Received: 7 September 2024 | Revised: 31 October 2024 | Accepted: 23 January 2025 | Published online: 21 February 2025

Journal of Comprehensive Business Administration Research
2025, Vol. 00(00) 1–12
DOI: 10.47852/bonviewJCBAR52024285

RESEARCH ARTICLE

Common Method Bias in Social and Behavioral Research: Strategic Solutions for Quantitative Research in the Doctoral Research

Mohammad Rashed Hasan Polas[1,*]

[1]*Department of Business Administration, Sonargaon University, Bangladesh*

Abstract: This paper addresses the critical issue of common method bias (CMB) in social and behavioral research, emphasizing its impact on the validity and reliability of quantitative studies, particularly in the context of doctoral-level research. CMB arises when data collection methods in doctoral research, such as self-report surveys, artificially inflate or deflate relationships between variables, leading to distorted findings. This can result in misleading conclusions, such as overstating the link between job satisfaction and employee performance, which may have serious implications for both academic research and policymaking. The paper offers a comprehensive overview of the sources and effects of CMB, along with strategies to detect, prevent, and control it. It highlights key statistical techniques, including Harman's single-factor test, marker variable approaches, and latent variable modeling, to minimize bias during data analysis. Additionally, it outlines best practices for study design, such as temporal separation, varying measurement methods, and ensuring data collection anonymity, to reduce CMB from the outset. By implementing these strategies, researchers can enhance the validity and generalizability of their findings, ensuring that results reflect genuine relationships rather than artifacts of the research process.

Keywords: common method bias, research validity, self-report surveys, measurement error, statistical techniques, study design

1. Introduction

The accuracy and reliability of research in the social and behavioral sciences have always been critical for advancing knowledge and informing policy decisions [1, 2]. However, a significant challenge to this reliability is common method bias (CMB) in doctoral-level research, a type of bias that occurs when measurement techniques artificially inflate or deflate the observed relationships between variables. CMB often arises in studies that rely heavily on self-reported data, where participants report on both independent and dependent variables using the same measurement method, leading to spurious correlations or attenuated associations [3]. This bias can distort findings, misrepresent the true relationships between constructs, and ultimately undermine the validity of research conclusions.

CMB is particularly problematic in social and behavioral research because of the reliance on self-report surveys, interviews, and other subjective methods of data collection. For example, in studies investigating the relationship between job satisfaction and employee performance, a researcher might observe a positive association. However, this finding could be exaggerated or even false due to biases such as social desirability or common method variance, rather than reflecting a genuine underlying relationship [4]. These distortions can have profound implications for theory-building and the practical applications of research, as inaccurate findings can misinform organizational policies, interventions, or managerial strategies [1–3].

In the context of the Industry 4.0 era, where data-driven decisions shape industries and policy, mitigating biases like CMB is more urgent than ever. The rapid expansion of digital data collection and the increased reliance on self-report measures in large-scale surveys heighten the risk of CMB. As researchers navigate the challenges of this new data-driven environment, ensuring methodological rigor by addressing biases like CMB becomes essential to producing reliable and actionable insights [4]. Thus, tackling CMB is not merely a technical issue but a broader challenge in upholding the credibility of research in a world increasingly driven by complex, data-intensive methodologies [3, 5, 6].

This paper aims to address the growing concern of CMB in social and behavioral research by posing the following research questions:

1) What is the extent of CMB in social and behavioral research?
2) What are the major effects of method bias on the validity and reliability of social and behavioral research?
3) What strategies can researchers use to detect, prevent, and control sampling bias in social and behavioral research?
4) How can the application of best practices to reduce bias enhance the reliability of social and behavioral research?

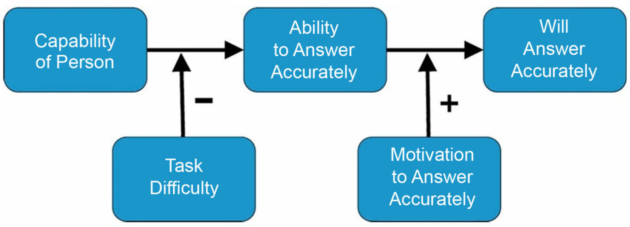
*Corresponding author: Mohammad Rashed Hasan Polas, Department of Business Administration, Sonargaon University, Bangladesh. Email: mrh.polas@su.edu.bd

In this paper, we provide an overview of the key strategies for identifying, preventing, and controlling CMB, exploring its sources, implications, and solutions. By offering both conceptual insights and practical guidelines, we aim to equip researchers with the tools needed to mitigate CMB and enhance the robustness of their studies, thereby contributing to the advancement of knowledge in the field.

When is method bias likely to be a problem?

Method bias can occur when respondents want to "please" rather than "correct" their answers. Indifference occurs when respondents' answers are less accurate because of a lack of knowledge, motivation, or ability. Factors affecting satisfaction include difficulty of the task, respondent ability, or fatigue from long questions. For example, respondents may choose the first appropriate answer, agree with the statement regardless of its content, or choose a neutral answer to avoid exerting effort. Krosnick et al. [7] explained that indifference occurs when respondents are unable or unwilling to provide correct answers. Bias occurs when it (a) reduces responsiveness (e.g., cognitive limitations), (b) makes the task more difficult (e.g., problem-solving), (c) reduces emotional stress (e.g., fatigue), and (d) facilitates gratification (e.g., long-term research). Therefore, researchers need to pay attention to these situations and reduce bias by creating easier, more supportive, and more manageable research. Figure 1 [6] shows when method bias is likely to be a problem.

Figure 1
When is method bias likely to be a problem? [15]



2. The Concept of Common Methods Bias

In empirical research, especially in the social sciences, management, and psychology, the integrity of findings is often threatened by various biases that can affect the benefits. One of the main biases is CMB [8]. CMB occurs when the measurement method itself, rather than the actual measurement model, misrepresents the results. This phenomenon can lead to connections or connections between variables, which can ultimately affect the accuracy of the data and lead to relevant conclusions. Understanding and addressing CMB is important to increase the validity and reliability of scientific findings, thus contributing to the advancement of scientific knowledge. In a study examining the relationship between job satisfaction and organizational commitment using a self-reported survey, CMB may occur if respondents give consistently high ratings due to a desire to appear as committed employees [9].

CMB most often occurs in studies that rely on individual surveys in which respondents provide information about independence and achievement using the same measure [10]. Bias can occur for a number of reasons, including the tendency of respondents to give socially desirable answers, to be consistent in their responses, or to answer questions that are unclear or poorly answered. For example, in a survey assessing employee satisfaction and performance, if both measures are measured using self-assessments, the results will be influenced by respondents' desire to present themselves in a positive light rather than by their own personality and behavior [11].

To understand how CMB works, it is necessary to examine its sources and types. The sources of CMB can be broadly divided into three areas: respondent bias, item bias, and measurement bias [12–14]. Respondents indicated that bias occurs due to factors such as social desirability; they believed that there was greater acceptance of similar responses to the same question, which led to a tendency to agree with statements that did not fully address the content. In addition, bias related to the nature of the question, such as the question being unclear, difficult, or non-leading, could result in respondents providing similar responses [15, 16]. Content assessment biases arise from the content recorded, including factors such as the time of measurement, the environmental context, or the presence of the researcher, all of which can influence the response [17, 18].

