



# Quantitative Research Methods in Business and Management Studies: A Critical Review of Empirical Practices

Zulkifly Baharom

**Tunku Puteri Intan Safinaz School of Accountancy (TISSA-UUM), College of Business, Universiti Utara Malaysia, Malaysia**

**DOI: <https://dx.doi.org/10.47772/IJRISS.2026.10100313>**

**Received: 15 January 2026; Accepted: 23 January 2026; Published: 04 February 2026**

## ABSTRACT

Quantitative methods continue to dominate business and management research, yet concerns persist about the rigor and relevance of prevailing empirical practices. This critical literature review (CLR) examines how ritualized reliance on statistical significance testing, linear modeling assumptions, and conventional measurement approaches has limited explanatory depth and reproducibility in contemporary studies. Drawing on a systematic analysis of 50 highly cited articles published between 2016 and 2025, the review identifies three recurring methodological shortcomings: overreliance on p-values, linear bias in complex and dynamic contexts, and persistent measurement challenges in advanced modeling. The review further synthesizes emerging methodological shifts, including Bayesian inference, machine learning (ML), and big data analytics, that seek to address these limitations. Building on this synthesis, the paper proposes a Multi-Dimensional Rigor Framework (MDRF) that reconceptualizes methodological rigor as an integrative construct comprising inferential, modeling, and data rigor. The framework emphasizes alignment between statistical reasoning, analytical modeling, and data characteristics rather than adherence to procedural benchmarks alone. The paper concludes by outlining implications for researchers, journal editors, and practitioners, advocating a shift from symbolic statistical compliance toward substantive, context-sensitive, and predictive quantitative inquiry.

**Keywords:** Bayesian inference, Machine learning in management research, Methodological rigor, Quantitative research methods, Replication crisis

## INTRODUCTION

### The Quantitative Landscape

Quantitative methods remain the dominant mode of inquiry in business and management research, shaping knowledge production across finance, marketing, operations, strategy, and organizational studies (Köhler et al., 2017). Their appeal lies in the promise of objectivity, generalizability, and analytical precision, particularly in theory testing and policy-relevant research. Advances in statistical software, computational capacity, and data availability have further normalized increasingly complex quantitative analyses, making them a benchmark for publication in leading journals.

However, the widespread adoption of quantitative techniques has not been matched by a commensurate deepening of methodological understanding. In many cases, methodological sophistication is inferred from the use of advanced tools rather than from the coherence among research questions, data characteristics, and analytical logic. As a result, quantitative dominance has increasingly coexisted with concerns about superficial rigor, limited interpretability, and fragile empirical findings.

### The Problem

Beneath the apparent sophistication of contemporary quantitative research lies a persistent “black box” in empirical practice. Researchers frequently rely on heuristic rules and standardized reporting conventions, most notably the pursuit of  $p < 0.05$  as a proxy for rigor, without sufficient engagement with the methods’ underlying



assumptions, limitations, or interpretive scope (Memon et al., 2023). This procedural orientation encourages a ritualized form of statistical practice in which methodological compliance substitutes for substantive reasoning.

Such practices contribute to what has been described as a “cargo-cult” statistical culture, in which symbolic indicators of rigor (stars of significance, threshold-based fit indices, or high  $R^2$  values) are prioritized over theoretical coherence, effect magnitude, or contextual plausibility. The cumulative consequence is a weakening of empirical credibility, as evidenced most visibly by the replication crisis, in which a substantial proportion of published findings fail to withstand reanalysis or independent replication (Burger et al., 2023; Köhler et al., 2017).

## The Research Gap

The limitations of current quantitative practices reflect a deeper epistemological mismatch between the complexity of business phenomena and the analytical models commonly used to study them. Business environments are inherently dynamic, nonlinear, and context-dependent, characterized by feedback loops, threshold effects, institutional contingencies, and sudden structural disruptions (Küçükvar et al., 2019). Yet empirical research continues to rely predominantly on linear, static modeling frameworks, such as ordinary least squares regression, that assume stability, additivity, and homogeneous effects (Segura et al., 2018).

This mismatch constrains the explanatory and predictive power of quantitative research, leading to oversimplified representations of complex organizational realities. The resulting gap is therefore not merely methodological but conceptual: existing analytical conventions are often ill-suited to capture the phenomena they purport to explain. Addressing this gap requires rethinking methodological rigor beyond procedural correctness toward a more integrative and context-sensitive approach.

