inclusive approach promotes a more comprehensive understanding of CMB while also increasing the relevance and applicability of research findings, as discussed by Petticrew and Roberts., (2006) in the context of systematic literature reviews.

The author took the view of expanding the literature scope to also review empirical research conducted by other authors which did not meet the screening criteria, and the following has been discovered:

In a survey data research study, there is an element of the data that represents factors that influence all items similarly as in “an average,” as well as an element of the data that embodies factors that are interested in the individual items in the data. This results in a situation where the respondent's ratings are a composite of all the evaluations, which produces both an overall rating or perspective and a different perception of each item separately. As soon as an average is considered, this creates the introduction of a component that is common to all items.

As a point of departure in understanding the problem that this study seeks to resolve, an understanding of univariate and multivariate analysis is key.

A single variable is the subject of a univariate analysis, which also looks at its distribution, summary statistics, and connections to other variables. It entails the analysis and interpretation of data from just one dimension or viewpoint. Calculating means, medians, and standard deviations, doing chi-square or t-tests, and producing frequency distributions or histograms are a few examples of univariate analysis approaches (Hair et al., 2010; Tabachnick & Fidell, 2007).

On the other hand, multivariate analysis examines two or more variables concurrently to comprehend their linkages and patterns. It considers how different variables interact and looks for intricate connections that univariate analysis can miss. Multiple cluster analysis, structural equation modelling, factor analysis, and regression analysis are a few examples of multivariate analytic approaches (Singh, 2013).

Multivariate analysis is applicable in the setting of factor analysis. A set of observed variables' underlying latent factors are sought after using factor analysis. To find common dimensions or factors that account for their covariation, it studies the interactions between a number of observed variables. Factor analysis offers insights into the underlying structure of the data and aids researchers in understanding the underlying constructs or dimensions being assessed by taking into account the joint behaviour of many variables (Sing , 2013).

To find the underlying latent factors, factor analysis analyses a number of variables at once, making it a multivariate technique. Due to the fact that univariate analysis, which focuses on a single variable, does not take into consideration the relationships between other variables, factor analysis cannot be performed using this method (Hair et al., 2010; Singh, 2013; Tabachnick & Fidell, 2007).

Each observation or analytical unit in multivariate data is described by a set of values spanning various variables. These factors might be continual (e.g., height, age), categorical (e.g., education level, gender), or ordinal in nature (e.g., Likert scale ratings). A matrix or data table can be used to display multivariate data, where each row corresponds to a single individual and each column to a single variable (Tabachnick & Fidell, 2007).

To investigate, analyse, and interpret correlations, patterns, and dependencies among the variables, multivariate data analysis techniques are used. These methods include, but are not limited to, factor analysis, structural equation modelling (SEM), cluster analysis, multivariate regression analysis, principal component analysis (PCA), and multivariate analysis of variance (MANOVA) (Hair et al., 2010; Singh, 2013; Tabachnick & Fidell, 2007).

When analysing multivariate data, researchers might find intricate connections and patterns that would not be seen when looking at the variables separately. By taking into account several variables at once, researchers can develop a more thorough understanding of the phenomenon they are studying and come to more reliable conclusions and predictions (Hair et al., 2010; Singh, 2013; Tabachnick & Fidell, 2007).

Studying connections between customer preferences, analysing the effects of numerous independent variables on an outcome, looking at patterns of response across numerous survey items, identifying latent factors underlying a set of observed variables, and exploring clusters or groups within a dataset based on various characteristics are examples of common applications for the analysis of multivariate data (Hair et al., 2010; Singh, 2013; Tabachnick & Fidell, 2007).

Multivariate data analysis, in general, offers a solid foundation for comprehending the relationships and complexities included in datasets containing numerous variables, allowing researchers to reach more insightful and insightful findings.

We can therefore deduce that, while multivariate analysis involves the simultaneous examination of numerous variables to understand their interrelationships, univariate analysis concentrates on a single variable and studies it independently. Multivariate analysis is useful and required to examine the relationships between the observable variables in factor analysis, which seeks to reveal latent factors.

It is typical practise in factor analysis to average item responses to derive a mean value, which can offer valuable insights into the underlying hidden factors. The idea that all the items in a factor are measuring the same underlying construct or latent variable is the foundation for averaging item answers (Hair et al., 2010; Tabachnick & Fidell, 2007).

Factor analysis seeks to uncover the latent factors that explain the covariation among a group of observed variables or items. By averaging the item responses, we produce composite scores or summary measures for each factor. These composite scores reflect the latent construct's average level for the measurement (Hair et al., 2010).

Several factors make averaging item answers advantageous; these include:

Reduction of Measurement Error: We can lessen the impact of potential random measurement error on individual items by averaging responses from multiple things. The underlying link between the items and the latent factor can be distorted by measurement error, although averaging helps to reduce this error (Hair et al., 2010; Tabachnick & Fidell, 2007).

