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ADDRESSING COMMON METHOD BIAS, OPERATIONALIZATION, SAMPLING, AND DATA COLLECTION ISSUES IN QUANTITATIVE RESEARCH: REVIEW AND RECOMMENDATIONS

Mumtaz Ali Memon*[1], Ramayah Thurasamy[2], Jun-Hwa Cheah[3], Hiram Ting[4], Francis Chuah[5] and Tat-Huei Cham[6]

[1]NUST Business School, University of Sciences and Technology (NUST), Islamabad, Pakistan
[1]Faculty of Business, Sohar University, Sohar, Oman
[2]School of Management, Universiti Sains Malaysia, Penang, Malaysia
[2]Department of Information Technology & Management, Daffodil International University, Bangladesh
[3]Norwich Business School, University of East Anglia, Norwich, United Kingdom
[4]Faculty of Hospitality and Tourism Management, UCSI University, Sarawak, Malaysia
[5]School of Business Management, Universiti Utara Malaysia, Kedah, Malaysia
[6]UCSI Graduate Business School, UCSI University, Kuala Lumpur, Malaysia

Corresponding email: mumtazutp@gmail.com

ABSTRACT

When editing regular and special issues of numerous journals, we have observed several recurring shortcomings in the manuscripts, particularly in relation to methodology. Many of these manuscripts are often found lacking in providing critical methodological information or justifying the use of the selected methods, thus resulting in desk rejection at the preliminary stage or major revision in the review process. Although the theoretical and managerial aspects of manuscripts are essential to publication consideration, methodological flaws can be detrimental. It is therefore of no surprise that failures to address methodological concerns are some of the common reasons for a manuscript to be rejected from publication, even after going through several rounds of revision. The purpose of this editorial is to provide clear guidelines on effectively reporting the methodological section in a quantitative manuscript in the fields of business and social sciences. Specifically, we present a set of recommendations on implementing and reporting operationalization, instrument validation, sampling techniques, questionnaire administration, and common method bias. Researchers, whether students or academics, should consider these guidelines to ensure methodological rigor in their research projects.

Keywords: *Common method bias, operationalization, sampling, questionnaire administration*

Type: Editorial

INTRODUCTION

It has been six years since we launched the Journal of Applied Structural Equation Modeling (JASEM). Seven volumes and twelve issues are published to date, thus giving us the opportunities to (re)learn and (re)consider many things from all submissions. In addition, we have jointly edited special issues for a good number of reputable journals in the fields of social science, including European Business Review, International Journal of Manpower, Journal of Strategic Marketing and Journal of Hospitality and Tourism Technology. As we review each submitted paper, with the assistance of reviewers in a double-blind review process, we are also able to assess the overall quality of the submissions and identify common strengths and deficiencies.

We have observed several recurring shortcomings in the manuscripts submitted to JASEM and our special issues, most notably in the methodology sections. These sections often lack the necessary efforts or rigor, with requisite methodological information frequently omitted. At times, we are compelled to reject manuscripts even after two rounds of revision, due to the authors' consistent failures to address or provide justification as a response to method-related concerns. The shortcomings we have encountered include insufficient information on context (country, industry, population), inadequate or absent details on the inclusion and exclusion criteria for respondents, improper operationalization of key constructs (such as inconsistencies between the scales used and the definitions adopted), and a lack of comprehensive explanations for instrument validation, pretesting, and pilot studies.

According to Jordan and Troth (2020) "A rigorous method is an important part of editors' and reviewers' assessments of a manuscript for publication, in the main, to ensure more trustworthy findings" (p.4). Although such rigor is not always easy to achieve, we consider it essential for each submission to provide a thorough account of the research methods, from the initial approach to the final data gathering. Merely stating, for example, that "data were collected from 300 employees" or "questionnaires were validated by experts" is insufficient. We encourage authors to be thoughtful in writing this section, not only to demonstrate their efforts in carrying out research activities but also to assure the editors and reviewers the methodological rigor of their work. It is worth noting that on numerous occasions, authors have failed to justify their sample sizes, and even when they do, they often rely on rules of thumb that are incompatible with their chosen sampling methods.