## Objective and Contribution

This paper presents a CLR of contemporary quantitative empirical practices in business and management research. Its objectives are threefold. First, it systematically identifies and critiques the dominant methodological shortcomings that persist despite advances in analytical tools. Second, it synthesizes emerging methodological trends, including Bayesian inference, ML, and big data analytics, that address these limitations. Third, and most importantly, the paper advances an MDRF that reconceptualizes methodological rigor as a higher-order construct comprising inferential, modeling, and data rigor.

By reframing rigor as an integrative, multidimensional concept, this review moves beyond narrow evaluations based on statistical significance or model fit. The proposed framework offers a unifying lens for assessing methodological quality across traditional and emerging quantitative approaches, thereby contributing to ongoing debates about rigor, relevance, and credibility in business and management research.

## METHODOLOGY

This study adopts a CLR approach, particularly suited to examining entrenched methodological assumptions, evaluating dominant research practices, and advancing conceptual synthesis. Unlike systematic literature reviews that prioritize exhaustive coverage, a CLR emphasizes depth of critique, theoretical interpretation, and the identification of conceptual tensions within influential bodies of work. Accordingly, this review focuses on highly cited empirical studies that shape methodological norms in business and management research.

To ensure a comprehensive and reproducible review, a systematic search and selection process was employed.

## Search Strategy

A structured literature search was conducted using the Scopus database, which is widely recognized for its comprehensive coverage of high-quality, peer-reviewed journals in business, management, and economics. Scopus is widely used in methodological and review-based studies because of its standardized indexing, citation tracking, and disciplinary breadth.



The initial search string was designed to capture research that engages with quantitative methods and methodological reflection in business and management contexts:

("quantitative research" OR "statistical methods") AND ("business" OR "management") AND ("methodological rigor" OR "paradigm shift" OR "new framework" OR "trends").

This broad query ensured sensitivity to diverse methodological discussions while avoiding premature exclusion of relevant studies.

### Selection and Screening Process

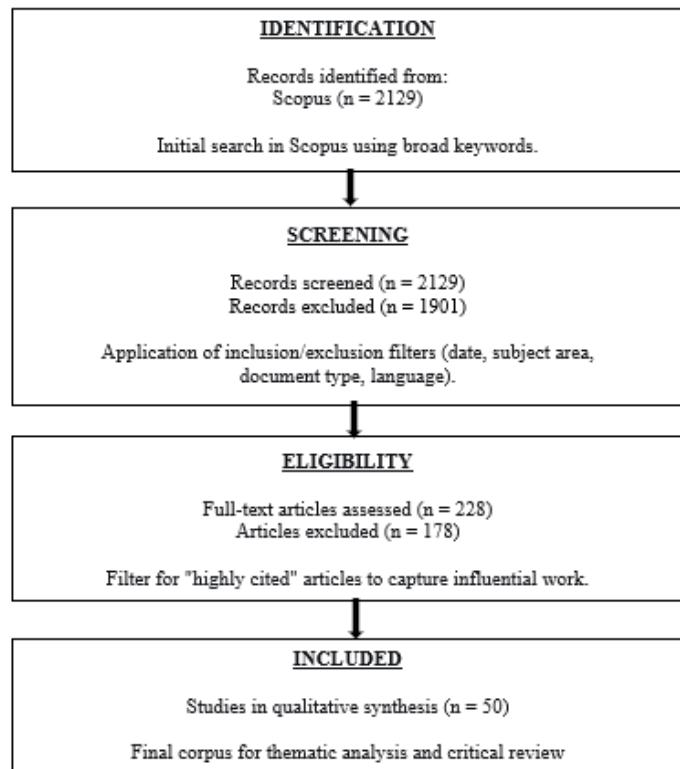
The initial search yielded 2,129 records. To enhance relevance and analytical focus, the results were refined using predefined inclusion criteria. Articles were limited to peer-reviewed journal publications in business and economics, published in English between 2016 and 2025. This period (2016–2025) spans a full decade of critical methodological debate following the widespread acknowledgment of the replication crisis and encompasses the rapid emergence and adoption of transformative analytical trends such as ML, Bayesian inference, and big data analytics in business research. The timeframe ensures the review is both historically grounded in recent reform movements and contemporarily relevant to ongoing shifts in quantitative practice.