Enhanced Reliability: By merging data from various indicators, averaging item responses improves the measurement's accuracy. A more accurate and consistent estimate of the latent component is produced when numerous items can measure the same construct with reliability (Hair et al., 2010; Tabachnick & Fidell, 2007).

Increased Precision: By using a broader pool of data, averaging item answers yields a more accurate estimate of the latent factor. The accuracy of factor loadings, which express the strength of the association between the latent factor and the observed items, is improved by the enhanced precision (Hair et al., 2010; Tabachnick & Fidell, 2007).

Facilitation of Interpretation: By averaging item responses, factor analysis results are easier to interpret. Factor scores generated by averaging give a clearer understanding of the latent variables and how they relate to the observed items as opposed to analysing each item independently (Hair et al., 2010; Tabachnick & Fidell, 2007).

We must always keep in mind that average item responses assume that all the items are equally significant and measure the same underlying construct. Prior to averaging the pieces, it is also crucial to confirm their legitimacy and dependability. To determine whether averaging item responses is appropriate and to check the general model fit and validity of the component structure, one can use confirmatory factor analysis or exploratory factor analysis (Hair et al., 2010; Tabachnick & Fidell, 2007).

In factor analysis, averaging item answers is a popular and beneficial method that improves the accuracy, precision, and interpretability of the latent factors and offers deeper understanding of the underlying constructs being assessed (Hair et al., 2010; Tabachnick & Fidell, 2007).

In the literature review, it was mentioned earlier that there are multiple causes of CMB and given that we have a lot of causes associated with CMB, the effect of these causes would be that an average response is embedded in the actual manifest data. It should also be noted that while this study seeks to focus on the averaging phenomena on response variables, this study focuses on a single battery of variables and not multiple batteries (more than one factor). To better explain this phenomenon a lecturer evaluation example is used.

Lecturer evaluation example*:*

In evaluating how participants perceived the lecture after having gone through a course, a survey is normally conducted. The reality is that, when participants/students complete the evaluation, they would normally have an overall impression of the lecturer. Furthermore, they would not rate every item uniquely, and literature shows this as there is a level of bias in the responses. One or two items may be rated higher or lower. If they like the lecturer they will give the lecturer on average good scores, if they dislike the lecturer they might highlight issues around content, timely delivery of the lecture content, marking turnaround times, etc, What these participants are essentially doing is to conceive or have an overall perception of the lecturer and are essentially giving an overall rating with some ups and downs based on unique constructs but in fact they would have made up their mind that the lecturer deserves a 7/10 rating on average and as such they might give scores of 8s and 6s but it would all average out to the 7/10 rating. This may be a result of having a preconceived score; the way in which the questions have been framed; misaligned scales due to understanding or conceptualisation of the meaning behind response criteria (verbal anchors) such as “somewhat agree”, “agree”, “somewhat disagree”, “disagree”; or other inherent reasons which all combined lead to Common Method Bias resulting in similarities of responses across a number of items hence the requirement to get an average of the variables or items.

The explanation and example suggest that CMB may lead to an averaging phenomenon since it concentrates on the factors linking the variables that make up the respondent's overall assessment while still introducing each item's particular factor separately. This prompts the inquiry of whether accounting for CMB influences the phenomenon of averaging.

CHAPTER 5: NEW TECHNIQUE (“The Model”)

The author thanks Professor Anthony Stacey (Former Wits University Professor) for his innovative and significant contribution in developing the model discussed in this section.

The proposed technique introduces a new parametric mathematical method for detecting and correcting common method bias (CMB) in survey data, filling a significant gap in current methodologies. Unlike previous approaches that relied solely on statistical analyses or procedural remedies to detect CMB, this method provides a systematic and theoretically grounded framework for quantifying and mitigating bias. By incorporating mathematical modelling, the proposed method allows researchers to directly estimate the degree of bias in manifest ratings and recover unbiased latent ratings, overcoming the limitations of traditional approaches that may lack precision or fail to account for the underlying bias mechanisms. Furthermore, the technique's parametric nature allows for easy adjustment of the bias parameter, giving researchers more control and transparency when dealing with CMB. Overall, the proposed method provides a more robust and comprehensive approach to detecting and correcting bias in survey data, which improves the validity and reliability of research findings across disciplines.

To determine whether CMB exists and how it affects study outcomes, a research approach was used, which is described in this section. To address CMB and improve the validity and reproducibility of the results, the methodology uses techniques from latent variable modelling. Below is a description of the research's layout, its methods for gathering information, and its statistical evaluations.

Clarifying the Proposed Model: Key Aspects and Unique Features

In order to cope with common method bias (CMB), the suggested model attempts to fill in the gaps and limitations found in the methodological and statistical approaches currently in use. This methodology is intended to detect and mitigate CMB in survey data in a more thorough and reliable manner. The main features of the suggested model and its distinctions from previous models are listed below:

1. **Key Aspects of the Proposed Model**

- Combination of Latent and Manifest Variables:

- The model combines manifest (observed) and latent (unobserved) variables to more accurately represent the underlying scores independent of CMB.
- By isolating the bias from the actual data, this dual technique enables a more accurate estimation of the underlying constructs.