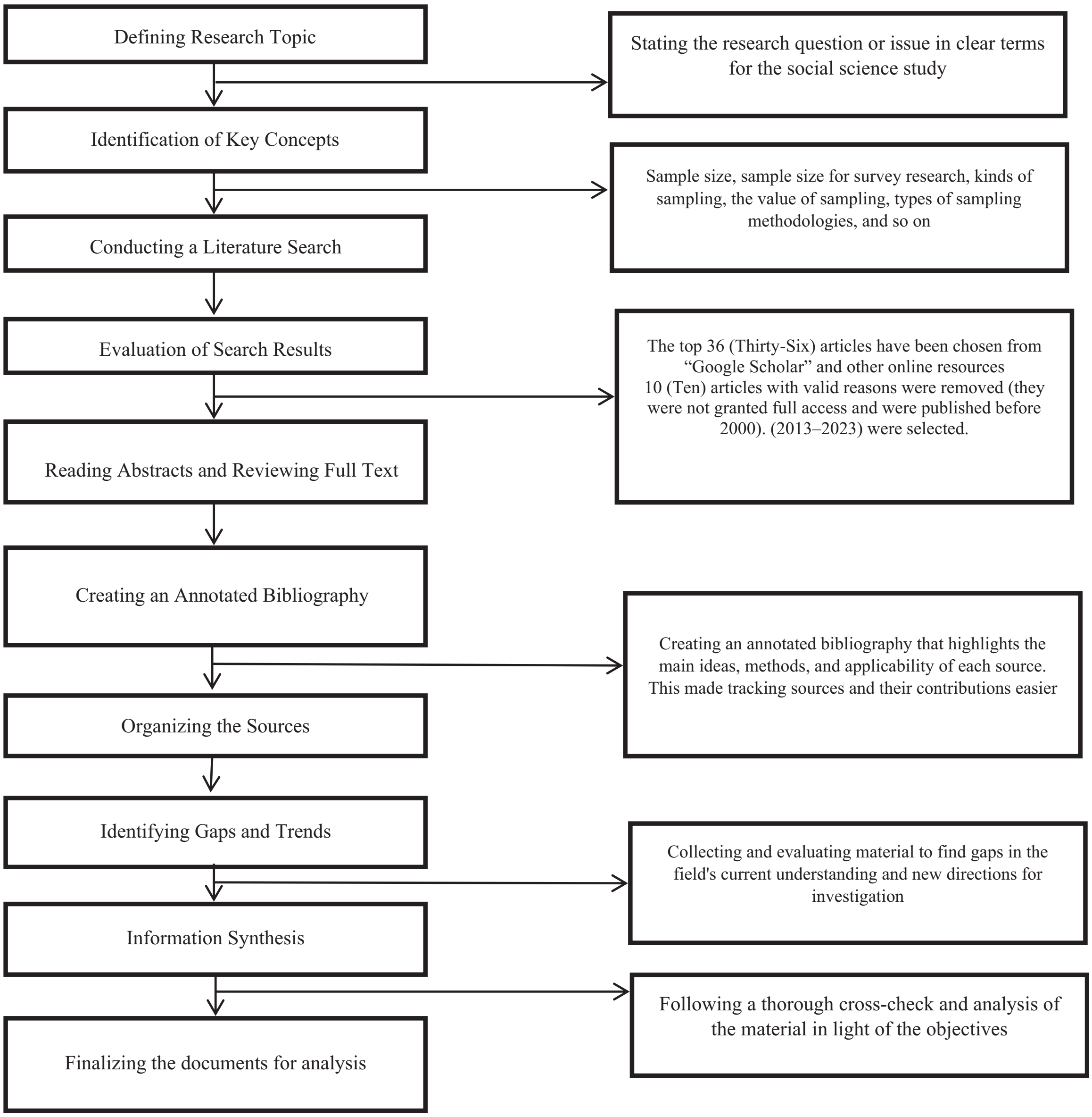
3. Methodology of the Study

This paper serves as an in-depth literature review that provides clear guidelines and relevant examples for social and behavioral science researchers to prevent common methods bias (CMB) [19]. To ensure the rigor of the study, the author developed and implemented a detailed process called the Ten Commandments, which form the basis of this study. This study meticulously follows the following ten steps throughout our study.

Figure 2 shows the sampling and research process. After determining the research objectives, the author conducted extensive searches on various academic databases, including WoS, SCOPUS, Google Scholar, DOAJ, JSTOR, and other online platforms [19]. The search was guided by a carefully selected list of topics directly related to the research focus, including methods such as sampling, sample types, sample values, and major regrets. This comprehensive literature search utilized a total of 40 research articles and online resources to provide a framework for the definition of the study's sample and its strengths and limitations. However, it is important to note that the descriptions in this study are based on the researcher's own observations and observations [19]. This meticulous process is necessary to ensure the reliability of the findings.

An important part of the quality control process involves a thorough review of the content of the selected articles to ensure that it is relevant and consistent with the research objectives. Each site is rigorously assessed before inclusion in the analysis, with a selection process guided by a clearly focused process that is aligned with the objectives of the analysis. Articles that are clearly presented and provide explanatory content that supports the main purpose of the review are selected for further review [19]. Search and discover the importance of science. Articles published before 2000 were intentionally excluded from the study because they were considered less relevant to the current situation. After following the inclusion process, purposive sampling was used to carefully remove all entries from the data, ensuring that only variables and relevant effects were retained for detailed analysis.

Figure 2
The sampling process



3.1. Selection criteria for literature review sources

The selection of research articles for this literature review was conducted systematically, following specific inclusion and exclusion criteria to ensure the relevance and quality of the sources. The process was designed to capture a comprehensive range of insights on CMB, particularly within the context of social and behavioral sciences and in the era of Industry 4.0. Priority was given to articles published within the last 10 years (2013–2023) to ensure the inclusion of up-to-date research findings and methodological advancements related to CMB. However, seminal works on CMB, regardless of publication date, were also considered to provide foundational context for more recent discussions.

Articles were selected based on their methodological rigor and relevance to the topic. Both empirical studies and theoretical discussions were included to provide a balanced view of how CMB has been addressed across different research designs. Empirical studies that used quantitative data analysis methods to detect and mitigate CMB were prioritized, as they align closely with the focus of this paper.

The articles were chosen specifically for their direct relevance to CMB and related methodological concerns. Studies focusing on the detection, prevention, and correction of CMB were included, along with papers that discussed statistical techniques for addressing bias in social and behavioral research. Additionally, papers exploring methodological challenges in Industry 4.0 contexts were selected to reflect the contemporary importance of addressing CMB in large-scale, data-driven research environments.

Articles that explicitly addressed CMB, provided empirical evidence on the impact of CMB, or proposed methodological solutions were included. Additionally, studies that discussed CMB in relation to quantitative research methods and the evolving research landscape in Industry 4.0 were considered. Articles that were not directly related to CMB, or those that provided only superficial mentions of CMB without significant discussion or analysis, were excluded. Studies focusing solely on qualitative methods or unrelated methodological issues were also omitted to maintain the focus on quantitative research. Articles were sourced from reputable academic databases such as Scopus, Web of Science, Google Scholar, and IEEE Xplore, ensuring that the literature review was built upon high-quality, peer-reviewed sources.