The objective of this editorial is to offer clear and fundamental guidelines for quantitative researchers on effectively reporting the methodological aspects of their manuscripts. We present several checklists that can be utilized by researchers, including experienced academicians and students alike, when crafting the methods sections, subsections, or chapters of their research projects, theses, or dissertations. These self-explanatory checklists cover topics such as operationalization, instrument validation, sampling and questionnaire administration, and common method bias (see Table 1-4). Moreover, the editorial also recommends pertinent literature and best practices that researchers should consider ensuring methodological rigor in their projects.

Operationalization

Operationalization is a fundamental aspect of quantitative research that contributes to the clarity of study constructs and the accuracy of instruments used. It helps to avoid confusion and ambiguity in the research process. Failure to operationalize constructs will lead to poor measurement, where respondents will misunderstand the intended meaning of the measurement items (statements or questions used during a survey) and subsequently provide invalid responses. As a result, researchers will have difficulties in addressing their proposed research questions even if they have completed their data collection in a proper manner. In this editorial, we refer to operationalization as a two-dimensional activity that consists of 1) concretely defining the constructs or variables under consideration for the research, and 2) selecting scales (items) that best measure these constructs. It is important to note that many of the constructs in management and social sciences have multiple definitions. Therefore, researchers must carefully select the most appropriate definition of a construct that aligns with their study objectives.

Further, this is the time to clarify whether a construct is unidimensional or multidimensional. If a construct is previously measured as both unidimensional and multidimensional, authors have the privilege to select any of these operationalizations with a justification. However, it is always beneficial to adopt the most recent approaches as we notice that many of the constructs that were previously measured as unidimensional, are recently recommended to be considered as multidimensional (e.g., Hunsu et al., 2022, Howard & Crayne, 2019). Also, authors need to confirm if it is a formative (observed variables form the construct and are believed to cause the construct) or reflective (observed variables are indicators of the construct and the construct causes the variables) (See Ringle et al., 2020, p. 1624).

Once defined, researchers should select scales that align with the chosen definitions. For example, the construct of "engagement" in the fields of human resources and organizational behavior has multiple definitions, such as personal engagement (Kahn, 1990), employee engagement (Shuck et al., 2017), work engagement (Schaufeli et al., 2002), and job engagement and organizational engagement (Saks, 2006), among others. If authors define employee engagement as "work engagement", the scale chosen must specifically measure the work engagement construct and not the other forms of engagement. We recommend that authors explicitly state the operational definition being adopted in the study. For example, they could state, "In this study, the concept of engagement is operationalized as work engagement, which encompasses an individual's vigor, absorption, and dedication towards their work."

Lastly, we strongly recommend that authors report the original source, the one who initially developed the scale. However, if you adopt or adapt the items from a recent paper which uses the same scale, you are advised to cite both sources. Though it is not mandatory, it is useful to show the reliability (Cronbach's Alpha or Composite Reliability) and validity (average variance extracted) scores mentioned in the source paper. We suggest referring to Coltman et al., (2008) and de Oliveira et al. (2019) as examples when reporting the operationalization of the constructs. Table 1 summarizes the reporting guidelines related to operationalization.

Table 1: Reporting Guidelines on Operationalization

Issue	Criteria	Reporting Recommendations
Operationalization	Define constructs or variables under consideration for the research.	▪ Define the construct and mention if it has multiple definitions. Choose one definition and state that your study adopts this definition. ▪ Explain whether the construct is unidimensional or multidimensional in your study and provide a justification. ▪ Clarify whether the construct is reflective or formative and explain the reasons.
	Select scales (items) that best measure the constructs of the study	▪ Mention which scale is adopted/adapted, and its number of items. ▪ Explain how the selected scales best measure the construct and represent the operational definition of the construct. ▪ Cite the original source, the developer. ▪ If the scales are taken from another source, not from the original source, then cite both. ▪ Report the reliability of the scales mentioned in the source paper with citation. ▪ Report a sample item. ▪ Provide all scales/items in the appendix.