Both empirical research articles and review papers were included to capture methodological practices and reflective debates.

Following this refinement, 228 articles remained. To align with the objectives of a critical literature review, a further screening step was applied to identify highly cited articles that exert disproportionate influence on methodological conventions and research norms within the field. This process yielded a final sample of 50 articles, which were subjected to in-depth qualitative analysis. Data extraction was completed on January 12, 2026.

The results of this process are presented in Table 1.

Table 1: Summary of the Article Selection Process





---

## Thematic Analysis and Synthesis

The selected articles were analyzed iteratively using an interpretive thematic approach. Rather than applying predefined categories, themes were inductively developed through repeated reading and comparative assessment of methodological assumptions, analytical choices, and reported limitations. This process enabled the identification of recurring patterns and tensions across the studies.

Three overarching thematic clusters emerged from the analysis: (1) critiques of prevailing quantitative practices, (2) emerging methodological shifts addressing these critiques, and (3) integrative perspectives on enhancing methodological rigor. These themes structure the presentation of findings and inform the development of the proposed MDRF.

## LITERATURE REVIEW I: A CRITICAL ASSESSMENT OF CURRENT EMPIRICAL PRACTICES

This section critically examines dominant empirical practices that continue to shape quantitative research in business and management studies. Rather than evaluating individual techniques in isolation, the review focuses on recurrent patterns of methodological reasoning that constrain explanatory depth, credibility, and practical relevance. Three interrelated critiques emerge from the literature: the persistence of a p-value–centric research culture, the dominance of linear modeling assumptions in complex contexts, and unresolved measurement challenges in advanced quantitative models.

### The p-value Culture and The Replication Crisis

Null hypothesis significance testing (NHST) remains deeply entrenched in quantitative business and management research, fostering a research culture in which dichotomous statistical outcomes, “significant” versus “non-significant,” often determine a study’s perceived value (Memon et al., 2023). In this context, statistical significance functions less as an inferential tool and more as a gatekeeping mechanism for publication.

The dominance of p-value thresholds incentivizes questionable research practices, including selective reporting, data-dependent model specification, and post hoc hypothesis refinement. These behaviors directly contribute to the replication crisis, in which a substantial share of published findings fail to replicate when reanalyzed or tested in new samples (Burger et al., 2023). Importantly, the crisis reflects not merely statistical error but a deeper epistemic problem: the conflation of procedural compliance with scientific understanding.

As Köhler et al. (2017) note, an excessive focus on achieving  $p < 0.05$  diverts attention from effect magnitude, theoretical plausibility, and contextual interpretation. Consequently, statistical analysis becomes a symbolic ritual that undermines the development of cumulative knowledge and weakens confidence in empirical claims.

### Linear Bias in a Non-Linear World

A second dominant critique concerns the pervasive reliance on linear modeling frameworks, particularly ordinary least squares regression, to analyze phenomena that are inherently nonlinear, dynamic, and context-dependent. Business systems exhibit threshold effects, feedback loops, complementarities, and sudden regime shifts, all of which challenge the assumptions of linearity and constant marginal effects (Küçükvar et al., 2019).

Despite this complexity, linear models remain the default analytical choice in much empirical research, largely because of their interpretability and computational convenience. However, this “linear bias” often leads to model misspecification, unstable parameter estimates, and limited predictive accuracy (Segura et al., 2018). Relationships that are contingent, asymmetric, or nonlinear are frequently forced into additive structures that obscure meaningful variation.

The persistence of linear bias reflects not only technical inertia but also epistemological conservatism. When analytical simplicity is prioritized over representational adequacy, quantitative research risks producing elegant but misleading explanations that fail to capture the realities of volatile business environments.



## Measurement Challenges in Advanced Quantitative Models

The growing use of advanced quantitative techniques, particularly structural equation modeling (SEM), has heightened longstanding measurement challenges in business and management research. While SEM enables modeling of latent constructs and complex causal structures, its effective application depends critically on sound measurement theory and rigorous construct validation (Al-Khatib et al., 2022; Khan et al., 2019).