- Mathematical Framework:
  - The model uses a specific mathematical formula to depict CMB in survey data:

$$y_{ij} = (1-\alpha)x_{ij} + \alpha(m\sum x_i)$$

where y_{ij} is the manifest rating, x_{ij} is the latent rating, and α represents the degree of bias.

  - This formula makes it easier to comprehend how the mean of the unbiased ratings and the observed ratings are weighted to create the manifest ratings.
- Matrix Representation:
  - The model expresses the link between latent and manifest ratings using matrix algebra. In order to convert between these scores and provide a methodical approach to identifying and mitigating CMB, the matrix A and its inverse A^{-1} are essential.
- Multivariate Analysis Emphasis:
  - The model primarily uses multivariate analysis methods, including factor analysis, structural equation modelling, and multivariate regression analysis, to comprehend the interactions and latent structures between variables.
  - By focusing on this aspect, it is possible to go deeper into the fundamental structure of the data and provide more valid and dependable findings.

2. How the Proposed Model Differs from Existing Models

- Integration of Multivariate and Univariate Approaches:
  - The suggested model incorporates both univariate and multivariate approaches, in contrast to typical models that might only concentrate on

one or the other. This allows for a more comprehensive understanding of CMB.

  - This kind of integration guarantees a thorough handling of the intricacies of CMB.

- Explicit Handling of Bias Through Alpha Parameter:
  - Compared to conventional models, the α parameter's introduction clearly defines the amount of bias, which is an innovative method.
  - This explicit approach allows for a more exact correction of CMB in the data.
- Application Across Diverse Contexts:
  - The suggested model is intended to be adaptable and useful in a range of research settings and fields.
  - The model's extensive usefulness stems from its ability to adapt to various data kinds and research situations, thanks to its flexible mathematical and statistical framework.

3. **Practical Implementation and Validation**:**
   - To guarantee the model's efficacy in practical implementations, iterative refinement and pilot testing are among the implementation strategies included in the model.
   - This practical emphasis guarantees the model's viability and dependability in real-world applications, in addition to its theoretical soundness.

Key Aspects and Unique Features Conclusion

A thorough and reliable framework for tackling typical method bias in survey research is provided by the suggested model. Through the integration of latent and manifest variables, the use of a lucid mathematical representation, and the emphasis on multivariate analysis, the model offers notable improvements over current methodologies. It is unique among CMB mitigation strategies because to its ability to handle bias explicitly using the α parameter and its adaptability to various scenarios.

5.1. Research Design:

Objective: Examining the potential existence of CMB and its impact on the interactions between latent variables is the main goal of this study.

Sample Selection: Based on the context and goals of the research, a purposive sample technique will be used to choose data that meet the inclusion criteria.

Data Collection Instruments: Secondary data collection.

Measurement Instrument Design: Model development and SPSS.

5.2. Data Collection Procedures:

The below outlines the process that should be followed in gathering data for the purposes of testing the model.

Pretesting: A pretest must be used to assess the measurement items' readability and clarity as well as the suitability of the response format.

Data Collection: There must be cross-sectional data collection. The datasets to be used must be from existing and former research conducted by research supervisor which have already had the relevant ethical clearances. To reduce reliance on a single data collecting method, a variety of survey data must be used, including objective measurements and archive data.

5.3. Statistical Analyses:

Descriptive Statistics: Descriptive analyses must be performed to investigate the sample's characteristics and the distribution of the variables.

Confirmatory Factor Analysis (CFA): The measurement model's fit must be evaluated using CFA, and the validity and dependability of the latent variables must also be confirmed. This analysis must show how distinctive the constructs are and show any measurement problems.

Common Method Bias Assessment: Statistical methods like the common latent factor method or the marker variable methodology must be used to assess the presence of CMB. These techniques will assist in determining the percentage of variance that may be attributable to common method variance and aid to separate it from the actual variance of the constructs.

The below formula as derived from logic has been shown as a plausible method that shows/depicts common method bias in survey data.

The proposed model appears to be a latent variable model that identifies and addresses common method bias (CMB). In this model, CMB is identified and addressed by calculating manifest ratings (Y ij) as a weighted average of observed ratings (x ij) and the respondent's unbiased ratings. The parameter α indicates the degree of bias in manifest ratings. Lower values indicate less bias, while higher values indicate more bias. The model allows for the estimation of latent ratings (X i) from manifest ratings, which aids in the detection and correction of survey bias. This approach gives researchers a systematic method for quantifying and mitigating CMB, which improves the validity and reliability of research results.

"Let the latent ratings for the *i*'th respondent (i = 1 to n) to the *j*'th item (j = 1 to m) be x_{ij}.