Instrument validation

Authors should provide a detailed account on instrument validation. Absence of a rigorous instrument validation procedure will more than often compromise validity and reliability, particularly in the data analysis stage. In addition, failing to conduct instrument validation will result in a waste of time and financial resources in the long run, because inaccurate or unreliable measures may lead to inaccurate findings, thus misleading discussion, and conclusion. As a rule of thumb, authors are expected to perform and report three essential procedures: face validity, content validity, and pretesting. These procedures must be completed prior to data collection. The first two validations, face validity and content validity, should be confirmed by multiple experts in the field. Determining a person's expertise and the number of experts is a subjective matter as its decisions are hinged upon the types and complexity of research. For basic research which empirically investigates behaviors and uses only one source of data, would normally require a minimum of three or five experts. Experts, in turn, are those who possess the domain knowledge. They are usually selected based on their publication in the reputable journals. Nevertheless, their position (thus their roles) and/or industrial experience may also be considered due to its relevance to the research. It is important to note that the onus is on the authors or researchers to identify the right experts to provide the required validation.

These experts are tasked with validating the questionnaire based on two primary criteria: Firstly, they assess face validity by examining the clarity, appropriateness, logical connections, and format of the questionnaire items. During this process, they scrutinize clarity (i.e., ensuring the wording and phrasing of questions are clear, concise, and easily understandable), appropriateness (i.e., verifying the suitability of items for the target population and the absence of offensive, biased, or sensitive content), and logical connections (i.e., ascertaining that the relationship between the questions and the construct is evident and easily understandable, even for those not deeply familiar with the topic). Additionally, experts evaluate the overall structure of the questionnaire, including response options (e.g., Likert scales), and ensure that the format is user-friendly (i.e., with appropriate font size, style, length, and readability) and easy to follow (i.e., with detailed instructions) for the target population.

Secondly, experts assess content validity by focusing on several key aspects that specifically relate to the relevance, representativeness, and comprehensiveness of the questionnaire items of the construct. When evaluating content validity, experts must consider the theoretical foundation, ensuring that the questionnaire items are grounded in relevant theories and existing literature. They should also examine the construct coverage to verify that the questionnaire comprehensively addresses all pertinent dimensions or facets of the construct. Additionally, they should evaluate item relevance to confirm that each item directly relates to the construct being measured and captures its essential features. Furthermore, they need to check for item redundancy to eliminate any overlapping items that could affect the reliability and validity of the instrument. Authors are thus advised to submit a complete package for expert evaluation, including the questionnaire, conceptual/theoretical framework of the study, study objectives, operational definitions, and explanations of adapted items with justifications for any changes made before the expert validation. Although face-to-face interaction with experts is highly recommended for validation, obtaining feedback via email is beneficial for future reference as evidence, provided that it is not done haphazardly. Saunders et al. (2023, Chapter 11), Kumar et al. (2013, Chapter 7) are recommended readings to know basic guideline related to instrument validation. For reporting, de Oliveira et al., (2019) can be referred as they have meticulously demonstrated the process of instrument validation.

Finally, authors must conduct and report the pretesting of the questionnaire. Collecting data without pretesting with a local sample (actual members of the population) can lead to inaccuracies in survey results (Colbert et al., 2019). All items, whether adopted or adapted, should be pretested to confirm whether the respondents have clearly understood all the questions or statements (Kumar et al., 2013). Hulland et al. (2018) assert, "Despite the abundance of guidance for researchers on formulating questions and constructing questionnaires, it is often challenging for even experts to foresee all potential issues that may occur during survey administration" (p. 8). Thus, it is imperative that surveys undergo thorough pretesting prior to main data collection.

Various methods exist for pretesting survey questionnaires, including informal pretesting with a small sample of respondents, cognitive interviews, and debriefing (Memon et al. 2017, Willimack et al., 2023). Regardless of the chosen method, respondents should be recruited from the target population. For instance, if the study aims to explore the impact of work overload on organizational commitment among nurses, the pretesting sample should consist of nurses.