A recurring issue in the reviewed literature is the mis-specification of measurement models, most notably the inappropriate treatment of formative indicators as reflective constructs or vice versa. Such errors fundamentally distort construct meaning and compromise substantive interpretation. Additionally, researchers frequently rely on global fit indices as the primary indicators of model adequacy, often overlooking concerns about content validity, discriminant validity, and nomological consistency.

Common method bias (CMB) further exacerbates these challenges, particularly in cross-sectional survey designs in which predictors and outcomes are measured within the same respondents (Memon et al., 2023). Collectively, these issues create an illusion of methodological rigor, where statistical sophistication masks underlying weaknesses in measurement fidelity and theoretical grounding.

The relationship between these critical shortcomings and the emerging trends discussed in the next section is shown in Figure 1.

Figure 1: Conceptual Link Between Methodological Critiques and Emerging Trends

Critiques of Current Practice	Emerging Methodological Shifts
p-value Culture & Replication Crisis	Bayesian Inference
Linear Bias in a Non-Linear World	Machine Learning (ML)
Measurement Challenges (SEM, CMB)	Big Data Analytics

Taken together, these critiques highlight a structural tension between how quantitative research is typically conducted and the complexity of the phenomena it seeks to explain. Importantly, the literature not only diagnoses problems but also points toward methodological innovations that challenge conventional practices. The conceptual relationship between these entrenched critiques and emerging methodological responses is illustrated in Figure 1, which serves as a bridge to the discussion of methodological shifts in the next section.

## LITERATURE REVIEW II: EMERGING TRENDS AND METHODOLOGICAL SHIFTS

This section reviews three methodological shifts that have gained prominence in response to the limitations of prevailing quantitative practices. Rather than representing a wholesale rejection of traditional statistical approaches, these trends reflect efforts to address specific weaknesses in inferential logic, model specification, and data adequacy. The discussion focuses on ML, Bayesian inference, and big data analytics, highlighting both their potential contributions and unresolved challenges.

### Integration of Machine Learning

The growing integration of ML techniques marks a notable shift in quantitative business and management research, particularly in response to the limitations of linear modeling frameworks. Unlike traditional



econometric approaches that emphasize parameter estimation and hypothesis testing, ML algorithms prioritize predictive performance and pattern discovery, making them well-suited to capturing nonlinear, high-dimensional, and interactive relationships (Ye et al., 2024).

ML applications have expanded rapidly across domains such as demand forecasting, customer behavior analysis, and operational optimization (Song et al., 2021; Qi et al., 2016). By relaxing linearity and additivity assumptions, ML methods directly address the “linear bias” identified in prior empirical work. However, these advantages come with important trade-offs. Many advanced ML models operate as “black boxes,” offering limited interpretability and weak alignment with theory-driven explanations.

Consequently, the contribution of ML to methodological rigor depends not only on predictive accuracy but also on how these tools are integrated with substantive theory, validation strategies, and transparency-enhancing techniques such as model comparison and explainable AI approaches.

### **Bayesian Inference**

Bayesian inference has gained renewed attention as an alternative to frequentist NHST, particularly in response to concerns about p-value-centric research practices. Unlike NHST, which relies on dichotomous decision rules, Bayesian methods provide a coherent framework for probabilistic reasoning, enabling researchers to quantify uncertainty and update beliefs in light of new evidence (Du et al., 2023).

By producing posterior distributions and credible intervals, Bayesian analysis promotes continuous inference rather than threshold-based conclusions. This shift aligns more closely with the inferential goals of business and management research, where decisions are inherently probabilistic and informed by prior knowledge. Bayesian approaches also facilitate cumulative learning by explicitly incorporating existing evidence through prior distributions.

Nevertheless, Bayesian methods pose their own challenges, including sensitivity to prior specification and a need for greater statistical expertise. As such, their contribution to rigor lies not in methodological novelty per se but in fostering greater transparency, interpretive nuance, and inferential coherence when appropriately applied.

### **Big Data Analytics**

The growing availability of large-scale, high-velocity, and heterogeneous datasets has broadened the empirical frontier of quantitative business research. Big data analytics enables the examination of phenomena at unprecedented levels of granularity, drawing on sources such as digital transaction logs, online reviews, social media activity, and sensor-generated data (Rangaswamy et al., 2022; Qi et al., 2016).