Let the manifest rating for the *i*'th respondent to the *j*'th item be y_{ij}, being a weighted aggregation of the observed ratings for the *i*'th respondent to the *j*'th item and the mean of the *i*'th respondent's unbiased ratings.

That is: $y_{ij} = (1-\alpha).x_{ij} + \alpha.{}^{\sum x_i}/_{m}$ where α ($0 \leq \alpha < 1$) is the degree of "bias" in the manifest ratings being the weighting of $\bar{x}$. (Note that $\alpha \neq 1$ unless $y_{i1} = y_{i2} = \ldots = y_{im}$, in which case x_{ij} cannot be estimated.)

Now let $\mathbf{X}_i$ and $\mathbf{Y}_i$ be row vectors [1 x m] of the latent and manifest ratings for the *i*'th respondent, respectively.

Then $\mathbf{Y}_i = \mathbf{X}_i.\mathbf{A}$ where $\mathbf{A}$ is a square matrix [m x m] equal to:

$$\begin{bmatrix} 1-\dfrac{\alpha(m-1)}{m} & {}^{\alpha}/_{m} & \cdots & {}^{\alpha}/_{m} \\ {}^{\alpha}/_{m} & 1-\dfrac{\alpha(m-1)}{m} & \cdots & {}^{\alpha}/_{m} \\ \cdots & \cdots & \cdots & \cdots \\ {}^{\alpha}/_{m} & {}^{\alpha}/_{m} & \cdots & 1-\dfrac{\alpha(m-1)}{m} \end{bmatrix}$$

Now $\mathbf{X}_i = \mathbf{Y}_i.\mathbf{A}^{-1}$"

Logic Application:

Figure 8 below is an example of how the logic/model shall be applied using excel.

Summary of the logic

(Given any value of alpha (cell M1) we can calculate the manifest dataset (columns N to W) either line-by-line (above) or by multiplying the latent dataset by matrix A (below)

– the results are identical. Therefore, we can get back to the latent dataset (columns Z to AI) by multiplying the manifest dataset by the inverse of matrix A.

In practice we have only an empirical (manifest) dataset with CMB. We want to get back to the unknown (latent) dataset which should not have CMB, by choosing the appropriate value for alpha)

Latent (unknown) dataset, X — α = 0,66

	Var01	Var02	Var03	Var04	Var05	Var06	Var07	Var08	Var09	Var10	Mean
Response 01	5	10	10	0	9	7	1	0	3	7	5,2
Response 02	10	2	4	3	2	9	6	6	1	10	5,3
Response 03	4	4	5	7	10	3	2	7	8	8	5,8
Response 04	10	6	9	9	3	10	3	5	3	3	6,1
Response 05	5	9	9	9	9	7	6	9	9	5	7,7
Response 06	8	7	8	9	6	8	8	8	5	8	7,5
Response 07	10	9	10	8	6	7	7	6	8	10	8,1
Response 08	3	2	7	4	8	3	0	4	5	9	4,5
Response 09	8	7	5	9	9	4	4	4	8	6	6,4
Response 10	4	8	4	8	2	8	5	8	7	9	6,3
Response 11	7	8	4	4	3	5	5	8	8	3	5,5
Response 12	9	8	6	9	7	8	7	8	5	5	7,2
Response 13	8	7	6	9	6	8	7	8	7	8	7,4
Response 14	4	3	7	0	6	6	0	6	8	5	4,5
Response 15	4	4	7	4	2	6	1	5	5	3	4,1
Response 16	7	3	7	3	2	4	8	6	8	8	5,6
Response 17	7	5	8	9	6	3	6	5	7	5	6,1
Response 18	5	3	8	6	4	8	7	4	6	5	5,6
Response 19	2	6	3	1	6	1	0	6	4	2	3,1