While several rules of thumb exist for determining pretesting sample size, typically, 3-5 respondents from the target population are deemed sufficient. In fact, some might even conduct several rounds (2-3 times) of pre-testing to ensure the validation comes to a consensus, especially when researchers are trying to conduct a complex study design (e.g., experimental or longitudinal). Researchers must identify participants who are willing to read each question and offer comprehensive feedback. However, we encourage all researchers to consider using pretests prior to running their main studies whether they are using previously established scales or developing fresh scales.

Table 2: Recommendations for Reporting on Instrument Validation

<table>
<tr><th>Issue</th><th>Description</th><th>Reporting Recommendations</th></tr>
<tr><td>Face Validity</td><td>Experts confirm the clarity, appropriateness, logical connections, and format of the questionnaire items.</td><td rowspan="2">▪ Explain what face validity is and what it does.
▪ Explain what content validity is and what it does.
▪ Report how many experts were approached, their designations, years of experience, and other inclusion criteria.
▪ Report the process. How the experts were contacted (email/face-to-face) and when it was conducted.
▪ Report experts' feedback in detail and their concerns.
▪ Report what revisions were made based on experts' feedback.
▪ Report what expert recommendations were ignored/not incorporated, and why</td></tr>
<tr><td>Content Validity</td><td>Experts confirm the relevance, representativeness, and comprehensiveness of the questionnaire items</td></tr>
<tr><td>Pretesting</td><td>Ensuring respondents understand all the questionnaire items and there is no ambiguous item.</td><td>▪ Explain what pretesting is, why it was carried out.
▪ Report on which pretesting method was employed.
▪ Report on how many respondents were recruited.
▪ Report respondents' feedback in detail.
▪ Report what revisions were made based on respondents' feedback.
▪ Report which recommendations were ignored/not incorporated, and why.
▪ Report how many rounds of pretesting were carried out.</td></tr>
</table>

When reporting on pretesting, researchers should describe the process, specify the respondents and their number, detail the feedback received, and, most importantly, outline the changes made based on respondent feedback. Remember, pretesting does not require any statistical analysis, and it only ensures that respondents understand the items clearly. In contrast to pretesting, a pilot study uses statistical analysis (e.g., reliability and/or validity analysis). We often notice researchers using pretesting and pilot study interchangeably, which is incorrect. Both have different processes, methods, purposes, and outcomes.

For a better understanding of pretesting, we recommend researchers consult our previous work Memon et al. (2017) and recent work by Wardropper et al. (2021), which thoroughly discusses pretesting and pilot study, including sample criteria and various implementation methods. Also, researchers are encouraged to refer to Colbert et al. (2019) and Buschle et al. (2022) for a better understanding and to know more about new approaches related to pretesting (e.g., Qualitative Pretest Interview). Table 2 summarizes the recommendations for reporting the instrument validation process and its various activities.

Sampling Strategy & Questionnaire Administration

Researchers are expected to explicitly discuss the sampling strategy and techniques employed as well as provide explanations regarding questionnaire administration. Using an inappropriate sampling strategy and technique can result in reduced cost-and-time efficiency during data collection, decreased precision of estimates due to lower variability in the data, and, to a certain degree, limited generalizability of the findings to the population (depending on the sampling strategy) with a greater degree of confidence. Moreover, failing to conduct proper questionnaire administration will increase the potential for numerous errors (i.e., population-specific errors, sample frame error, selection error, non-response error, and sampling errors) or inconsistencies in data collection. Therefore, authors (or researchers) should provide information about the administration process, including the mode of administration, the number, and type of contacts.