These developments address limitations of small, static, and self-reported datasets by enhancing temporal sensitivity and contextual richness. However, the shift toward big data also redefines methodological rigor. Issues of data quality, representativeness, and construct validity become more salient as the volume and variety of data increase. Moreover, reliance on proprietary or opaque data sources raises concerns about replicability and transparency.

Ethical considerations, including privacy, consent, and algorithmic bias, further complicate the use of big data in business research (Burger et al., 2023). Accordingly, data abundance does not automatically translate into rigorous research; instead, rigorous research depends on careful data governance, validation, and alignment of data characteristics with analytical objectives.

Collectively, these methodological shifts signal a move away from narrow procedural conceptions of rigor toward more flexible, context-aware, and analytically diverse approaches. However, none of these trends, in isolation, resolves the challenges identified in contemporary quantitative practice. Instead, they highlight the need for an integrative framework that aligns inferential logic, modeling strategy, and data characteristics. This need motivates the development of the MDRF, presented in the following section.



## SYNTHESIS: THE PROPOSED MULTI-DIMENSIONAL RIGOR CONCEPTUAL FRAMEWORK

The following section discusses advanced methodological shifts. Readers less familiar with these techniques may find the summaries of Bayesian inference, machine learning, and big data analytics helpful in understanding their role in enhancing rigor.

### Purpose and Rationale of the Framework

In response to critiques of prevailing quantitative practices and the emerging methodological trends reviewed in the preceding sections, this study proposes an MDRF for business and management research. The framework is not intended as a prescriptive methodological template or a substitute for established statistical standards. Rather, it serves as a conceptual synthesis that redefines methodological rigor as an integrative, higher-order construct.

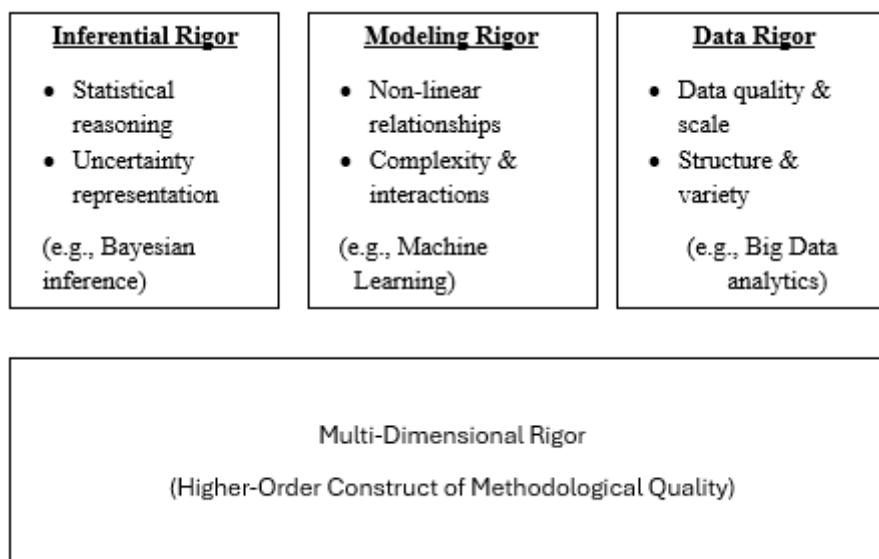
Existing evaluations of quantitative rigor often emphasize procedural compliance, such as adherence to significance thresholds, model fit indices, and sample-size heuristics. While these criteria are not without value, their isolated application risks conflating methodological form with substantive quality. The proposed framework addresses this limitation by shifting the focus from individual techniques to the alignment of inferential reasoning, analytical modeling, and data characteristics.

### Structure of the Multi-Dimensional Rigor Framework

As illustrated in Figure 2, the MDRF conceptualizes methodological rigor as a higher-order construct comprising three interdependent dimensions: inferential rigor, modeling rigor, and data rigor. These dimensions are presented as parallel rather than hierarchical or causal, reflecting the premise that no single dimension alone is sufficient to ensure rigor.

The framework emphasizes that robust quantitative research arises when inferential logic, model specification, and data properties are mutually coherent and collectively appropriate to the research question. Consequently, weaknesses in any one dimension can undermine overall rigor, regardless of the sophistication of the others.