Manifest (known) dataset, Y — Calculated line-by-line

	Var01	Var02	Var03	Var04	Var05	Var06	Var07	Var08	Var09	Var10
Response 01	5,13	6,83	6,83	3,43	6,49	5,81	3,77	3,43	4,45	5,81
Response 02	6,9	4,18	4,86	4,52	4,18	6,56	5,54	5,54	3,84	6,9
Response 03	5,19	5,19	5,53	6,21	7,23	4,85	4,51	6,21	6,55	6,55
Response 04	7,43	6,07	7,09	7,09	5,05	7,43	5,05	5,73	5,05	5,05
Response 05	6,78	8,14	8,14	8,14	8,14	7,46	7,12	8,14	8,14	6,78
Response 06	7,67	7,33	7,67	8,01	6,99	7,67	7,67	7,67	6,65	7,67
Response 07	8,75	8,41	8,75	8,07	7,39	7,73	7,73	7,39	8,07	8,75
Response 08	3,99	3,65	5,35	4,33	5,69	3,99	2,97	4,33	4,67	6,03
Response 09	6,94	6,6	5,92	7,28	7,28	5,58	5,58	5,58	6,94	6,26
Response 10	5,52	6,88	5,52	6,88	4,84	6,88	5,86	6,88	6,54	7,22
Response 11	6,01	6,35	4,99	4,99	4,65	5,33	5,33	6,35	6,35	4,65
Response 12	7,81	7,47	6,79	7,81	7,13	7,47	7,13	7,47	6,45	6,45
Response 13	7,6	7,26	6,92	7,94	6,92	7,6	7,26	7,6	7,26	7,6
Response 14	4,33	3,99	5,35	2,97	5,01	5,01	2,97	5,01	5,69	4,67
Response 15	4,07	4,07	5,09	4,07	3,39	4,75	3,05	4,41	4,41	3,73
Response 16	6,08	4,72	6,08	4,72	4,38	5,06	6,42	5,74	6,42	6,42
Response 17	6,41	5,73	6,75	7,09	6,07	5,05	6,07	5,73	6,41	5,73
Response 18	5,4	4,72	6,42	5,74	5,06	6,42	6,08	5,06	5,74	5,4
Response 19	2,73	4,09	3,07	2,39	4,09	2,39	2,05	4,09	3,41	2,73

Latent (unknown) dataset, $X = Y.A^{-1}$

	Var01	Var02	Var03	Var04	Var05	Var06	Var07	Var08	Var09	Var10
Response 01	5	10	10	-0	9	7	1	-0	3	7
Response 02	10	2	4	3	2	9	6	6	1	10
Response 03	4	4	5	7	10	3	2	7	8	8
Response 04	10	6	9	9	3	10	3	5	3	3
Response 05	5	9	9	9	9	7	6	9	9	5
Response 06	8	7	8	9	6	8	8	8	5	8
Response 07	10	9	10	8	6	7	7	6	8	10
Response 08	3	2	7	4	8	3	-0	4	5	9
Response 09	8	7	5	9	9	4	4	4	8	6
Response 10	4	8	4	8	2	8	5	8	7	9
Response 11	7	8	4	4	3	5	5	8	8	3
Response 12	9	8	6	9	7	8	7	8	5	5
Response 13	8	7	6	9	6	8	7	8	7	8
Response 14	4	3	7	-0	6	6	-0	6	8	5
Response 15	4	4	7	4	2	6	1	5	5	3
Response 16	7	3	7	3	2	4	8	6	8	8
Response 17	7	5	8	9	6	3	6	5	7	5
Response 18	5	3	8	6	4	8	7	4	6	5
Response 19	2	6	3	1	6	1	0	6	4	2

Matrix A — m = 10

0,41	0,07	0,07	0,07	0,07	0,07	0,07	0,07	0,07	0,07
0,07	0,41	0,07	0,07	0,07	0,07	0,07	0,07	0,07	0,07
0,07	0,07	0,41	0,07	0,07	0,07	0,07	0,07	0,07	0,07
0,07	0,07	0,07	0,41	0,07	0,07	0,07	0,07	0,07	0,07
0,07	0,07	0,07	0,07	0,41	0,07	0,07	0,07	0,07	0,07
0,07	0,07	0,07	0,07	0,07	0,41	0,07	0,07	0,07	0,07
0,07	0,07	0,07	0,07	0,07	0,07	0,41	0,07	0,07	0,07
0,07	0,07	0,07	0,07	0,07	0,07	0,07	0,41	0,07	0,07
0,07	0,07	0,07	0,07	0,07	0,07	0,07	0,07	0,41	0,07
0,07	0,07	0,07	0,07	0,07	0,07	0,07	0,07	0,07	0,41

Manifest dataset, Y — Calculated using matrix multiplication **X.A**

	Var01	Var02	Var03	Var04	Var05	Var06	Var07	Var08	Var09	Var10
Response 01	5,13	6,83	6,83	3,43	6,49	5,81	3,77	3,43	4,45	5,81
Response 02	6,9	4,18	4,86	4,52	4,18	6,56	5,54	5,54	3,84	6,9
Response 03	5,19	5,19	5,53	6,21	7,23	4,85	4,51	6,21	6,55	6,55
Response 04	7,43	6,07	7,09	7,09	5,05	7,43	5,05	5,73	5,05	5,05
Response 05	6,78	8,14	8,14	8,14	8,14	7,46	7,12	8,14	8,14	6,78
Response 06	7,67	7,33	7,67	8,01	6,99	7,67	7,67	7,67	6,65	7,67
Response 07	8,75	8,41	8,75	8,07	7,39	7,73	7,73	7,39	8,07	8,75
Response 08	3,99	3,65	5,35	4,33	5,69	3,99	2,97	4,33	4,67	6,03
Response 09	6,94	6,6	5,92	7,28	7,28	5,58	5,58	5,58	6,94	6,26
Response 10	5,52	6,88	5,52	6,88	4,84	6,88	5,86	6,88	6,54	7,22
Response 11	6,01	6,35	4,99	4,99	4,65	5,33	5,33	6,35	6,35	4,65
Response 12	7,81	7,47	6,79	7,81	7,13	7,47	7,13	7,47	6,45	6,45
Response 13	7,6	7,26	6,92	7,94	6,92	7,6	7,26	7,6	7,26	7,6
Response 14	4,33	3,99	5,35	2,97	5,01	5,01	2,97	5,01	5,69	4,67
Response 15	4,07	4,07	5,09	4,07	3,39	4,75	3,05	4,41	4,41	3,73
Response 16	6,08	4,72	6,08	4,72	4,38	5,06	6,42	5,74	6,42	6,42
Response 17	6,41	5,73	6,75	7,09	6,07	5,05	6,07	5,73	6,41	5,73
Response 18	5,4	4,72	6,42	5,74	5,06	6,42	6,08	5,06	5,74	5,4
Response 19	2,73	4,09	3,07	2,39	4,09	2,39	2,05	4,09	3,41	2,73