Although the use of 40 research articles may seem limited, the selected studies represent a targeted and relevant sample of the existing literature on CMB. This focused approach allows for a more in-depth exploration of strategies to detect, prevent, and mitigate CMB, particularly in social and behavioral sciences. Future reviews may expand on this work by incorporating a broader range of studies as the field continues to evolve.

CMB can be specialized based on the type of research being conducted. Here's an explanation of how different approaches can be applied:

1) Ensuring that respondents feel comfortable being honest can reduce social desirability bias, a common form of CMB in surveys.
2) Introducing a time gap between the measurement of predictor and outcome variables can minimize CMB.
3) Using varied scales or formats (e.g., Likert scale vs. open-ended responses) to measure different variables helps reduce the likelihood of method bias.
4) Randomly assigning participants to different conditions can minimize biases introduced by participants' expectations or self-report methods.
5) Blinding participants to the study's hypotheses can reduce the risk of CMB by preventing them from trying to answer in ways they think the researcher expects.
6) Using different methods to assess the same construct (e.g., self-report combined with behavioral measures) can minimize CMB.
7) Ensuring that observers or data collectors are well-trained and follow standardized procedures can reduce biases introduced by human error or judgment.
8) Collecting data from multiple sources (e.g., interviews, direct observations, archival data) can help cross-check results and reduce CMB.
9) Introducing significant time lags between data collection points helps to mitigate biases caused by memory or social desirability, as participants may feel less pressure to provide consistent responses over time.

These specialized solutions align with different research methodologies and help target specific sources of CMB, providing more nuanced and effective strategies for mitigating bias.

4. Techniques for Identifying Common Methods Bias (CMB)

CMB poses a threat to the validity of research findings, especially in studies that rely on self-reported data. CMB occurs when the amount of bias due to the measurement method rather than the measurement design affects the results. Differences can cause the relationship between the two to increase or decrease, thus breaking down the relationship [18]. Identifying and minimizing CMBs is important to ensure the integrity of empirical research. Various types of studies have been developed to analyze CMB, each with specific applications and contexts. This paper covers four key factors in depth: Harman's single-factor test, confirmatory factor analysis (CFA) methods, latent methods, and unmeasured latent method construct (ULMC). We will explore how these technologies work and how to use them and provide real-life examples to illustrate their applications.

4.1. Harman's single-factor test

Harman's single-factor test is one of the most commonly used methods to detect CMB. This is a simple statistical method that involves performing exploratory factor analysis (EFA) on each variable in the study. The main idea is to load all variables onto a single key [20]. If one factor is present and explains most of the variation (usually more than 50%), this indicates the presence of CMB because it indicates that the response is affected by a factor such as a method rather than a single factor.

The test starts with EFA that includes all variables without any changes. You need to examine the unchanged solution to see the number of factors contributing to the variance of the data. If a large portion of the difference is explained, this indicates the presence of CMB. Most researchers use 50% of the variance explained by a factor as the threshold for indicating a potential CMB. Researchers may collect data using self-report questionnaires in which employees rate their motivation levels and self-assess their work. Using Harman's one-way test, CMB is indicated if the analysis shows that a single value explains 60% of the variance. This may be because participants are trying to be similar in their responses or are being influenced by the same measurement environment (e.g., the same questionnaire being administered at the same time). Harman's single-factor test is often used in organizational research where data on multiple constructs (e.g., job satisfaction, organizational commitment, and job performance) are recorded simultaneously through self-observation. For example, in a survey about workplace performance, if employees are responding to questions about satisfaction, commitment, and engagement, and it's all based on a single factor, this may indicate that these responses reflect more of the bias of the survey model (such as positive responses) rather than the standard deviation [21].

4.2. Confirmatory factor analysis (CFA) marker technique

The CFA marker technique is one of the best methods of CMB testing. This process involves adding a different variable (a variable that should be considered to have no relationship with the main sample under study). Variables were included in the CFA model in order to test whether they loaded on other factors indicating the presence of CMB [21]. The CFA marker technique selects a marker variable that has no theoretical relationship to any of the study's key variables of interest. This variable is subsequently included in the CFA model alongside the major constructs. If the marker variable loads onto the same components as the core constructs, or if it accounts for a considerable part of variance in conjunction with the other variables, CMB may be present. The idea is that any significant loading of the marker variable onto other constructs indicates technique bias rather than a genuine link between the constructs [6].

For example, consider a research study on the relationship between leadership and employee engagement. Researchers might include other indicators that are unrelated to leadership or engagement, such as attitudes toward environmental sustainability. If the CFA model shows that this measurement variable has a significant effect on leadership and engagement, this may indicate that the results were influenced by the process, such as how the study was observed by the participants, or by the study setting.

The latent factor technique is widely used in psychology and education to measure constructs such as self-esteem, academic achievement, and motivation through self-reports. For example, a similar method could be incorporated into research on student motivation and academic achievement to accommodate any CMB that may arise because of differences in self-reports across levels. This would help ensure that conclusions drawn about the relationship between motivation and performance are not biased by the data collection process.

4.3. Latent methods

Latent methods are statistical methods used to account for unobserved (hidden) variables that may affect the relationship between variables in a study. These methods are particularly useful for reporting bias (CMB) because they allow researchers to model and control for unmeasured factors that may indicate bias. In the context of CMB, latent methods involve creating latent variables that represent shared variables that arise from the measurement method rather than the true construct being studied [22].

For example, in a survey of employee satisfaction, the underlying variable would be "overall satisfaction," measured by a series of questions about the job, such as salary, work environment, and management. In studies focusing on CMB, scientists may include these processes in the model. This problem covers all the differences among the variables observed through the data collection (e.g., self-report survey). By including the latent factors, researchers can separate the different processes of the relationship between the constructs. This involves adding a latent variable that contains bias to each measure (question) in the study, assuming that the bias is not measured but affects many differences. Respondents may give positive or negative answers because of social needs or other factors unrelated to the actual sample (answers to the questions) and the study).

Latent methods enable researchers to uncover hidden processes connecting observed variables, controlling for biases like response tendencies. By modeling underlying relationships, they ensure findings reflect actual constructs rather than data collection artifacts. These methods, particularly structural equation modeling (SEM), enhance research validity in self-reported studies by accounting for process bias without direct measurement. Introducing techniques like ULMC helps differentiate processes, focusing on true relationships. However, the validity of latent methods hinges on the accurate representation of underlying variables; incorrect assumptions may skew results, underscoring the importance of careful application in research [15].

4.4. Unmeasured latent method construct (ULMC)

The ULMC approach involves including unmeasured latent variables in the model to account for variance due to measurement. Unlike the latent process, which involves measuring the latent variable, ULMC assumes that process bias is not directly measured but can be determined by the relationship between the variables. The ULMC approach includes a method factor that is not directly observed in the model but is assumed to influence all observed variables. This unmeasured latent factor captures the shared variance attributed to the measurement method. By including this method factor, researchers can account for the common variance due to the method, reducing the impact of CMB on the relationships among the constructs of interest [21].