Firstly, the chosen sampling technique, whether probability or non-probability, must be justified. Mention specific type of the probability sampling (e.g., simple random, stratified random, systematic random, etc.) or non-probability sampling (e.g., snowball, quota, convenience, purposive, etc.) technique that was used. As expressed in our previous work (see Memon et al., 2017), we maintain the view that in the absence of a complete sampling frame (a complete list of individuals, objects, or units in a population from which a sample will be selected), a carefully implemented non-probability sampling technique may prove superior to a probability-based approach, yielding higher response rates and collecting more relevant datasets. Although we do not discourage or promote the use of any specific sampling techniques, we expect authors to provide a solid justification for their adoption. Merely stating that "convenience sampling was employed" is neither encouraged nor considered an appropriate way of reporting. Detailed information must be provided to address several questions, including: Which sampling technique was employed and why? How was it implemented? Was data collected in a single attempt, or were there multiple phases? If there were multiple phases, how many samples were collected in each? Was data collection conducted face-to-face or online, and if so, in what proportions? How were respondents approached? How was anonymity ensured? What was the overall duration of data collection, and when did it take place (month/year)?

Furthermore, authors are required to elucidate the inclusion and exclusion criteria for respondents. If data were collected from a particular industry, sector, or group of respondents, authors must justify their selection and expound on the relevance of the study variables to the chosen industry, sector, or respondents. For instance, if authors are "investigating the impact of personality traits on abusive supervision in the telecommunication sector," they must initially establish that employees in the telecommunication sector are indeed experiencing abusive supervision. Selecting a context or setting for the study without due consideration also hinders the development of practical recommendations. Table 3 summarizes the recommendation on reporting sampling and questionnaire administration process and related methodological aspects. We recommend several references, including Rowley (2014), Memon et al. (2017), Hulland et al., (2018), and Berndt (2020) for a better understanding of the use of both probability and non-probability sampling techniques and their pros and cons. We recommend articles by Memon et al. (2020) and Sim et al. (2022) that can be used as sample material for reporting different aspects of sampling and data collection.

Table 3: Recommendations for Reporting on Sampling and Questionnaire Administration

Issue	Description	Reporting Recommendations
Sampling	Explain sampling technique(s) employed in the study.	▪ What is the unit of analysis of the study? Individual or organization? ▪ Define the sampling strategy used (probability/non-probability). ▪ Report which specific type of probability/non-probability sampling technique was employed (e.g., Snowball, Simple Random, etc.) ▪ Explain why it was the most appropriate sampling technique. ▪ Report if any inclusion/exclusion criteria were used. ▪ Report if more than one sampling technique was used and why.
Questionnaire administration / Data collection	Explain questionnaire administration process and its various aspects.	▪ Explain who the respondents of the study were and why. ▪ Was data collected in a single attempt, or were there multiple phases? ▪ If there were multiple phases, how many samples were collected in each? ▪ Report the mode of data collection (online, face-to-face, mail, etc.) and justify. Indicate proportions if more than one mode was employed. ▪ How were respondents approached? (e.g., direct contact, via managers, etc.). ▪ How was anonymity or confidentiality ensured? ▪ Report the overall duration of data collection, including when it took place (month/year). ▪ Mention if any external/natural/organizational/cultural factors affected the response rate or mode of data collection (e.g., COVID-19, accessibility, strikes, geographical dispersion). ▪ Report if any reminders were sent. How many samples were collected without a reminder and how many after a reminder. ▪ Report if any statistical tests (e.g., t-tests, ANOVA) were performed to check the

		difference between different groups of respondents, such as samples collected via two different sampling techniques, or those who responded without a reminder and those with reminders. ▪ Report the response rate and, if applicable, justify it. ▪ Report how many samples were collected and how many of them were excluded during the initial screening. Also, report exclusion criteria. ▪ Report how many samples were considered for the final data analysis.

Common Method Bias

Common method bias (CMB) is increasingly becoming a significant concern for quantitative researchers, as it compromises research rigor. Jordan and Troth (2020) explained that CMB occurs when data for all variables (independent, dependent, moderating, and mediating) are collected using the same method. In other words, the relationships between two or more constructs are biased because they are measured with the same method (Podsakoff & Organ, 1986). Previous research (Cote and Buckley, 1986; Cooper et al. 2020) has indicated that the occurrence of common method variance is higher in studies that examine subjective constructs, such as job attitudes (41%), whereas studies that focus on more tangible and behavioral measures, such as job performance, is lower (23%).