Figure 2: The Multi-Dimensional Rigor Framework (MDRF)



### Inferential Rigor

Inferential rigor refers to the logical coherence and transparency with which statistical evidence is interpreted and uncertainty is represented. Within the proposed framework, inferential rigor extends beyond the mechanical application of NHST to encompass effect estimation, uncertainty quantification, and cumulative reasoning.



Practices such as reporting effect sizes alongside interval estimates, conducting a priori power analyses, and performing robustness and sensitivity checks enhance inferential rigor. Bayesian approaches further enhance inferential rigor by enabling probabilistic interpretation and the explicit incorporation of prior knowledge. Collectively, these practices shift inference away from dichotomous decision rules toward a more nuanced evaluation of evidence.

## Modeling Rigor

Modeling rigor concerns the extent to which analytical models adequately capture the structural complexity of the phenomena under investigation. In business and management research, this includes attention to nonlinearity, interaction effects, dynamic relationships, and contextual heterogeneity.

Traditional linear models may remain appropriate in certain settings; however, their routine application to complex systems risks oversimplification. ML techniques offer flexible alternatives for capturing high-dimensional and nonlinear patterns, but their contribution to rigor depends on careful validation, transparency, and theoretical grounding. Modeling rigor, therefore, reflects not methodological novelty but the appropriateness of model choice relative to the research context.

## Data Rigor

Data rigor refers to the quality, structure, and suitability of the data used to support quantitative analysis. As research increasingly relies on large-scale, unstructured, and real-time datasets, rigor cannot be inferred from sample size alone. Instead, measurement validity, representativeness, temporal alignment, and data provenance become central concerns.

Big data analytics expands empirical possibilities but also introduces new risks, including noise, bias, and opacity. Ensuring data rigor, therefore, requires explicit data governance practices, validation procedures, and ethical considerations. Within the proposed framework, data rigor complements inferential and modeling rigor by grounding analytical results in reliable and meaningful empirical foundations.

## Integrative Interpretation

The MDRF underscores that methodological rigor is not achieved by excellence in any single dimension. Highly sophisticated models applied to weak data, or large datasets analyzed with poor inferential logic, may yield misleading conclusions. Rigor, by contrast, arises from the alignment and mutual reinforcement of inferential reasoning, modeling strategy, and data characteristics.

By adopting this integrative perspective, the framework offers a unifying lens for evaluating both traditional and emerging quantitative approaches, enabling more reflective methodological choices and strengthening the credibility of empirical research in business and management studies.

It is important to note that the MDRF is intended as a conceptual and evaluative heuristic rather than a testable empirical model. Its purpose is to guide reflective methodological alignment, not to prescribe a fixed set of procedures.

## DISCUSSION

This discussion examines the implications of the proposed MDRF for key stakeholders in business and management research. Rather than reiterating prior critiques, the section reflects on how reframing methodological rigor as an integrative construct reshapes research practice, evaluation standards, and the translation of quantitative findings into decision-making contexts.

### Implications for Researchers

For researchers, the MDRF signals a fundamental shift in how quantitative quality is conceived and enacted. Rather than equating rigor with statistical significance or methodological sophistication alone, researchers are



encouraged to assess the coherence among inferential reasoning, modeling choices, and data properties.

This perspective promotes methodological pluralism, in which analytical tools are selected for their suitability to the research question rather than by disciplinary convention. Researchers are thus prompted to move beyond the pursuit of statistical significance toward practices that emphasize effect estimation, uncertainty representation, model appropriateness, and validation across contexts. Engaging critically with emerging methods, such as ML and Bayesian inference, becomes a matter of reflective integration rather than technical adoption.

### Implications for Journal Editors and Reviewers

Journal editors and reviewers play a central role in shaping methodological norms in the field. The proposed framework suggests that evaluation criteria should extend beyond procedural indicators, such as significance thresholds or fit indices, to include assessments of methodological coherence and transparency.

Editorial policies that encourage reporting effect sizes, interval estimates, robustness checks, and validation strategies can help realign publication incentives with substantive rigor. Moreover, valuing replication studies, null findings, and methodologically sound research that prioritizes clarity over novelty may contribute to a healthier, more cumulative research ecosystem. Importantly, the framework does not prescribe uniform standards but rather offers a lens for more consistent evaluation of methodological appropriateness.