Inverse Matrix A^{-1}

2,75	-0,2	-0,2	-0,2	-0,2	-0,2	-0,2	-0,2	-0,2	-0,2
-0,2	2,75	-0,2	-0,2	-0,2	-0,2	-0,2	-0,2	-0,2	-0,2
-0,2	-0,2	2,75	-0,2	-0,2	-0,2	-0,2	-0,2	-0,2	-0,2
-0,2	-0,2	-0,2	2,75	-0,2	-0,2	-0,2	-0,2	-0,2	-0,2
-0,2	-0,2	-0,2	-0,2	2,75	-0,2	-0,2	-0,2	-0,2	-0,2
-0,2	-0,2	-0,2	-0,2	-0,2	2,75	-0,2	-0,2	-0,2	-0,2
-0,2	-0,2	-0,2	-0,2	-0,2	-0,2	2,75	-0,2	-0,2	-0,2
-0,2	-0,2	-0,2	-0,2	-0,2	-0,2	-0,2	2,75	-0,2	-0,2
-0,2	-0,2	-0,2	-0,2	-0,2	-0,2	-0,2	-0,2	2,75	-0,2
-0,2	-0,2	-0,2	-0,2	-0,2	-0,2	-0,2	-0,2	-0,2	2,75

Figure 8: Excel representation of "the model"

5.4. Illustration Of The Parametric Mathematical Method On A Random Dataset (“The Model”)

The section briefly discusses how the proposed model is used and put to the test. Outlined below are three analyses that gets performed to fulfil the study's goals.

1. Analysing a set of random data: A set of random data is examined in the first analysis. This analysis seeks to show how averaging behaves as a factor and its impacts. The author hopes to explain how the factors relate to one another and how averaging affects the outcomes by analysing the random data. The understanding of the next analyses is aided by this analysis.
2. Contrived data set: The creation of a data collection with preset features is required for the second analysis. This data set is purposefully created by the author to show how the model may be used to identify the inherent

characteristics of the variables. The author can evaluate the model's efficacy and accuracy in capturing the required attributes by changing the features in the data set. The possibilities of the model are demonstrated through this analysis, which acts as a controlled experiment.

3. Real data set: Utilising real data for the third analysis. The model is applied to actual data sets gathered from a particular context or domain, as stated in section 5 of the article. The author wants to evaluate the model's applicability and performance in a real-world setting by using real data. This examination sheds light on the model's practical consequences and prospective uses.

By conducting these three analyses, the author hopes to demonstrate the model's effectiveness and robustness. The assumption is that this approach will allow for a thorough evaluation of the model's capabilities using a variety of data types, including random data, carefully constructed data sets, and real-world data. This strategy helps to strengthen the validity and generalizability of the study's conclusions.

5.5. Illustration Of The Method On An Empirical Dataset

The author describes the model's application to an actual data set that is gathered from a particular context or domain in this section. To better comprehend the model's practical consequences and prospective applications, it is important to evaluate the model's applicability and performance in a realistic setting.

5.6. Data Collection and Preparation

The author outlines the procedure for gathering and preparing real data sets for analysis. This often entails selecting a demographic or sample that is pertinent to the research goals. To obtain the necessary information, the author may use a variety of techniques, including surveys, experiments, observations, or data already in the public domain.

After the data is gathered, it goes through a step of preparation to make sure it is suitable for analysis. This calls for the formatting, transformation, and cleaning of data. To meet the model's needs, the author may deal with missing values, outliers, and inconsistent data by performing the necessary transformations. It is also possible to use data pretreatment methods like normalisation or standardisation to make proper analysis easier.

5.7. Model Application

The author applies the model to the actual data set after the data has been gathered and prepared. The model is customised for the situation or research domain. The variables and connections noted in the research framework are plotted on the data gathered, and the proper statistical methods are used for analysis.

