Publishing Quantitative Research in EMJ:

Some Editorial Guidelines and Recommendations

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1. Introduction

At the *European Management Journal* (EMJ), our mission is to publish manuscripts that challenge "the status quo through critically informed empirical and theoretical investigations, and present the latest thinking and innovative research on major management topics, while still being accessible and interesting to non-specialists" (Muratbekova-Touron, 2024, p. 147). To achieve our mission, it is key that research published in EMJ be on the one hand designed rigorously, maintaining high standards of analytical precision while promoting transparency and reproducibility, and on the other hand be accessible to diverse audiences. A significant number of submissions received at EMJ are quantitative.

Rigorous and state-of-the-art quantitative research that is transparent and reproducible is central for advancing theories, informing practice, and guiding policy decisions. However, the value and credibility of quantitative research, and consequently its impact, are undermined when study designs are flawed, analytical strategies and procedures are outdated and non-transparent, and overall communication is ineffective. At EMJ, as at many other leading journals, such issues almost inevitably lead to submissions being rejected outright. Moreover, submissions that pass the "desk reject" hurdle are highly unlikely to survive the review process because methodological flaws often cannot be addressed post hoc.

Many submissions face similar challenges, such as implementing a study design or method that is not suitable to address a research question. The most common problems could often have been prevented easily. In this editorial, we briefly outline these challenges and address the most common issues with quantitative submissions received at EMJ. Based on our observations, we provide recommendations for publishing quantitative research in EMJ and beyond. Particularly, we discuss common problems in terms of study design (Section 2), analytical rigor and robustness (Section 3), and transparency and replicability (Section 4) before concluding with some recommendations on how to communicate sophisticated quantitative research effectively in a transparent way (Section 5). To increase the feasibility of our recommendations, we point to quantitative papers published in EMJ following best practices. We hope our recommendations and best practices help authors to increase the value of their work and contribute to management theory and practice in a meaningful way.

Our editorial is not directed exclusively to authors but also to editorial board members and current and future reviewers of EMJ. In clearly highlighting our expectations concerning quantitative research, our observations and recommendations are equally helpful in facilitating reviewers in developing their constructive feedback for authors and their recommendations regarding a submission's suitability for publication in EMJ. By fostering a culture striving for rigor, transparency, and inclusivity in our review process, we aim to elevate the quality of quantitative research published in EMJ and ensure its relevance to a broad spectrum of audiences.

2. Study Design

As management researchers, the validity and robustness of our research often rely on gaining access to rich data about organizations and their members. This often turns out to be a challenging and cumbersome endeavor, which is why data access may lead to difficult and sometimes problematic choices in a study's design. However, the study design stage is one of the most critical stages in any research project, as it determines the validity, robustness, and last the overall contribution that academic work can make. In this regard, sample selection and construction, cross-sectional and single-source data, measurement operationalization, and insufficient control variables are the most common areas that present recurring challenges, frequently leading to manuscript rejection in academic journals such as EMJ. This section briefly addresses common difficulties encountered in submissions to EMJ, as well as some recommendations to overcome some challenges.

Sample Selection and Construction. Challenges in accessing data and participants often result in studies with insufficient sample sizes. This can reduce the statistical power of the analysis, increasing the likelihood of failing to detect an effect when one truly exists. Authors should think about the desired level of statistical power before planning data collection and determine the required sample size based on these considerations (Cashen & Geiger, 2004; Mone et al., 1996). Additionally, authors should discuss their considerations and reasoning in their manuscripts so that readers can understand how the sample size was determined and can assess how strong the presented findings are. Authors should also address the topic of statistical power transparently in their analysis and limitations sections. Cashen and Geiger (2004) provide very clear and useful recommendations in this respect, which we recommend following. A good example in EMJ of how to discuss sample selection transparently is Borini et al. (2012). The EMJ paper by García-Cruz et al. (2024) is a good example of assessing the statistical power underlying a sample.