The existence of CMB often leads to ambiguous conclusions, which can have serious repercussions on theory development and practical implications. In particular, it can cause overestimation or underestimation of the relationships between variables, which in turn, erroneously influence the validity and contribution of the study findings (MacKenzie & Podsakoff, 2012). In some cases, CMB may also affect the reliability of the measures, leading to inaccurate or inconsistent results, which can undermine the credibility of the study (MacKenzie & Podsakoff, 2012). Although the issue of CMB and its severe effects remain debatable (see Spector, 2006; Antonakis et al., 2010; Antonakis et al., 2014; Bozionelos & Simmering, 2022; Cruz, 2022; Simha, 2023), we urge the authors to provide scientific justification for the procedures they have employed.

The use of single-source and single-wave data is a significant concern in organizational behavior journals, as well as other related fields such as marketing, human resource management, social psychology, information systems, advertising, vocational behavior, and organizational psychology (see Malhotra, Schaller & Patil, 2017; Schwarz et al., 2017; Wingate et al., 2018; Cooper et al., 2022; Simha, 2023). Therefore, researchers in these disciplines employ various strategies to address this issue, including post-data collection methods—performing various statistical assessments (e.g., Harman's Single Factor, Marker Variable, etc.)—and pre-data collection procedural remedies.

While some editors emphasize using statistical assessment, such as the marker variable approach, as a gold standard for submission, we encourage authors to focus more on pre-data collection procedural remedies. We believe that post-data collection statistical assessments offer limited benefits even if we can identify datasets affected by CMB. The crucial question is whether we can collect the data again? If so, then statistical procedures are appropriate. However, if the answer is no, then procedural remedies hold greater value than post-data collection methods, as they have been proven to minimize common method variance.

Several a priori, pre-data collection procedural strategies, can be employed to minimize CMB. Drawing on previous studies (e.g., Podsakoff et al., 2003, Reio, 2010; Podsakoff et al., 2012; Johnson et al., 2011, Schwarz et al., 2017) and recent studies (e.g., Cooper et al., 2020; Jordan & Troth, 2020) we suggest various strategies, such as clarifying research purpose and instructions, ensuring item clarity, minimizing common scale properties, including reversed coded items, and separating data collection. They suggest that providing informative coversheets, clear instructions, and emphasizing participation benefits can reduce CMB likelihood. Concise surveys with minimal redundancy further improve accuracy. Moreover, crafting clear, concise questions without double meanings enhances response accuracy and minimizes CMB.

Reducing similarities of scale properties between independent and dependent variables also helps lessen CMB. Employing more than one Likert-type scales (e.g., using both 7-point and 5-point) and adjusting anchors (e.g., from 'never' to 'every time' or 'extremely unlikely' to 'extremely likely') while maintaining content validity of the questionnaire can be useful procedural strategies. Balancing positive and negative items without compromising the content validity or conceptual meaning of the scale also helps mitigate CMB (Jordan & Troth, 2020). Although the inclusion of reversed-coded items is debatable (see Dalal & Carter, 2014; Dueber et al., 2021, Schwarz et al., 2017), negatively worded items act as "speed breakers" that disrupt CMB patterns and encourage participants to focus more on the questionnaire items. Lastly, researchers can separate independent and dependent variable items through temporal separation (time delays between measures), proximal separation (interspersing measures with fillers), and psychological separation (cover stories or instructions) (Jordan & Troth, 2020).

Despite the popularity of separation strategies, particularly temporal separation, they are not always recommended for studies involving human respondents (customers, employees, managers, patients, CEOs, etc.). Challenges in collecting and matching the same respondent multiple times can compromise confidentiality and anonymity. Moreover, locating the same respondents and securing their agreement to participate multiple times is difficult, affecting overall response rates. Consequently, researchers may need to rely on smaller datasets, limiting the generalizability of their findings. Hence, Reio (2010) wisely pointed out that time is like money. Asking a company to stop its employees from working so they can take part in a study with several self-report sessions might not be possible. It is reasonable for a company to restrict data collection to a single session. However, this situation doesn't mean the research is automatically unreliable because of possible CMB. Instead, it means that we should carefully check for any signs of CMB. Likewise, Spector (2019) notes, "comparisons of corresponding cross-sectional versus longitudinal correlations in meta-analyses do not uniformly find larger correlations from cross-sectional designs (e.g., Nixon et al., 2011; Pindek & Spector, 2016), and even when cross-sectional correlations are larger, it is not necessarily due to common method variance" (p. 126).