Suitable statistical techniques are used to estimate the model's parameters, such as regression coefficients, factor loadings, or correlations between latent variables. To construct the model and carry out the analysis, the author may use programming languages or software created expressly for data analysis, such as the SPSS programme stated in the article.

5.8. Analysis and Interpretation

The author applies the model to the actual data set after the data has been gathered and prepared. The model is customised for the situation or research domain. The variables and connections noted in the research framework are plotted on the data gathered, and the proper statistical methods are used for analysis.

Suitable statistical techniques are used to estimate the model's parameters, such as regression coefficients, factor loadings, or correlations between latent variables. To construct the model and carry out the analysis, the author may use programming languages or software created expressly for data analysis, such as the SPSS programme stated in the article.

5.8. Validation and Generalization

The author then analyses the actual data set to confirm the model's performance and applicability. The findings are compared with existing theories, previous research, or expected outcomes to validate the model's predictive capabilities and its alignment with established knowledge in the field. The author may also assess the generalizability of the model to other similar contexts or domains, discussing its potential applications and limitations.

By applying the model to real data, this analysis in section 5 aims to provide empirical evidence of the model's effectiveness in a practical setting. The insights gained from this real-world application contribute to the overall understanding of the phenomena under study and provide valuable implications for decision-making, policy formulation, or further research in the respective field.

CHAPTER 6: CONCLUSION AND RECOMMENDATION

6.1. Introduction

Specific studies, such as those by Zangirolami-raimundo and Leone (2018), Podsakoff et al. (2013), and Kock et al. (2021), shed light on the nuances of dealing with CMB. The emphasis on the usefulness of cross-sectional studies, the negative impact of CMB, and proposed solutions highlight the complexities of this research challenge. Keiser & Payne (2019), Jordan & Troth (2020), Jakobsen & Jensen (2015), Fuller et al. (2016), Bozionelos & Simmering (2022), and Antonakis et al. (2010) make valuable contributions to the literature by delving into specific aspects of CMB, such as impression management bias in employee surveys and the investigation of causal claims in social science research.

In this comprehensive review, we looked at a variety of methodological and statistical techniques for detecting and mitigating common method bias (CMB) in research studies. Our findings highlight the importance of addressing CMB to ensure the validity and reliability of research findings across multiple disciplines. By synthesizing insights from the literature, we have provided a nuanced understanding of each technique's strengths, weaknesses, and practical implications.

6.2. Summary and Conclusion

In conclusion, the comprehensive theoretical and conceptual literature review spanning the years 1990 to 2024 revealed significant research gaps in the domain of organizational behaviour and performance evaluation, particularly concerning common method bias (CMB). Despite significant contributions from key studies such as Podsakoff et al. (2003), Williams and Anderson (1994), and Lindell and Whitney (2001), ongoing gaps necessitate new methodological advances. These gaps include methodological challenges stemming from common approach biases, a lack of investigation into contextual factors, and an ongoing need for novel measurement methodologies, experimental designs, and statistical solutions.

While major studies, such as Podsakoff et al. (2003), have made significant progress in understanding and addressing CMB, the current research landscape highlights the ongoing need for novel strategies to mitigate common method biases. Future research should not only expand on current recommendations, but also investigate novel measurement methodologies, experimental designs, and statistical treatments. Future research should focus on direct comparisons between latent-variable models and traditional approaches, examining their efficacy and limitations in a variety of research settings.

Addressing common method bias is critical to ensuring the integrity and validity of research results. Researchers can reduce biases, improve the reliability of their findings, and contribute to the advancement of knowledge in their respective fields by using a wide range of methodological and statistical techniques. Collaboration among researchers, methodologists, and statisticians is critical for developing best practices and increasing methodological rigor when addressing common method bias. Finally, a systematic and integrative approach to addressing common method bias will result in more robust and credible research findings, facilitating progress and innovation across disciplines.

Methodological Techniques:

We discussed blinding techniques, randomized responses, counterbalancing, procedural remedies, scale anchoring, data source triangulation, longitudinal designs, control variables, multimethod approaches, and measurement validation. These techniques provide useful strategies for reducing biases inherent in data collection procedures, strengthening research designs, and ensuring the validity of findings.

Statistical Techniques:

We investigated several statistical methods, including confirmatory factor analysis (CFA), multiple informant approaches, item order randomization, multitrait-multimethod matrices, common latent factor approaches, cross-validation, Bayesian techniques, bootstrapping, nonlinear structural equation modelling, latent growth curve modelling, partial correlation analysis, residual correlation analysis, multilevel modelling, multigroup analysis, and structural equation modelling. These statistical tools offer sophisticated analytical frameworks for determining measurement validity, accounting for method variance, and investigating complex relationships between variables.

While the literature has made commendable advances in understanding and addressing CMB, there is a constant call for more research and innovation. The identification of research gaps, along with recommendations for future studies and methodological improvements, emphasizes the importance of continuously improving the rigor and quality of behavioural research. Overall, the literature review from 1990 to 2024 emphasizes the changing nature of CMB research, highlighting the need for ongoing efforts to ensure the dependability and validity of findings in the fields of organizational behaviour and performance evaluation.