Another common practice that can be problematic is the use of convenience samples. Many researchers resort to convenience samples due to their practicality (Fernández-Mesa et al., 2020). While their use may be justified in certain situations and contexts, these samples may not be representative of the target population, limiting the robustness and generalizability of findings. Submissions to EMJ should therefore justify sampling rationales thoroughly and discuss potential limitations arising from sampling choices transparently (for a good example see Bartel-Radic & Giannelloni, 2017).

Finally, a particular problematic practice in sampling is inappropriate selection of key informants in survey-based research. For example, investigating leadership or strategic decisions based on a sample of students with no management experience compromises a study's validity. The use of student samples can be appropriate. Yet student samples need to be well justified and, most importantly, well aligned with the research question. An example published in EMJ is the research conducted by Maes et al. (2014), who studied the development of entrepreneurial intentions among business students at the verge of deciding on their future careers. The immediate career choice makes the use of student samples appropriate in this context.

In general, researchers need to consider potential biases that different key informant choices might involve. For instance, in investigating leadership behavior or employee creativity, self-perceptions of key informants might be distorted. In such situations, it might be more appropriate to ask someone observing that behavior to rate it (e.g., the supervisor rates the subordinate’s creativity). Or when researching team dynamics, it may be important to have more than one team member as informants, in order to really capture the phenomenon at the team level. Aligning the study population with the research question is essential. Poorly aligned designs can lead to biases and/or the inability to test key hypotheses. In this respect, we recommend thoroughly scrutinizing the choice of informants and their suitability to address a research question in a valid, reliable, and robust way (for a good example see Li et al., 2014). Rationales behind selecting key informants and potentially resulting limitations need to be discussed. Thus, submissions to EMJ should thoroughly justify the selection of respondents and information sources.

Cross-Sectional and Single-Source Data. Inappropriate design choices are another common issue frequently leading submissions to EMJ being rejected. Cross-sectional datasets are common but are often unsuitable for questions involving causality or change over time. This is a key validity issue in quantitative research, and to address it, longitudinal, panel, or experimental data studies are essential. For example, the study by Morf and Bakker (2024) used a weekly diary design to explore dynamic variations in transformational leadership, demonstrating how repeated measurements over time can reveal hidden patterns. Generally, data from a single source (e.g., self-reported surveys) at a single point in time carry risks that give rise to biases (such as common method variance, which we briefly address later in this editorial). Introducing time lags into data collection is a viable way to mitigate the causality problem. For instance, collecting survey data at two time points (e.g., the second survey captures the dependent variables approximately a year after the first survey collecting data on the independent variables) can establish a causal relationship between independent and dependent variables (Mom et al., 2019). A way to address potential key informant biases could be collecting independent and dependent variables from a different source (e.g., survey data combined with archival objective performance data) or different respondents (e.g., the leader rates the follower's creativity and the follower rates leadership behavior).

Designing studies that allow testing multiple hypotheses through complementary approaches, as well as using a combination of qualitative and quantitative methods to deepen the understanding of the phenomenon, is advisable. A good example in EMJ for this is Morf and Bakker (2024). Similarly, Fernández-Mesa and Alegre (2015) used data from multiple sources (surveys and practitioners' journals) to strengthen the reliability and validity of their dependent variable measurement.

We are well aware that longitudinal, panel, or experimental study designs may not always be feasible, due for instance to insurmountable data accessibility or resource constraints. And certainly, there are research questions that can be addressed appropriately with cross-sectional designs: for instance, many research questions in segmentation research. In such cases, it is important to justify why cross-sectional data are gathered and how they contribute to the existing literature in a novel way. Thus, submissions to EMJ generally need to address and justify design choices clearly in relation to their research questions. As well, it is crucial to discuss resulting limitations transparently to potentially test and assess their impact empirically. Alternatively, EMJ submissions can outline how future research should address such limitations. Complementing findings with additional analyses and/or comparing them with existing literature is also advisable.