Considering the severe challenges associated with time-lagged or longitudinal study approaches, such as increased research design complexity, respondent attrition, and difficulty in determining the appropriate delay between two or more time points (Jordan & Troth, 2020), we neither recommend nor discourage researchers from implementing temporal separation strategies. However, we strongly recommend that authors employ procedures such as proximal and psychological separation methods to minimize CMB and report them in detail in their manuscripts. We further expect that whatever strategies authors have employed are logically justified and supported by compelling evidence. In agreement with Spector (2019), we also believe that neither cross-sectional designs are weak nor are longitudinal designs always as valuable as commonly assumed. Spector (2019) concluded that "each has its place in our arsenal of research design tools, with the cross-sectional design being an efficient and invaluable go-to tool for investigating important organizational phenomena (p. 136). Hence, we welcome submissions employing either design with rigor and high transparency in reporting."

Furthermore, while the collection of data from multiple sources (e.g., employees and their supervisors) for dependent and independent variables is often suggested to mitigate CMB, it can pose significant challenges for researchers in the fields of business, management, and social sciences. Obtaining data from even a single source can be difficult, making multiple sources particularly challenging for students and early career researchers. Therefore, researchers should approach such research designs with caution, considering the additional time, resources, access to diverse stakeholders, and, most importantly, expertise required to design and execute multi-source data collection and analysis strategies. Regardless of the chosen design, each strategy or aspect must be justified, with careful consideration given to the "why" behind the decision, and explicitly reported in their manuscripts. For a comprehensive overview of recommendations on reporting both procedural and statistical strategies to address CMB, refer to Table 4.

We recommend researchers to go through past studies (e.g., Podsakoff et al., 2003, Reio, 2010; Johnson et al., 2011; Schwarz et al., 2017) and some recent papers (e.g., Spector, 2019; Jordan & Troth, 2020; Cooper et al., 2020, Bozionelos & Simmering, 2022; Cruz, 2022; Simha, 2023) for better understanding of the debate on common method bias and related strategies to minimize it. For reporting, the work by Woosnam et al. (2022) and Su et al. (2022) can be good reference points as they have applied both procedural and statistical strategies in addressing CMB. For researchers interested in using post-hoc statistical analysis, such as the marker variable technique, we recommend referring to Miller and Simmering (2022), who have developed a new marker variable, "attitude towards the color blue," along with its corresponding scale, to detect common method variance.

Table 4: Recommendations for Reporting on Common Method Bias

Issue	Description	Reporting Recommendations
Common Method Bias (CMB)	Explain Procedural strategies that were used to minimize CMB.	▪ Briefly explain CMB and why it matters in the study. ▪ What procedural strategies were used and how did these help in minimizing CMB? ▪ Explain in detail with examples that show authors' efforts in implementing the strategies. ▪ Report on potential issues that hinder your efforts on minimizing CMB.
	Explain statistical strategies that were used to assess the likelihood of CMB.	▪ Explain CMB and why it happens. ▪ Report on which statistical technique was used and how it is appropriate in identifying issues related to CMB? ▪ Which statistical application (e.g., SPSS, SmartPLS, AMOS, etc.) was used for the statistical analyses related to CMB. ▪ Report results and interpret the CMB in light of existing rules and guidelines. ▪ Conclude whether there is no indication, slight indication or there is a severe issue of CMB. ▪ If the statistical analysis indicated the CMB issue, what authors did to address it? Any justification provided?

Final Note

In this editorial, we have provided a set of guidelines to assist researchers in achieving methodological rigor in their research projects. These guidelines cover various aspects, including the implementation and reporting of operationalization, instrument validation, sampling techniques, questionnaire administration, and addressing CMB. It is important to note a few key considerations when reading and applying the content presented in this paper.