In studies examining technology adoption in organizations, data on constructs like perceived ease of use and perceived usefulness are often collected using self-reported measures. To control for CMB, a ULMC can be added to the model, which helps account for any common variance due to the use of self-reported data. This ensures that the relationships between perceived ease of use, perceived usefulness, and technology adoption intentions are not confounded by CMB. ULMC is particularly useful in healthcare research where patient-reported outcomes (like quality of life, satisfaction with care, and treatment adherence) are collected. For instance, in a study examining the effects of a new treatment on patient satisfaction and quality of life, introducing a ULMC can help control for CMB, ensuring that the observed relationships are not biased by the common self-report method [6].

4.5. Post hoc statistical control of common method bias

Post hoc statistical control for CMB involves using statistical methods to account for process-related changes after data are collected. There are many ways to achieve different results. One commonly cited method is the partial correlation method of Lindell and Whitney [15], where "sign changes" are used to adjust the correlation of focal variables to control for CMB [21]. [23] reported that this technique is often used to show that CMB is not significant, but its validity remains debatable. Another technique involves imputing all study variables to a single latent trait and examining the correlation between the residuals. As of 2008, this method has been used in over 49 studies by Richardson et al. [23]. They find this model unreliable because it can eliminate negative variance in cases where there are many similar factors, leading to false results. Multi-trait multi-method (MTMM) matrices provide a more robust approach but are resource intensive and are rarely used in modeling. Given the limitations and inefficiencies of these techniques, it is recommended that these methods not be used to control for CMB because they tend to produce estimates that are lower than expected without correction.

5. Prevention Strategies for Common Methods Bias (CMB)

CMB is a pervasive issue in behavioral research that arises when the measurement method introduces systematic variance in the data, leading to biased estimates of relationships among variables [5]. This bias is particularly problematic in studies relying heavily on self-reported data, where the responses can be influenced by the measurement context, the respondent's desire to present themselves in a favorable light, or the phrasing of questions. To ensure the validity and reliability of research findings, it is crucial to adopt strategies that prevent or minimize the impact of CMB [3].

This section explores various prevention strategies for CMB, including research design strategies, procedural remedies, and statistical controls. We will investigate each strategy, discuss how they work, provide guidance on their implementation, and illustrate their application with real-life examples.

5.1. Research design strategies

Research design strategies are proactive measures implemented at the planning stage of a study to reduce the likelihood of CMB. These strategies are designed to prevent the CMB from contaminating the data, ensuring that the observed relationships among constructs reflect the true underlying relationships rather than artifacts of the measurement method.

5.1.1. Use of multiple data sources

One of the most effective ways to prevent CMB is to use multiple data sources for measuring different constructs. This approach involves combining self-reported data with other types of data, such as behavioral data, peer evaluations, or archival records. By triangulating data from different sources, researchers can minimize the impact of common method variance that might arise from relying solely on self-reported measures [8]. When data on a particular construct are collected from multiple sources, the likelihood of CMB is reduced because each source has its unique biases and errors that are unlikely to overlap completely. For instance, self-reports may be biased by social desirability, whereas peer evaluations may be influenced by interpersonal relationships, and archival records might reflect organizational biases. The combination of these data sources provides a more comprehensive and less biased view of the construct being measured [9].

In studying employee performance, researchers can combine self-reported job satisfaction data, prone to social desirability bias, with unbiased HR performance metrics for accurate insights. Similarly, in examining leadership and engagement, integrating self-reports from managers, peer evaluations from subordinates, and organizational engagement metrics like attendance and productivity helps control biases and strengthen findings. Triangulating diverse data sources ensures a more reliable understanding of relationships while mitigating self-report biases.

5.1.2. Temporal, methodological, and sources separation of measurement

Another effective strategy to prevent CMB is to separate the measurement of different constructs temporally, methodologically, or by source. This approach reduces the likelihood that the same measurement context will influence all measures, thereby minimizing the risk of CMB.

Temporal separation: It involves collecting data on different constructs at different points in time. By separating the data collection temporally, researchers can reduce the carryover effects where responses to earlier questions influence responses to later ones. This separation also helps reduce the consistency motif bias, where respondents feel compelled to maintain consistent responses across related items [10].

Methodological separation: It uses different methods to measure different constructs. For example, researchers might use surveys to measure one construct and observational methods to measure another. This approach reduces the risk that the same method will introduce similar biases across all measures [10].

Source separation: It involves collecting data on different constructs from different sources. For example, self-reports might be used to measure one construct (e.g., attitudes), while behavioral data from another source (e.g., actual behavior observed by a third party) might be used to measure another construct. This approach minimizes the risk that the same respondent biases will influence all measures [10].

To reduce CMB, studies can use temporal and methodological separation in data collection. For example, job stress might be measured via self-reported surveys at Time 1, while health outcomes are assessed through medical records at Time 2. Similarly, workplace intervention studies can measure baseline well-being before the intervention, collect intervention data through observation, and assess post-intervention well-being later. This approach minimizes bias by avoiding reliance on the same method or timing for all measurements, ensuring a clearer evaluation of relationships or intervention impacts.

5.1.3. Reverse or mix item wordings

To minimize response consistency bias, researchers can use both positively and negatively worded items in questionnaires. This approach encourages respondents to think carefully about their answers, disrupting patterns of consistent or automatic responses. Additionally, it reduces acquiescence bias, where participants agree with all items regardless of content, enhancing the validity of the collected data.

For example, in a customer satisfaction survey, researchers might include statements like “I am satisfied with the service” and “I am dissatisfied with the service.” By mixing positively and negatively worded items, the survey reduces the likelihood of patterned responses, where respondents might otherwise agree or disagree with all items without considering their content.

Also, assume a study on organizational commitment, where researchers are concerned about consent bias in self-reported data. By including both positively worded items (e.g., “I feel a strong sense of belonging to my organization”) and negatively worded items (e.g., “I do not feel a strong sense of belonging to my organization”), the survey design compels respondents to consider each statement carefully, reducing the risk of biased responses.

5.2. Practical solutions for reducing common method bias (CMB)

In addition to research design strategies, several procedural remedies can be implemented during data collection to minimize the risk of CMB. These include techniques such as ensuring respondent anonymity, using psychological separation, and carefully constructing survey items.

5.2.1. Ensuring respondent anonymity

Ensuring respondent anonymity reduces socially desirable responding and self-presentation biases, key sources of CMB. When assured of confidentiality, participants are more likely to provide honest answers, improving data accuracy. For instance, in studies on sensitive topics like unethical behavior, drug use, or illegal activities, anonymity reduces fear of judgment or repercussions, encouraging truthful self-reports and minimizing bias [11].

5.2.2. Psychological separation

Psychological separation reduces CMB by creating distinctions between survey sections, using varied instructions, response formats, or presentation styles. For instance, a study on job satisfaction and organizational commitment might use a Likert scale for one construct and a ranking scale for another, disrupting consistency patterns. Similarly, in consumer behavior research, mixing open-ended and multiple-choice questions prevents respondents from adopting uniform response patterns. This approach minimizes consistency motifs and halo effects, enhancing data validity [14].