Measurement Operationalization. One key issue we frequently observe in EMJ submissions is weak or even inappropriate measurement of the variables of interest. While many papers propose and extensively discuss a phenomenon, they fail to capture it empirically. Researchers often fail to clearly define the boundaries and meanings of the constructs and variables they study, which can result in inconsistent, confusing, or even inappropriate measurement operationalization. Particularly when developing new measures, but also when relying on existing measurement approaches, researchers must provide solid evidence of their suitability, validity, consistency, and reliability, ideally through pilot studies and/or validity and reliability checks (see Chiva et al., 2007; Flatten et al., 2011; Zakrzewska-Bielawska et al., 2024). A common potentially problematic practice in this respect is the use of perceptual measures of company performance, especially when a single-informant design is used (Meier & O'Toole, 2012). While we acknowledge that there might be situations where no other alternative is available and that these types of measures can be reliable and valid when implemented carefully (Singh et al., 2016), authors relying on such measures should demonstrate extra effort to provide evidence of measurement reliability and validity. For instance, Strobl et al. (2023) provide a good example for how a subjective measure of firm performance can be validated by gathering additional objective archival data for a subsample of the study. Generally, thorough literature reviews are recommended to identify validated and state-of-the-art measurement approaches.

Reducing items in questionnaires or adapting measures without proper validation may compromise reliability and validity. It also prevents effective knowledge building, because such practices hinder comparison with existing research. When existing validated measures are used, it is of course important to ensure their validity within the study's context and make adaptations where necessary. For instance, scales measuring leadership styles might need to be adapted to make it clear whose leadership is measured (e.g., “my direct supervisor” vs. “the CEO of our company”). However, any modifications need a transparent discussion and a thorough justification. Employing shortened scales alongside original versions in pilot tests can confirm their consistency and relevance (see Slavec et al. (2017) for an example of a pilot study).

Similar claims can be made for the adoption of empirical proxies in archival data-based research. Selecting appropriate empirical proxies for testing a proposed theoretical framework is crucial for a well-executed study. Therefore, we encourage authors to invest a substantial amount of time in identification of appropriate empirical proxies in the existing literature or in the development of their own constructs (if feasible), following the well-established methodological guidelines and recommendations of Lambert and Newman (2022). However, as editors, we also understand that there are some theoretical mechanisms that are quite difficult (if possible at all) to tease out empirically due to the lack of data or for other important reasons. In such circumstances, we advise authors to perform an array of robustness tests in order to rule out possible alternative explanations or mechanisms. Moreover, it is also advisable to be rather cautious when presenting and discussing empirical findings, and to explicitly acknowledge this fact in the limitations section of the study. Submissions to EMJ should provide a transparent overview of the measures and any adaptations. This can be done by submitting an online appendix including, in the case of survey methods, the exact wording of survey items, together with any instructions given to respondents.

Insufficient Control Variables. A final point that we would like to highlight is that many quantitative submissions fail to incorporate important control variables in their work, resulting in omitted-variable bias. We highlight this in the study design section, because while archival data sources may provide the opportunity to recollect additional controls post hoc, survey designs need to account for the inclusion of important control variables in the study design stage. For instance, the inclusion of marker variables to control for social-desirability and other response biases (see our recommendations for dealing with common method variance in Section 3) needs to be acknowledged when a survey is designed. Generally, the selection and justification of controls should be conducted with rigor similar to that for the main variables of interest. Schweizer et al. (2023) is a good example of clear and transparent discussion of control variables.

Control variables are essential in management research to account for external influences on key relationships, yet studies often include, for instance, basic demographic controls (e.g., gender, age, tenure) without explaining their theoretical relevance clearly. This leads to situations where theoretically relevant controls are missing but theoretically irrelevant, yet easily available controls are included. Thus, we also want to highlight the need for a more transparent and theoretically grounded choice of control variables (Bernerth & Aguinis, 2016). The general rule should be that any variable that is theoretically expected to be correlated with a dependent and a hypothesized independent variable should be included as a control (Becker, 2005). Thus, again, it is important that authors conduct thorough literature reviews in order to be able to identify all relevant controls in the context of their research.