Finally, the methodological techniques discussed provide useful strategies for reducing biases in data collection procedures, improving research designs, and ensuring the validity of findings. However, limitations remain, including the difficulty in comprehensively addressing common method biases. Similarly, the statistical techniques studied offer sophisticated analytical frameworks for determining measurement validity, accounting for method variance, and investigating complex relationships between variables. However, these techniques may not capture all of the nuances of common method biases and may overlook contextual factors that influence data interpretation. Thus, while these techniques represent significant advances in research methodology, there is still a need for innovative models that can effectively address the limitations of existing approaches while also providing more robust solutions for mitigating common method biases.

6.3. Recommendations And Future Work

Based on the discussions and the insights derived from the literature review and model application, the following recommendations are suggested:

Refine and validate the proposed model: The proposed statistical model could be critical in helping to deal with CMB in survey research using statistical methods. Additional research and sensitivity tests are recommended in order to improve and validate the model. This will improve the model's resilience, trustworthiness, and generalizability across multiple situations or domains.

Collect high-quality and diverse data: The accessibility of diverse, high-quality data is essential to the study's effectiveness. It is advised that the data gathering procedure be thoroughly planned, guaranteeing representativeness, reliability, and validity. Using multiple data sources or making use of already-existing datasets can provide the results with a broader perspective and improve their generalizability.

Engage in rigorous data analysis: In-depth data analysis is essential for obtaining insightful conclusions. It is advised to use sophisticated statistical methods and software tools to effectively analyse the gathered data. Additionally, performing sensitivity analyses, bootstrapping, or Monte Carlo simulations can provide a robust assessment of the model's performance and address potential limitations.

Interpret and communicate the findings effectively: For the study findings to be effectively communicated to multiple stakeholders, a clear and succinct interpretation of the analytical results is essential. It is advised to include thorough justifications for the conclusions' ramifications, practical significance, and limitations. A better comprehension of complex relationships or patterns within the data can also be facilitated using visual aids, such as graphs, charts, or diagrams.

Disseminate the research outcomes: It is advised to communicate the results through a variety of outlets, such as academic journals, conferences, or policy briefs, to maximise the impact of the research. Sharing the research findings with important parties, such as politicians, practitioners, or other researchers, might encourage additional debates, teamwork, and practical applications.

Pursue future research directions: Based on the information gained from the study, it is vital to determine potential directions for future research. This could entail investigating other factors, broadening the target audience or context, or using the model in new fields. Continuous investigation and study will increase our understanding and lead to the creation of novel solutions.

Finally, by implementing these suggestions, the proposed research has the potential to significantly advance the subject and offer useful information that may guide decision-making, the creation of policies, and future research endeavours. The proposed research can ultimately affect positive change and have a significant impact on the identified phenomena or problem through careful analysis, interpretation, and dissemination of the findings.

6.4. Proposed Model: “Stacey-Qangule” Model

Finally, this research study delves into the complexities of survey data research, emphasizing the interaction between univariate and multivariate analyses in understanding and addressing common method bias (CMB). The study emphasizes the importance of multivariate analysis, especially in the context of factor analysis, where it is critical to investigate the latent factors underlying a set of observed variables.

The discussion explains how multivariate analysis enables researchers to simultaneously examine, analyse, and interpret correlations, patterns, and dependencies among variables. Techniques like factor analysis provide insights into the underlying structure of data, which aids in understanding the latent constructs or dimensions being evaluated. This comprehensive approach contrasts with univariate analysis, which focuses on single variables independently and may miss complex relationships between variables.

The study focuses on the practical application of multivariate data analysis techniques such as factor analysis, structural equation modelling, cluster analysis, multivariate regression analysis, principal component analysis, and multivariate analysis of variance in a variety of research settings. The benefits of multivariate analysis, such as increased reliability, precision, and ease of interpretation, are highlighted.

The study focuses on the practical use of multivariate data analysis techniques in a variety of research scenarios, including factor analysis, structural equation modelling, cluster analysis, multivariate regression analysis, principal component analysis, and multivariate analysis of variance. The benefits of multivariate analysis, such as increased reliability, precision, and interpretability, are highlighted.

The study broadens the discussion of multivariate analysis and averaging item responses to include the concept of CMB. The lecturer evaluation example demonstrates how respondents can form a general impression of a lecturer, resulting in averaging of their responses. This is due to the CMB, which introduces common responses to multiple items.

The study expands on the topic of multivariate analysis and averaging item responses by introducing the concept of CMB. The lecturer evaluation example demonstrates how respondents can form a broad impression of a lecturer, resulting in an averaging effect in their responses. This is due to the CMB, which introduces common responses across multiple items.

CHAPTER 7: REFERENCES

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