5.2.3. Careful construction of survey items

To reduce CMB, survey items should avoid leading, double-barreled, or ambiguous questions. Clear, concise, and construct-relevant wording minimizes misinterpretation and measurement errors. For instance, instead of asking, “Do you find your work both challenging and rewarding?” researchers should use separate questions like, “Do you find your work challenging?” and “Do you find your work rewarding?" This ensures more accurate and unbiased responses [17].

5.3. Survey and instrument design techniques

CMB occurs when the measurement method itself introduces errors in the data, distorting the relationship between variables. This bias often occurs in survey-based research where all data are collected using the same method, such as personal surveys. A strong monitoring and instrumentation design are essential to minimizing CMB and ensuring that the data collected are properly related to the underlying construct [18]. Assessment and instrument design strategies aim to reduce the potential for CMB by addressing issues related to how questions are asked, the type of responses collected, and the overall structure of the survey report. These procedures include anonymization and confidentiality, the use of variable responses, and item selection. Below, we discuss these techniques in detail, examine their applications, and provide good examples.

5.3.1. Ensuring anonymity and confidentiality

Ensuring anonymity and confidentiality helps reduce social desirability bias, a common source of CMB. When respondents feel their answers are anonymous and confidential, they are more likely to respond honestly, especially on sensitive topics like unethical behavior, addiction, or mental health [20]. This approach alleviates fears of judgment or reprisal, minimizing biased responses. For instance, informing employees that their reports of unethical behavior are anonymous encourages accurate reporting. Anonymity prevents linking responses to individuals, while confidentiality ensures data are securely handled, enhancing the validity of research findings [21].

For example, a survey on youth drug use would ensure that respondents' responses are completely anonymous in order to encourage honest reporting of drug use. This approach is particularly useful in situations where certain behaviors are negatively stigmatized or legitimized.

5.3.2. Use of different scales

Using different responses is another good strategy to prevent CMB. By varying the scales used for different questions (e.g., Likert scale, semantic differential scale), researchers can reduce participants' standard or automatic responses. When using the same target (e.g., 5-point Likert scale for each question), participants will fall into certain response patterns, such as always choosing the neutral option or agreeing with all statements (acceptance bias). Researchers broke this pattern by providing different responses, forcing respondents to reflect more carefully on each question [6]. This difference in measurement reduces the risk of bias in responses and increases the reliability of the data. For some questions (e.g., "I believe this name is new"), choose "Strongly Agree" on a scale ranging from "disagree" to "disagree" and for others (e.g., "I do not trust" to "extremely"), choose "Strongly Agree" on a scale ranging from "do not trust" to "extremely"). This combination prevents participants from creating a sample response, thus encouraging more desirable and diverse responses. Researchers can use a 7-point Likert scale to measure customer satisfaction (e.g., "How satisfied are you with our service?") and a 5-point semantic differential scale to measure trust type (e.g., "Rating"). We will suggest three types, from "rarely likely" to "very likely." By changing the scale, the survey reduced the response rate and provided more insight into consumer behavior.

5.3.3. Randomization of item order

Randomizing the order of survey items is a technique used to reduce bias and reduce the effect of the order in which questions are asked on responses. This strategy prevents respondents from forming a pattern in the order of questions and ensures that their responses to each question are independent, which will guide their responses in the future, leading to conflict [15]. For example, after a respondent agrees with several positive statements, they may agree with the next statement, regardless of its content. Randomizing the order of questions reduces this tendency by preventing respondents from predicting the next question based on the current question. Respondents may begin to make connections among their responses (e.g., associating satisfaction with higher productivity). By randomizing the order of questions, researchers can ensure that each response is evaluated independently, thereby reducing the possibility of bias [23]. Questions of relevance (e.g., "I feel motivated to do my best at my job") and stress (e.g., "I often feel pressured to work"). This randomization reduces CMB by preventing participants from associating their feelings of participation with burnout.

These survey and instrument design techniques can be connected and integrated with different research areas to effectively reduce CMB. For example, in behavioral research involving both sensitive (e.g., negative attitudes) and negative (e.g., job satisfaction) factors, the content influences to ensure anonymity when different dimensions and decision elements can provide a way to reduce CMB. In business research examining consumer thinking and behavior, using different scales and random questions can reduce bias and increase research accuracy. It is important to use qualitative research and design tools to overcome bias in behavioral research [16]. By preserving anonymity and confidentiality, scientists can reduce the impact of CMB by using variable responses and object resolution and make data accurate and reliable. These ideas are supported by practical, real-life examples that highlight the importance of design thinking in making the most of research findings. By carefully planning and executing this process, scientists can solve CMB's problems and produce more reliable results, ultimately contributing to the advancement of knowledge in the field.

5.4. Statistical techniques to control for CMB

CMB refers to inconsistencies in research results that arise from measurement methods rather than constructs. This bias can affect the validity and reliability of research findings, especially in studies that rely on self-reported data. Statistical methods that control for CMB are important to ensure that correlations between variables have a real effect rather than a systematic approach. This section covers various statistics related to the management of CMB, explains how they work and their use in various situations, and provides good examples [16].

5.4.1. Use of control variables

Implementing control variable is a simple and effective technique for reducing the effects of CMB. Theoretically, the control variable is independent of the variable but may share the same model. By including these variables in the analysis, researchers can separate the variables associated with the occurrence of interest from the variables that may cause CMB. Control variables help explain extraneous influences that may affect the variance of the study. By statistically controlling these variables, scientists can reduce the amount of variation that is not explained by CMB [12].

For example, demographic variables such as age, gender, or occupation are often used as control variables because they are not directly related to the design of the study but may bias the response because they occur together. In studies investigating consumer loyalty, researchers may introduce age or occupation as control variables to account for the potential for CMB. If customers are affected by age or length of time with the company, controlling for these factors may help isolate the true effects of the independent variables on customer loyalty. For example, consider examining employee satisfaction and organizational commitment. To control for CMB, researchers may include control variables such as years of experience and educational background. By taking these factors into account, the analysis can determine the true relationship between employee satisfaction and organizational commitment, thereby reducing the impact of joint ventures.

5.4.2. Structural equation modeling (SEM) techniques

SEM is a powerful statistical technique that can estimate both measurement and model parameters simultaneously. SEM is particularly useful for CMB management because it allows researchers to model measurement errors and biases by separating them from structural relationships [4]. SEM can incorporate a matching process into the model to account for shared variability in measurements resulting from CMB. This approach allows researchers to estimate the relationship between latent constructs while accounting for the amount of bias due to the measurement method. SEM can estimate the connections between variables by showing the absolute measurement error. By including the same process in the model, scientists can control for the variability of the CMB and thus estimate the true relationship between the relationship and the change.

For example, SEM can be used to control for the CMB in studies of customer satisfaction and purchase intentions. By modeling the process model, the analysis can separate the true satisfaction of the purchase from the biases that studies (e.g., self-report) show. This approach ensures that the findings reflect real relationships rather than technical art.