3. Analytical Rigor and Robustness

We are well aware at EMJ that management researchers are usually not statisticians but rather users of statistical methods and tools. Nonetheless, as users we are still expected to apply tools and methods in an appropriate, correct, and skilful way and to stay up to date with the latest developments concerning the analytical methods and tools we use. Analysis and reporting standards change as our research fields evolve, and what used to be commonly acceptable is no longer appropriate. EMJ seeks to publish research that is methodically sound, rigorous, robust, and state-of-the-art. Despite our goals, we still receive many submissions relying on outdated or even inappropriate methods at odds with the requirements of the investigated datasets and the research questions examined, neglecting state-of-the-art standards such as assessing endogeneity biases or demonstrating robustness. Submissions facing such shortcomings risk outright rejection by editors or reviewers. Even in cases where a revise-and-resubmit decision is granted, such submissions face a higher risk of ultimately being unsuccessful if the original results cannot be replicated using appropriate analysis methods and tools. In the following, we address some of the most common problems we see in submissions to EMJ.

Outdated Methods. A classic and very common example of the application of outdated methods is mediation models. Mediation models, including moderated mediation and mediated moderation, are often used in management research (Aguinis et al., 2016). Many mediation studies that are submitted to EMJ still follow the procedures recommended by Baron and Kenny (1986), which have been substantially criticized in recent years by Zhao et al. (2010), Preacher et al. (2007), and many others. Therefore, we suggest following up-to-date recommendations for running a mediation analysis, such as those proposed by MacKinnon et al. (2007), Preacher et al. (2007) and Muller et al. (2005). Kidron and Vinarski-Peretz (2024) is a good example of a study published in EMJ rigorously testing moderated mediation.

Another important example is the rise of panel (longitudinal) data studies. In this context, we suggest that authors should adopt methods specifically developed for panel data (Arellano & Bonhomme, 2011; Hsiao, 2007; Phillips & Moon, 2000). Given that pooled ordinary least squares (OLS) estimators are based on unrealistic assumptions about panel data (Wooldridge, 2010), inferences should be drawn with the help of panel data estimators that are more accurate in making it possible to consider all the inter-individual differences and intra-individual dynamics in the data (Honoré, 2002; Hsiao, 2007; Phillips & Moon, 2000). A good example is the study of Romero et al. (2020), which rigorously assesses the straight-line globalization theory in a panel of 25 European countries using the fixed-effects panel estimator.

One of the most prominent topics where outdated methods are frequently applied is the topic of common-method bias in survey research. Despite long-standing and prominent criticism published in a host of different journals that it is unsuitable to address common-method variance (see for instance Baumgartner & Weijters, 2021; Podsakoff et al., 2003) with a Harman single-factor test, authors still rely on it and reviewers also occasionally ask for it. We call for a more careful state-of-the-art treatment of common-method bias. First of all, authors should take recommendations seriously to prevent common-method biases in the first place. For instance, Podsakoff et al. (2012) provide useful recommendations concerning potential procedural remedies. Second, we strongly recommend following more recent approaches for dealing with common-method variance, such as marker variable techniques acknowledging the source of method variance (Spector et al., 2019). Simmering et al. (2015) and Spector et al. (2019) provide useful recommendations on such techniques. In any case, papers in EMJ should transparently discuss potential biases related to common-method variance and resulting limitations.

The examples discussed above are not an exhaustive list but simply a recognition of the most outdated statistical practices that are frequently observed in submissions received at EMJ.

To enhance rigor and robustness at EMJ, we encourage authors to incorporate the latest methodological advances into their research.

Inappropriate Methods. We often receive studies that make causal claims without backing up their claims using appropriate causal methods. The OLS estimator is a workhorse of a large number of empirical papers using nonexperimental (observational) data. However, in many cases it is not well suited to making causal claims due to its sensitivity to serial correlation, selection issues, endogeneity, and many other potential empirical pitfalls (Baum et al., 2003; David et al., 2014; Heckman, 2010; Semadeni et al., 2014). Similarly, structuring equation modeling and partial least squares models are subject to a wide range of empirical pitfalls, limiting their adoption for causal claims (Antonakis et al., 2010; David et al., 2014; Sarstedt et al., 2024). We suggest that authors aiming to test causality in their works follow recommendations and guidelines developed by Antonakis et al. (2010) and Van der Stede (2014).