### Implications for Practitioners

For practitioners, enhanced methodological rigor directly affects the credibility and usability of research-based insights. Quantitative findings grounded in coherent inference, appropriate modeling, and reliable data are more likely to support sound strategic decision-making, risk assessment, and performance evaluation.

The MDRF provides practitioners with a heuristic for assessing the quality of empirical evidence, whether from academic studies, consultancy reports, or internal analytics. By prioritizing effect magnitude, contextual relevance, and predictive reliability over symbolic indicators of rigor, practitioners can better distinguish actionable insights from statistically impressive but substantively weak results.

Taken together, these implications underscore that methodological rigor is a collective responsibility shared by researchers, evaluators, and users of quantitative research. By adopting an integrative view of rigor, the field can move toward more credible, interpretable, and impactful empirical contributions that better reflect the complexity of contemporary business environments.

A synthesis of these implications and actionable recommendations appears in Table 2.

Table 2: Implications and Recommended Actions for Research Stakeholders

Stakeholder	Core Mindset Shift	Key Action Items
Researchers	From "finding significance" to "finding truth."	<ol style="list-style-type: none"><li>1. Prioritize effect sizes &amp; interval estimates over p-values.</li><li>2. Employ methodological pluralism; match method to question.</li><li>3. Conduct robustness checks &amp; out-of-sample validation.</li><li>4. Engage critically with emerging methods (ML, Bayesian).</li></ol>
Journal Editors & Reviewers	From "gatekeepers of novelty" to "guardians of rigor."	<ol style="list-style-type: none"><li>1. Mandate reporting of effect sizes, power, and robustness checks.</li><li>2. De-emphasize p-values in results framing.</li></ol>



		<ol style="list-style-type: none"><li>3. Publish replication studies and null results.</li><li>4. Reward methodological fit and transparency.</li></ol>
Practitioners (Managers, Consultants)	From "data as cost" to "rigorous insight as ROI."	<ol style="list-style-type: none"><li>1. Demand research citing effect magnitudes and predictive validity.</li><li>2. Support internal research teams in adopting robust practices.</li><li>3. Apply frameworks (e.g., Fig. 2) to evaluate external research quality.</li><li>4. Use rigorous findings for risk reduction and strategic planning.</li></ol>

## CONCLUSION

### Concluding Synthesis

This CLR examined prevailing quantitative practices in business and management research and identified persistent tensions between methodological convention and the complexity of contemporary organizational phenomena. While quantitative methods remain indispensable, their routine application, often centered on statistical significance testing, linear modeling assumptions, and procedural measurement standards, has constrained explanatory depth, reproducibility, and practical relevance.

By synthesizing critiques and emerging methodological developments, this paper advances an MDRF that reconceptualizes methodological rigor as an integrative construct comprising inferential, modeling, and data rigor. Rather than privileging any single technique or paradigm, the framework offers a unifying lens for evaluating methodological quality across traditional and emerging quantitative approaches. In doing so, it contributes to ongoing debates about rigor, relevance, and credibility in business and management research.

### Limitations

Several limitations should be acknowledged. First, as a critical literature review, this study prioritizes depth of interpretation over exhaustive coverage. Although focusing on highly cited articles enhances relevance, it may underrepresent emerging work that has not yet accumulated citations. Second, adopting advanced quantitative methods such as ML and Bayesian inference entails steep learning curves, increased computational demands, and heightened data requirements, which may limit their accessibility in certain research contexts.

Finally, although the proposed framework provides conceptual guidance, its application depends on researchers' judgment and domain expertise. Methodological rigor cannot be fully standardized, and the framework should be treated as a heuristic rather than a prescriptive set of rules.

### Future Research Directions

The MDRF opens several promising avenues for future research. First, as ML and algorithmic decision-making become increasingly embedded in business contexts, greater attention is needed to the ethical dimensions of quantitative analysis, including transparency, fairness, and explainability. Developing standardized approaches to ethical and explainable AI within management research is a critical priority.

Second, future studies may explore hybrid methodological designs that integrate the strengths of multiple approaches, such as combining ML for pattern detection with causal inference techniques or incorporating qualitative insights to inform Bayesian priors. Such integrations closely align with the framework's emphasis on coherence across the inferential, modeling, and data dimensions.