5.4.3. Partial least squares (PLS) path modeling

The partial least squares (PLS) method is a variation-based SEM technique that is less sensitive to CMB and is particularly useful in complex models and small sample research studies. PLS focuses on widening the gap between variables, making it robust to CMB effects [6]. The PLS model estimates the model by measuring the model's parameters while also showing the variance of the model's variance. PLS does not require normally distributed data and is suitable for complex models with many relationships and interactions. This modification makes PLS an important tool for manipulating CMB in the search for where the structure may be constrained.

For example, a researcher might use PLS to analyze data from a survey measuring perceived ease of use, perceived usefulness, and behavioral intentions to use technology. PLS provides a good way to estimate social structure while controlling for CMB by focusing on the most variable. PLS can be used to analyze data by assessing characteristics, such as operational willingness, perceived benefits, and adoption rates. Using the PLS method, researchers can estimate the relationship model while reducing the influence of CMB, especially when dealing with complex models with multiple predictors and compromises.

5.4.4. Advanced statistical techniques

Various advanced statistical techniques have been developed to provide greater control over the CMB. These methods include the Bayesian method and the MTMM method, both of which are particularly good at controlling bias.

Bayesian approach. Bayesian methods use prior distributions to control the CMB and allow scientists to incorporate their prior experience or beliefs about the constraints into the model. This approach provides a flexible framework for managing the CMB by integrating additional data beyond the observations [9]. Bayesian methods estimate the posterior distribution of parameters based on observations and prior distributions. This approach allows scientists to explain the underlying CMB by incorporating prior beliefs or evidence about the relationship between variables. Bayesian methods are particularly useful when experience is available and can be used to improve the accuracy of estimates. Bayesian methods are methods that involve prior classification based on prior research. By incorporating this prior knowledge, the analysis can provide a more accurate estimate of the potential CMB controlling relationship.

Multi-trait multi-method (MTMM) models. MTMM models can measure multiple attributes using multiple methods and provide greater control over the CMB. The MTMM model is particularly useful in assessing the convergence and divergence of constructs while controlling for influence. The MTMM model involves measuring multiple attributes using different methods (such as surveys, interviews, behavioral analysis) and assessing how well the measurements hold up to the same quality and the differences between the differences [10]. This approach allows researchers to separate the variation due to the nature of the variation from the measurement, allowing the model to be more accurate. Methods for measuring multiple attributes can involve (such as thoughts, feelings, behaviors) (such as surveys, focus groups, behavioral profiles) to assess multiple traits (e.g., attitude, intention, behavior). Researchers can control for the CMB using multiple measures and gain a better understanding of consumer behavior.

For example, research on leadership and employee performance can use MTMM to measure various traits (e.g., organizational effectiveness, employee motivation, job satisfaction) using a variety of methods (e.g., self-reports, peer evaluations, profile information). Using this approach, studies can better control for CMB and ensure that correlations are due to the design itself rather than the measurement method, and reliability.

Researchers can reduce the influence of CMB by using control variables, structural equation models, PLS models, and advanced statistical methods such as Bayesian methods and MTMM models. This method provides a good solution to ensure that research results reflect the truth behind the relationship between variables without the influence of the method. By carefully selecting and using these techniques, researchers can improve the quality of data analysis and increase the effectiveness of their studies.

6. Examples and Case Studies on Overcoming Common Methods Bias

CMB poses significant challenges to the validity of findings from many studies in the social sciences, especially when based on self-reported data. Carefully designed studies should be conducted on CMB that includes strategies to reduce the impact of this bias. This section presents illustrative examples and case studies that highlight the challenges faced by CMB and demonstrate successful mitigation strategies across different research areas.

Social Desirability Bias: Employees tend to view their leaders as both socially desirable and themselves as complicit in following the leadership style or expectations in the organization.
Consistency Motif Bias: Respondents may give the same answers to questions about clarity or consistency, regardless of their experience or views.

Several strategies can be used to reduce CMB in the study:

Multi-Source Data Collection: This study can collect data from multiple sources instead of relying solely on personal advertisements. For example, peer or manager evaluations can be used to measure organizational change, while performance data from human resources can be used to evaluate employee benefits.
Temporal Separation of Measurement: By separating the measurement of independent and dependent variables over time, the study reduces the likelihood of consistency bias. For example, leadership can be measured at the beginning of the study, while employee benefits can be measured weeks later. By employing these strategies, the study can more accurately capture the true relationship between transformational leadership and employee outcomes, minimizing the impact of CMB [16].

6.1. Case studies on successful mitigation

Mitigating CMB in Health Research: A study was conducted to evaluate the relationship between patient satisfaction and clinical outcomes in a clinical setting. Researchers face problems with CMB because both constructs were originally measured using self-report questionnaires, which makes the results subject to biases such as self-report uncertainty and social needs [18].
Mixed-Methods Approach: To overcome CMB, the researchers used a mixed method that combined quantitative research with qualitative interviews and clinical observations. They used a self-report survey to improve patient satisfaction, but they also collected objective clinical data (e.g., test results, clinical assessment) for clinical purposes and interviewed treatment professionals to better understand patient progress [18].
Methodological Triangulation: Researchers can cross-reference their findings by measuring the same building using multiple methods. For example, compare patient satisfaction scores with responses from quality interviews to provide more insight into the patient experience [24].

The mixed methods allow researchers to identify differences between self-reported patient outcomes and clinical outcomes. Patients who reported satisfactory scores tended to have poorer clinical outcomes, indicating a poorer response in self-reported data. The inclusion of clinical observations and physician interviews helps contextualize these findings and provides insight into patient satisfaction and clinical effectiveness. It may be effective in reducing CMB in health research [20]. By integrating different types of data, researchers can improve their findings, reduce the impact of bias, and gain a better understanding and insight into the construction. Challenges and solutions related to CMB in quantitative research in the social sciences. Researchers can reduce the impact of CMB and increase the effectiveness and efficiency of their findings by using techniques such as multi-site data collection, temporal separation, and triangulation techniques. This approach not only improves the quality of the research but also ensures that the results reflect real relationships rather than artifacts resulting from the process.

7. Best Practices for Researchers: Overcoming Common Methods Bias

CMB is a major challenge in many studies in the social sciences, especially when relying on self-reports. Researchers should use best practices in research design and data collection to ensure the validity and reliability of their findings [15, 25]. The following guidelines offer simple strategies to reduce CMB and improve research results.

7.1. Guidelines for designing surveys

7.1.1. Ensure clear, concise, and neutral wording

To reduce CMB, accuracy and proportionality in questions are important. Ambiguous or critical questions may cause respondents to respond biased by misunderstanding the question or giving the socially expected answer. To avoid this, researchers must ensure that all questions in the survey are clear, precise, and unbiased [12].

Clear Wording: Questions should be clear and concise, using simple language that all respondents can easily understand, regardless of their background or education. Avoid using jargon or complex terms that could confuse respondents and bias their responses.
Concise Wording: Each question should be as short as possible and still convey the appropriate message. Long questions can tire respondents or cause misunderstandings, leading to incorrect answers [26].
Neutral Wording: Researchers should avoid any language that might cause participants to respond in a certain way. For example, questions that solicit socially expected answers or ask questions in a biased manner will bias results. Conversely, the wording of the question should not imply a "correct" or "ideal" answer [17].