Endogeneity. An important issue that many papers do not address is potential endogeneity biases in their research. A failure to consider and account for various sources of endogeneity in a study can lead to inaccurate estimates, leading to serious threats to internal validity and erroneous conclusions about causal relationships between the investigated variables (David et al., 2014; Morton & Williams, 2010; Wooldridge, 2010). For instance, a firm's ability to innovate depends on managers' personal characteristics (i.e., soft skills and risk perceptions), which are problematic to observe and measure (Ardito et al., 2025). Similarly, a wide range of factors determining corporate governance structures of a firm are subject to the endogeneity problem (Miroshnychenko & De Massis, 2020; Wintoki et al., 2012), and thus there is a need to account for endogeneity biases in a typical corporate governance study. Apart from a clear identification strategy, authors are expected to use appropriate econometric remedies such as panel data estimators (Hsiao, 2007; Wooldridge, 2010), instrumental variable estimators

(Bascle, 2008; Baum et al., 2003), and many others (Semykina & Wooldridge, 2010; Terza et al., 2008). For instance, consider the study of Sacristán-Navarro et al. (2022), which helps to identify the role of institutional context in firm ownership concentration using a longitudinal panel dataset of firms across the globe. Notably, this study employs a dynamic panel data estimator, making it possible to account for various sources of endogeneity simultaneously in the empirical analyses.

Bulletproof identification strategies and good instrumental variables are quite difficult to find in nonexperimental studies (Antonakis et al., 2019; David et al., 2014; Jiang, 2017). Sometimes this leads to situations where no suitable instruments are available to conduct instrumental variable analyses (see for instance Bascle, 2008). In such situations, we recommend assessing the sensitivity of the results in terms of endogeneity biases. Statistical tools such as investigating the impact threshold of a confounding variable (ITCV) and the robustness of inference to replacement (RIR) are recommended in this respect (Busenbark et al., 2021; Busenbark et al., 2022). ITCV provides insights into how strongly omitted variables would have to correlate with the dependent and a hypothesized independent variable to alter an observed interference. RIR identifies how many observations in a data set would have to be replaced with zero-effect observations to overturn an observed effect (Busenbark et al., 2021). RIR statistics are suitable to assess the sensitivity of results in relation to all sources of endogeneity (Busenbark et al., 2022; Frank et al., 2013).

While the topic of endogeneity has long been neglected in survey research, this is no longer appropriate. Recent updates in statistical software packages used to analyze survey data should facilitate research and ease the pain of conducting such analyses. For instance, a prominent PLS software package now offers the possibility of investigating endogeneity using Gaussian copulas (Eckert & Hohberger, 2023). That said, authors are advised to check carefully which analytical procedures are the right ones, as different sources of endogeneity might need different analytical strategies, and certain methods come along with specific data requirements.

For submissions to EMJ, we advise authors to take causality claims and endogeneity issues seriously in their work. When conventional tests cannot be conducted, sensitivity analyses as outlined above are recommended, especially when the aim of the research is not to identify precise parameter estimates but rather to make causal inferences, as is often the case in management research (Busenbark et al., 2022). Generally, authors should be cautious in their empirical claims and discuss potential endogeneity concerns in the *Limitations* section of the study.

Survivorship and Sample Selection Bias. Another frequent problem with quantitative papers is that they are often subject to either survivorship or sample selection bias. We find that many authors focus on "survivors" (firms that still operate in the marketplace) and do not consider in their analysis those firms, industries, or individuals that do not exist anymore (Elton et al., 1996). In this context, the regression estimates may provide a distorted picture of the reality by overestimating the effects because "non-survivors" are systematically excluded from the analysis. Many authors also rely on convenience samples of individuals, firms, industries, and so on. Authors also sometimes systematically exclude (consciously or unconsciously) certain members or groups of a population due to some specific attributes potentially distorting their empirical analyses. To address survivor and selection biases, we encourage authors to employ sample-selection models in their analyses (see Heckman, 1979; Lennox et al., 2012). A good example of an article that adopts sample-selection models to correct for the sample selection problem is the study of Schweizer et al. (2023), as these authors leverage Heckman's two-step model to understand the effect of serial acquisitions on shareholder value. If running such analyses is not possible, the above-mentioned sensitivity analysis based on RIR provides insights to elevate potential external validity concerns (Busenbark et al., 2021)