1. The guidelines provided here are of a general nature and do not take into account the diverse academic cultures, environments, and roles such as supervisors, examiners, editors, and reviewers, as well as individual personalities and their understanding of the methodological aspects of quantitative research. Policies, culture, and expectations vary and so do academics. There are many academics, whether they are supervisors or examiners, who are always willing to support research students and go the extra mile. In contrast, there are others who only negatively critique. For instance, based on our regular interactions with research students from various countries, we have observed that some supervisors and examiners advise students to use lengthy scales (constructs with many items) even when shorter versions of the variables are already available. Similarly, there are those who insist on collecting a minimum of 400 samples for any quantitative study, regardless of the type of respondents, the nature of the research, or the sampling techniques employed. These individuals adhere strictly to the "384 rule of thumb" (Krejcie & Morgan, 1970), without considering its assumption. Moreover, certain individuals hold the belief that data collected through non-probability sampling techniques should not be utilized in any academic research. Additionally, there are those who push students to collect data at multiple points in time, sometimes as many as 4-6 times, thereby placing a considerable burden on students. Even for seasoned professors, collecting data at a single time can be challenging. It is therefore understandable that students may feel compelled to engage in questionable research practices (Suter, 2020) as well as data fabrication and other unethical practices to meet these unrealistic demands. Neither we nor our research work can instantly address all the concerns raised earlier. Therefore, it is important for researchers, especially research students, to familiarize themselves with the specific expectations set by their respective universities' policies, supervisors, examiners, and other panel members. Engaging in constructive conversations with them in a timely manner is crucial for success. When it comes to validating research instruments, seeking the opinions of experts, as well as your examiners or referee panel, can prove to be immensely helpful. Their feedback on your questionnaire can serve as a valuable lifeline, ensuring the quality of your study. By implementing their recommended revisions, you can avoid potential criticism in the future. In addition, it is advisable to share recent developments with your supervisor. During one-on-one meetings, approach the topic with politeness and humility, explaining how the information is relevant to your study and the new insights you have gained. By doing so, you can foster a productive dialogue and enhance your supervisor's understanding of the field.

2. We find ourselves in the era of Artificial Intelligence (AI), where AI applications such as ChatGPT have become increasingly popular. Academics can wisely leverage these tools to enhance their research skills and knowledge. However, it is crucial to approach their use with caution and ensure they are employed as a source of learning rather than as a means of outsourcing. Engaging in the latter can impede the learning process. It is important to note that utilizing AI to generate content on your behalf is considered highly unethical and undermines academic integrity. With the advancements in AI text detection software, such as Turnitin and others, it has become easier to distinguish between human-written and AI-generated texts. Instead, focus on utilizing these applications in a manner that promotes productive learning and deepens your understanding of quantitative methods and related matters. For instance, using prompts to learn how to interpret the results of specific tests,

like the t-test or regression analysis, can be highly beneficial, particularly for those who are less familiar with these concepts. It is imperative to uphold academic integrity and adhere to ethical standards throughout every step of the academic journey.

3. In the process of crafting this editorial, we were thrilled to learn about the release of Covariance-Based Structural Equation Modeling (CB-SEM) in SmartPLS 4.0 (Ringle et al., 2022). This astonishing development has surpassed our expectations. SmartPLS has already garnered recognition as the preferred choice among researchers in business and social sciences, due to its user-friendly interface, ease of use, and innovative features (Memon et al., 2021). The software also offers several advanced analytical options, such as necessary condition analysis (NCA), multigroup (MGA) analysis, and PROCESS for moderated-mediation, mediated-moderation, and moderated-moderator, making it a distinctive tool for data analysis. The inclusion of CB-SEM not only elevates the capabilities of the software, but also empowers researchers to conduct robust analyses and enjoy their analytical tasks. We anticipate similar progress and continuous advancements in the field of quantitative methods and advanced data analytical techniques from other developers. It is our sincere hope to witness a constant evolution in these domains, enabling researchers to delve deeper into their analyses and uncover novel insights.

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