For example, in a job satisfaction survey, researchers should not ask basic questions, such as "Do you agree that our company is a good place to work?" Instead, researchers should use neutral statements, such as "Please rate your satisfaction with your current job."

7.2. Use a balanced mix of positive and negative items

Such positive and negative elements in surveys can help reduce response bias and encourage respondents to give inconsistent answers, known as presupposition bias. This approach encourages respondents to think carefully about each question, resulting in increasingly diverse responses.

Positive and negative item balance: A combination of positive and negative questions encourages respondents to consider individually rather than relying on answers (e.g., I agree with all statements). For example, an organizational commitment survey might include positive statements such as "I am happy working for this company" and negative statements such as "I often think about leaving my job" [27].
Mitigating consistency bias: This strategy reduces confusion where participants may feel forced to answer all questions the same way because of the pattern. By changing the wording of the questions, researchers can reduce this bias and obtain reliable data [27].

For example, when studying customer satisfaction, researchers should not only use positive words such as "I am happy with good products" but also include negative words such as "I usually dislike these things." This balance prevents participants from agreeing with all items and encourages them to carefully evaluate each statement based on their own experiences.

7.3. Practical application and contextual relevance

These best practices are not only robust but can be applied across many research areas. Whether you're conducting environmental research, healthcare research, or consumer research, these tips can help reduce CMB and improve data quality.

In organizational research: When examining factors such as job satisfaction, leadership effectiveness, or organizational commitment, an open, unbiased, and mixed-methods approach will prevent people from performing tasks by providing the desired response or following a response pattern, which will lead to the accuracy of the employee's behavior and evaluation [17].

In health research: Using these strategies in studies measuring patient satisfaction, treatment adherence, or health behaviors may help reduce potential bias by patients seeking to impress their doctors or present themselves in a positive light [18, 28].

By using these best practices, researchers can reduce the impact of CMB on science, thereby increasing the validity and reliability of scientific results. The best approach to research design ensures that the data collected is influenced by the measurement structure, which provides greater trust and confidence in the research.

7.4. Best practices for data collection and analysis

Effective data collection and analysis are important for minimizing CMB in social research. Applying best practices in these areas can help researchers collect more accurate data and get better results.

7.4.1. Combine qualitative and quantitative methods

One of the best strategies for reducing CMB is to use a combination of methods that combine qualitative and quantitative data collection techniques. By combining different types of data, scientists can cross-check findings and reduce reliance on one of the data sources that typically contributes to the CMB in the first place [29].

Qualitative methods: Techniques such as interviews, focus groups, and surveys provide rich, detailed data that provide a deeper understanding of participants' attitudes and behaviors. This process helps the subject quantify the data and better understand the research results [6].

Quantitative methods: Standardized tools such as surveys and tests to measure behavior and behavior in larger samples. Combining these with quality data, researchers can verify the consistency and validity of their findings [11, 22].

For example, in studies evaluating educational outcomes, researchers may engage with students and teachers to better understand the educational issue. These qualitative data can be supplemented with quantitative measures, such as standardized test scores, to provide a more comprehensive and unbiased understanding of the factors that influence academic achievement. Using both methods allows for a more robust analysis and helps reduce bias that can result from relying on self-reported data.

7.5. Apply rigorous statistical techniques

Employing advanced statistical techniques is another essential practice for detecting and controlling CMB during data analysis. Methods such as SEM, CFA, and PLS modeling are effective in detecting and controlling measurement errors and changes.

Structural equation modeling (SEM): SEM allows researchers to model relationships between variables while accounting for measurement error. By integrating latent variables and controlling variance in different ways, SEM helps identify and treat CMBs [3, 30].

Confirmatory factor analysis (CFA): CFA can be used to test whether all variables load on a single factor indicating the presence of CMB. Researchers can make necessary adjustments to increase data accuracy by determining different methods from these methods.

Partial least squares (PLS) path modeling: PLS is particularly useful in research studies with complex models and small sample sizes. It is less sensitive to CMB and helps scientists estimate relative patterns while accounting for measurement errors [9, 31].

For example, in a study investigating employee engagement and job satisfaction, SEM can be used to identify differences between these constructs from biases in self-reporting. This approach allows researchers to refine their models and increase the accuracy and reliability of their findings. By combining qualitative and quantitative methods and using rigorous analytical methods, researchers can reduce CMB and increase the effectiveness of social science research. These best practices ensure that the data collected truly reflects the construct being studied, leading to more reliable research results.

8. Recommendations for Reporting CMB in Social Science Research

CMB is important for objectivity and reliability in social research. Researchers should provide detailed information about the steps taken to identify and control for single-source bias problem, demonstrate their commitment to rigorous methodology, and ensure the reliability of their findings [23]. Researchers need to clarify the methods used to detect and minimize CMB. This includes explaining the statistical tests or control methods used, such as Harman's single-factor test, CFA, or the inclusion of confounding variables. Providing a detailed description of this process can help readers understand how to deal with bias and support the validity of the study's results [32].

It is important that the results of any test for CMB be presented in the results. For example, if Harman's single-factor test is used, the researcher should report the percentage of variation explained by a single factor. A low percentage (e.g., below 20%) means that CMB is unlikely to be a major problem. Statements such as "Harman's single-factor test showed that no single factor explained more than 20% of the variance" are evidence that the study is not affected by CMB. By clarifying the method of defining and controlling for CMB, scientists increase the trust and transparency of their research, ensuring that their findings are robust and reliable [6].

9. Conclusion

In many studies in the social sciences, it is important to address CMB in ensuring the validity and reliability of research results. If not properly identified and managed, CMB can affect study results and lead to false conclusions. This paper describes several methods to detect, prevent, and reduce CMB, including using multiple sources, using statistical methods, and using rigorous research and design techniques. Each method has its own advantages, and a combination of these methods can provide a strong defense against CMB. Researchers are encouraged to use multiple techniques appropriate to their research topics to improve data quality and research results. By carefully considering the CMB, researchers can increase the credibility and impact of social science by ensuring that their findings are relevant to the phenomenon being studied and that there is no bias in the data collection process.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by the author.

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Mohammad Rashed Hasan Polas: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

References

[1] Jordan, P. J., & Troth, A. C. (2020). Common method bias in applied settings: The dilemma of researching in organizations. *Australian Journal of Management*, *45*(1), 3–14. https://doi.org/10.1177/0312896219871976

[2] Baumgartner, H., & Weijters, B. (2021). Dealing with common method variance in international marketing research. *Journal of International Marketing*, *29*(3), 7–22. https://doi.org/10.1177/1069031X21995871

[3] Saxena, M., Bagga, T., Gupta, S., & Kaushik, N. (2024). Exploring common method variance in analytics research in the Indian context: A comparative study with known techniques. *FIIB Business Review*, *13*(5), 553–569. https://doi.org/10.1177/23197145221099098

[4] Zhang, W., Yuan, G., Xue, R., Han, Y., & Taylor, J. E. (2022). Mitigating common method bias in construction engineering and management research. *Journal of Construction Engineering and Management*, *148*(9), 04022089. https://doi.org/10.1061/(ASCE)CO.1943-7862.0002364

[5] Speklé, R. F., & Widener, S. K. (2018). Challenging issues in survey research: Discussion and suggestions. *Journal of Management Accounting Research*, *30*(2), 3–21. https://doi.org/10.2308/jmar-51860

[6] Simha, A. (2024). Noblesse oblige—An entreaty to stop using common-method bias as a carnwennan of carnage. *Group & Organization Management*, *49*(3), 784–791. https://doi.org/10.1177/10596011231151549

[7] Krosnick, J. A., & Alwin, D. F. (1987). An evaluation of a cognitive theory of response-order effects in survey measurement. *Public Opinion Quarterly*, *51*(2), 201–219.