Robustness tests. We often see papers drawing conclusions based on one single test statistic from a single regression model rather than assessing a wider array of potential variations of the principal empirical findings with the help of robustness tests. In this context, a wide range of robustness tests can help to verify whether the presented empirical findings are sensitive to the adoption of alternative definitions of the variables of interest, alternative estimation techniques, alternative samples, and/or other potential empirical caveats. Empirical evidence becomes more convincing when robustness tests and sensitivity analyses are adopted to rule out possible alternative explanations and support obtained findings. For example, Casino-Martínez et al. (2019) make strong empirical claims by demonstrating that their principal findings are not sensitive to alternative variable definitions, alternative estimator techniques, alternative samples, or potential endogeneity biases. We therefore encourage submissions to EMJ to demonstrate the robustness of their findings and also to discuss potential robustness threats in the *Limitation*s section.

4. Transparency and Replicability

The term "replication crisis" is gaining increasing traction and attention in social sciences and in management research (Hensel, 2021). It refers to an ongoing scholarly debate in management and related fields about the extent to which studies are replicable and reproducible: that is, whether the same conclusions can be reached when a different team of researchers conduct an investigation following the same procedures outlined in a study (Wulff et al., 2023). Methodological transparency is central to this discussion and refers to the level of detail and openness regarding the specific procedures, decisions, and subjective judgments made throughout a scientific study (Aguinis et al., 2018). When methodological transparency is upheld, it becomes easier for researchers and the general readership to determine whether results are reliable and valid, as well as context-specific or generalizable to broader settings. Furthermore, by enabling other researchers to replicate research, such thorough reporting promotes effective cumulative knowledge production (Aguinis et al., 2024). EMJ is committed to enhancing the replicability and reproducibility of published management research. For this reason, we encourage authors to improve and increase the transparency of their work and to engage actively in open science practices such as study preregistration or making datasets available via platforms such as the open science framework (see https://osf.io).

We are aware that there are often good reasons preventing full transparency. For instance, non-disclosure agreements with organizations or individuals participating in research projects might prevent making certain information publicly available or provide clear instructions for which information can be made available in what way. Acknowledging that full transparency will be difficult to achieve in practice, we would like to encourage authors to be as transparent as possible in their work. Some steps can be followed in most situations, and we would like to highlight some in this section. Specifically, papers submitted to EMJ should be transparent in terms of the methods applied, the materials used, and the reporting of results.

Method Transparency. Being transparent in methodological choices is key not only to increasing reproducibility of research but also to judging the reliability, validity, and robustness of research. In Sections 2 and 3, we highlighted many important issues concerning designing impactful and solid studies. The rationales, preferences, and procedures guiding your design and method choices need to be documented transparently. Thus, submissions to EMJ should include thorough and detailed descriptions concerning issues raised in Sections 2 and 3 of this editorial that allow reviewers and readers to understand what has been done (what?) and how this came about (why?).

Material Transparency. Material transparency refers to making all resources used in implementing your study design available and enabling reviewers and readers to understand how your data were generated (how?). For instance, in Section 2, we discussed the importance of using effective measures in line with the study context. Researchers must report all materials and measures used, including their adaptations and the source of each scale. This includes manipulations and manipulation checks in experimental studies providing clear descriptions of the conditions, stimulus materials, and instructions given to participants (e.g. Batistič et al., 2022). When measures were translated, it is recommended that the translation procedure used, such as a translation–back translation method, be reported (e.g. Černe et al., 2024), to ensure linguistic and conceptual equivalence. For space reasons, this can be done via an online appendix (see for instance Pekkala & van Zoonen, 2022). Where this is not possible for the wider public (some survey scales have a copyright), authors should at least report a sample item (e.g. Karma et al., 2024). For the review process itself, the full set of items, including any instructions for respondents and response scales, must be submitted to enable reviewers to do their job properly. As highlighted in Section 2, control variables deserve attention similar to the main variables of interest. This also refers to transparent reporting of their measurement.