[8] Olteanu, A., Castillo, C., Diaz, F., & Kıcıman, E. (2019). Social data: Biases, methodological pitfalls, and ethical boundaries. *Frontiers in Big Data*, *2*, 13. https://doi.org/10.3389/fdata.2019.00013

[9] Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting and Social Change*, *173*, 121092. https://doi.org/10.1016/j.techfore.2021.121092

[10] Chang, S. J., van Witteloostuijn, A., & Eden, L. (2020). Common method variance in international business research. In L. Eden, B. B. Nielsen & A. Verbeke (Eds.), *Research methods in international business* (pp. 385–398). Springer. https://doi.org/10.1007/978-3-030-22113-3_20

[11] Manata, B., & Boster, F. J. (2024). Reconsidering the problem of common-method variance in organizational communication research. *Management Communication Quarterly*, *38*(3), 677–697. https://doi.org/10.1177/08933189231226242

[12] Kaltsonoudi, K., Tsigilis, N., & Karteroliotis, K. (2022). Critical review of the literature and current tendencies of the common method variance in sport management research. *Measurement in Physical Education and Exercise Science*, *26*(2), 103–115. https://doi.org/10.1080/1091367X.2021.1949322

[13] Bozionelos, N., & Simmering, M. J. (2022). Methodological threat or myth? Evaluating the current state of evidence on common method variance in human resource management research. *Human Resource Management Journal*, *32*(1), 194–215. https://doi.org/10.1111/1748-8583.12398

[14] Antonakis, J. (2017). On doing better science: From thrill of discovery to policy implications. *The Leadership Quarterly*, *28*(1), 5–21. https://doi.org/10.1016/j.leaqua.2017.01.006

[15] Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of Applied Psychology*, *86*(1), 114–121. https://doi.org/10.1037/0021-9010.86.1.114

[16] Fakhreddin, F. (2023). Nonresponse bias and common method bias in survey research. In P. Foroudi & C. Dennis (Eds.), *Researching and analysing business* (pp. 275–282). Routledge. https://doi.org/10.4324/9781003107774-21

[17] Jakobsen, M., & Jensen, R. (2015). Common method bias in public management studies. *International Public Management Journal*, *18*(1), 3–30. https://doi.org/10.1080/10967494.2014.997906

[18] Baumgartner, H., de Nisco, A., & Diamantopoulos, A. (2024). Addressing common method variance in country-and destination-image research: Two practical approaches. *Journal of Destination Marketing & Management*, *33*, 100906. https://doi.org/10.1016/j.jdmm.2024.100906

[19] Chiew, T. M., Mathies, C., & Patterson, P. (2019). The effect of humour usage on customer's service experiences. *Australian Journal of Management*, *44*(1), 109–127. https://doi.org/10.1177/0312896218775799

[20] MacKenzie, S. B., & Podsakoff, P. M. (2012). Common method bias in marketing: Causes, mechanisms, and procedural remedies. *Journal of Retailing*, *88*(4), 542–555. https://doi.org/10.1016/j.jretai.2012.08.001

[21] Conway, J. M., & Lance, C. E. (2010). What reviewers should expect from authors regarding common method bias in organizational research. *Journal of Business and Psychology*, *25*, 325–334. https://doi.org/10.1007/s10869-010-9181-6

[22] Polas, M. R. H. (2024). Sample selection in social science research: A holistic approach to methodological rigor. *Sustainable Economies*, *2*(1), 31.

[23] Richardson, H. A., Simmering, M. J., & Sturman, M. C. (2009). A tale of three perspectives: Examining post hoc statistical techniques for detection and correction of common method variance. *Organizational Research Methods*, *12*(4), 762–800. https://doi.org/10.1177/1094428109332834

[24] Fuller, C. M., Simmering, M. J., Atinc, G., Atinc, Y., & Babin, B. J. (2016). Common methods variance detection in business research. *Journal of Business Research*, *69*(8), 3192–3198. https://doi.org/10.1016/j.jbusres.2015.12.008

[25] Kong, H., Chiu, W. C., & Leung, H. K. (2019). Building creative self-efficacy via learning goal orientation, creativity job requirement, and team learning behavior: The key to employee creativity. *Australian Journal of Management*, *44*(3), 443–461. https://doi.org/10.1177/0312896218792957

[26] Doty, D. H., & Astakhova, M. (2020). Common method variance in international business research: A commentary. In L. Eden, B. B. Nielsen & A. Verbeke (Eds.), *Research methods in international business* (pp. 399–408). Springer. https://doi.org/10.1007/978-3-030-22113-3_21

[27] Kock, F., Berbekova, A., & Assaf, A. G. (2021). Understanding and managing the threat of common method bias: Detection, prevention and control. *Tourism Management*, *86*, 104330. https://doi.org/10.1016/j.tourman.2021.104330

[28] Kline, R. (2013). Exploratory and confirmatory factor analysis. In Y. Petscher, C. Schatschneider & D. L. Compton (Eds.), *Applied quantitative analysis in education and the social sciences* (pp. 171–207). Routledge. https://doi.org/10.4324/9780203108550

[29] Maydeu-Olivares, A., Shi, D., & Fairchild, A. J. (2020). Estimating causal effects in linear regression models with observational data: The instrumental variables regression model. *Psychological Methods*, *25*(2), 243–258. https://doi.org/10.1037/met0000226

[30] Podsakoff, P. M., & Podsakoff, N. P. (2019). Experimental designs in management and leadership research: Strengths, limitations, and recommendations for improving publishability. *The Leadership Quarterly*, *30*(1), 11–33. https://doi.org/10.1016/j.leaqua.2018.11.002

[31] Sande, J. B., & Ghosh, M. (2018). Endogeneity in survey research. *International Journal of Research in Marketing*, *35*(2), 185–204. https://doi.org/10.1016/j.ijresmar.2018.01.005

[32] Strauss, K., Parker, S. K., & O'Shea, D. (2017). When does proactivity have a cost? Motivation at work moderates the effects of proactive work behavior on employee job strain. *Journal of Vocational Behavior*, *100*, 15–26. https://doi.org/10.1016/j.jvb.2017.02.001

How to Cite: Polas, M. R. H. (2025). Common Method Bias in Social and Behavioral Research: Strategic Solutions for Quantitative Research in the Doctoral Research. *Journal of Comprehensive Business Administration Research*. https://doi.org/10.47852/bonviewJCBAR52024285