Reporting Transparency. In the *Data Analysis* section, researchers should specify the analytical methods used and provide a rationale for their choice. For example, Toyama et al. (2023) provide a good example of explaining the selection of exploratory factor analysis (EFA) versus confirmatory factor analysis (CFA). At EMJ, we often see that basic, yet crucial information is missing. For instance, authors regularly fail to explain how variables entered into a regression analysis were generated. It makes a difference whether a variable is calculated as an average of a set of items or whether factor scores from EFAs or CFAs are used. To enable accurate replication, this information is essential. To provide this, authors should specify the software used for analysis, including its name and version (e.g. Elgoibar et al., 2024). To maintain transparency when addressing data integrity concerns, researchers should also detail any actions taken to handle outliers or anomalies, such as whether some data points were eliminated or modified and the process through which this was done (e.g., imputation, listwise deletion). For example, outliers identified beyond a certain threshold may be excluded from analysis, or additional analyses may be conducted excluding outliers to confirm robustness (e.g. Kotiloglu et al., 2024).

Another important topic that often does not meet basic reporting standards is measurement evaluation. Authors are encouraged to report transparently on the validity and reliability of their measures. This includes reporting key statistics in line with the chosen method, such as item loadings, construct reliability or Cronbach's α, average variance extracted (AVE), heterotrait–monotrait (HTMT) ratio, and model fit. Furthermore, EMJ submissions should include a correlation table including all variables together with their descriptive statistics such as means, standard deviations, and ranges. In illustrating relationships among variables, correlation tables are foundational for meta-analytic research which is important for effective knowledge building.

Finally, we want to highlight some common issues with reporting transparency of the main analyses in submissions received at EMJ. Main analyses often lack clarity because of incomplete and insufficient reporting. For example, a common issue in studies doing structural equation modeling (SEM) is not reporting the results for control variables. Submission to EMJ should always include the complete set of results including the results of control variables. Thus, including tables providing complete overviews is advisable.

In general, tables and figures need to provide a sufficient level of clarity. Notes should be included that clearly explain abbreviations and other important information for interpreting the table. A prominent example of inadequate reporting is that authors regularly fail to explain whether the reported estimates are standardized or unstandardized. The decision between standardized and unstandardized coefficients has a huge impact on how results must be interpreted, especially when variables have different scales or units. While unstandardized coefficients maintain real-world meaning and are particularly useful in applied research contexts, standardized coefficients assist readers in evaluating the relative magnitude of relationships. Whenever feasible, we advise reporting both kinds of coefficients (e.g. Turja et al., 2024). This kind of dual reporting is beneficial because it enhances the interpretability of results while simultaneously improving comparability with other results. Another prominent example to improve upon is interaction plots. Authors often fail to outline at which values interactions are plotted. Finally, authors should ensure that all relevant statistics important for evaluating the robustness and validity of results are reported and discussed in the *Results* sections. Particularly, statistics of model significance and statistical power have to be highlighted in this respect. As an example, a table presenting hierarchical OLS regressions should report the estimate together with precise t-statistics or significance levels, the underlying sample size(s), F and F-change statistics in combination with degrees of freedom or significance levels, and R^2 and adjusted R^2 statistics. To address collinearity, authors might also include variance inflation factors (VIFs; e.g. Zacharias et al., 2023). These statistics are key to understanding and interpreting the meaningfulness and robustness of reported results. It is noteworthy that different methods might come along with different kinds of reporting standards. Therefore, before submitting a paper to EMJ, authors should familiarize themselves with common reporting standards. One way to do this is to consult several pieces of published work in EMJ and other leading journals in the field.

In general, to increase transparency and replicability, we want to highlight the possibility of submitting online appendices along with the main submission. Online appendices can provide overviews of the measurement, additional supplementary analyses, and method explanations, as well as output and code facilitating research replication.

5. Concluding Remarks

The main aspiration of any empirical article is to maintain rigor and adhere to the standards discussed earlier in this editorial. That said, as business and management researchers working with quantitative methods, we should not forsake the complexity of our empirical choices for simplicity in our communications. Thus, EMJ aims to increase readability and accessibility. This is essential, especially as we navigate a world facing growing challenges and crises, where business researchers seem more than ever to have their "lost cause found" (Walsh et al., 2003), that is, societal impact (George et al., 2016).

On one hand, we are encouraged to play a deeper role with our research in developing a nuanced understanding of the world's problems (Wickert et al., 2021). We aim to generate rapid solutions by partnering with academicians from other disciplines, industry practitioners, public policymakers, and society at large (Slawinski et al., 2023). On the other hand, much like business executives, we as business scholars face inevitable and important trade-offs to strategically address and simultaneously achieve multiple goals (Grewal et al., 2024).

Given this background, EMJ has built "a coherent identity as one of the world's top management journals, being innovative, method-agnostic, and forward-looking" (Kastanakis, 2021, p. 167). This means that our journal aims to cover diverse topics, propose equal opportunities for various methodologies, and include all business disciplines as our primary audience. The general trend toward societal impact and EMJ's positioning as an academic journal lead us to push for accessibility and effective communication in the quantitative articles we publish, because quantitative research is often perceived as more difficult to grasp. By doing so, we aim to align with the broader trends of generating societal impact and specifically to serve EMJ's mission of diversity and inclusion.

Summarizing, based on what we have discussed in this review, and taking the topic of accessibility of research seriously, several aspects can be addressed when reporting and presenting quantitative results for a broad and diverse audience. Researchers can

1. *Provide an overview of previous literature*, possibly with a table (e.g., Tables 1 and 2 and Figure 1 of Flatten et al. 2011).

2. *Explain in text the steps taken* regarding designing the study and sampling, the inclusion or exclusion of data, assumption testing of measures, and the specific analyses used (e.g., see Table 1 of Cheng and Shiu 2024). This includes details such as sample profiles (e.g., excluding post-docs), measurement model appropriateness (e.g., discriminant validity checks), and results (e.g., use of hierarchical OLS, heteroskedasticity, and multicollinearity checks) as seen in Shirokova et al. (2016).
3. *Always provide an overview of measures and items* in the text or an online appendix (e.g., Table 2 of Cheng and Shiu 2024).
4. *Present pre-tests, manipulations, and descriptive statistic***s** in a table (e.g., Table 3 and Figure 1 of Flatten et al. 2011 and Tables 1 and 2 of Garcia-Blandon et al. 2024).
5. *Display some model-free evidence* with examples and visuals (e.g., Figure 1 of Borah and Rutz 2024).
6. *Present actual results clearly*, potentially step by step. For example, start with a model that includes control variables, and then add main effects and interaction effects (e.g., Table 3 of Shirokova et al. 2016). This should be done vis-à-vis the hypotheses to demonstrate the connection with the research questions and hypotheses addressed.
7. *Visualize your theoretical frameworks, models, and empirical results to enhance readability*, making use of colors at least in the online version, so that conceptual figures and interaction effects speak for themselves (e.g., Figures 1 and 2 of Shirokova et al. 2016).
8. *Report robustness checks and post-hoc/sensitivity/counterfactual analyses* with an overview table to save space and increase clarity (e.g., Table 4 of Shirokova et al. 2016, Table 11 of Flatten et al. 2011, and Table 5 of Garcia-Blandon et al. 2024). Appendices can be used if page limits do not allow this in the main text.

Finally, the results having been presented, the final part of the manuscript should outline the extent to which the findings align with the existing literature and the theoretical framework adopted. In the discussion, we aim to provide insights that tie back to the introduction and conceptualization sections of the manuscript, ultimately addressing the research objective. Regarding the theoretical discussion and practical implications, authors are advised to be confident about the validity and boundaries of their research findings without overselling them. Limitations should be made transparent.

We hope this editorial offers helpful advice for authors wishing to submit to EMJ and to our esteemed reviewers. Our overall aim is to enhance the rigor and robustness of research published in EMJ, while at the same time making it more transparent and reproducible, as well as easier to read and more accessible. We are looking forward to your submissions!

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