Third, applying and refining the framework in emerging research domains, such as platform-based business models, the circular economy, and the sharing economy, can illuminate context-specific challenges to methodological rigor. Finally, pedagogical research on how quantitative methods are taught may play a crucial role in fostering the next generation of researchers capable of critical, integrative methodological reasoning.

These avenues, along with exemplary research questions, are outlined in Table 3.

Table 3: Proposed Future Research Directions and Exemplary Questions

Research Direction	Exemplary Research Questions
Ethical AI in Business Research	How can Explainable AI (XAI) techniques be standardized in ML-based management research? What frameworks can audit algorithmic bias in HR or finance models?
Hybrid Methodologies	How can qualitative case study insights be formally encoded as priors in Bayesian models? Can ML pattern detection be combined with causal inference (e.g., Double ML) for robust theory testing?
Rigor in Novel Contexts	How must the MDRF be adapted for research on platform ecosystems or the circular economy? What are the unique measurement challenges in the sharing economy?
Pedagogical Reform	What is the efficacy of a "methods-as-tools" curriculum vs. a software-procedural curriculum in developing critical methodological competence in PhD students?

Ultimately, the future of quantitative business and management research lies not in abandoning established methods but in moving beyond their ritualized application. By embracing a multidimensional, integrative conception of rigor, the field can generate empirically defensible, theoretically meaningful, contextually grounded, and practically relevant insights.

## REFERENCES

1. Al-Khatib, A. W., Al-Fawaeer, M. A., Alajlouni, M. I., & Rifai, F. A. (2022). Conservative culture, innovative culture, and innovative performance: A multi-group analysis of the moderating role of the job type. *International Journal of Innovation Science*, 14(3/4), 675–692. <https://doi.org/10.1108/ijis-10-2020-0224>
2. Burger, B., Kanbach, D. K., Kraus, S., Breier, M., & Corvello, V. (2023). On the use of AI-based tools like ChatGPT to support management research. *European Journal of Innovation Management*, 26(7), 233–241. <https://doi.org/10.1108/ejim-02-2023-0156>
3. Du, S., El Akremi, A., & Jia, M. (2022). Quantitative research on corporate social responsibility: A quest for relevance and rigor in a quickly evolving, turbulent world. *Journal of Business Ethics*, 187(1), 1–15. <https://doi.org/10.1007/s10551-022-05297-6>
4. Khan, M. A., Zubair, S. S., & Malik, M. (2019). An assessment of e-service quality, e-satisfaction and e-loyalty: Case of online shopping in Pakistan. *South Asian Journal of Business Studies*, 8(3), 283–302.
5. Köhler, T., Landis, R. S., & Cortina, J. M. (2017). From the editors: Establishing methodological rigor in quantitative management learning and education research: The role of design, statistical methods, and reporting standards. *Academy of Management Learning and Education*, 16(2), 173–192. <https://doi.org/10.5465/amle.2017.0079>
6. Kucukvar, M., Onat, N. C., Abdella, G. M., & Tatari, O. (2019). Assessing regional and global environmental footprints and value added of the largest food producers in the world. *Resources, Conservation, and Recycling*, 144, 187–197. <https://doi.org/10.1016/j.resconrec.2019.01.048>
7. Memon, M. A., Thurasamy, R., Cheah, J. H., Ting, H., Chuah, F., & Cham, T. H. (2023). Addressing common method bias, operationalization, sampling, and data-collection issues in quantitative research: A review and recommendations. *Journal of Applied Structural Equation Modeling*, 7(2), 1–14.



---

8. Qi, J., Zhang, Z., Jeon, S., & Zhou, Y. (2016). Mining customer requirements from online reviews: A product improvement perspective. *Information & Management*, 53(8), 951–963. <https://doi.org/10.1016/j.im.2016.06.002>
9. Rangaswamy, E., Nawaz, N., & Changzhuang, Z. (2022). The impact of digital technology on changing consumer behaviours with special reference to the home furnishing sector in Singapore. *Humanities & Social Sciences Communications*, 9(1). <https://doi.org/10.1057/s41599-022-01102-x>
10. Segura, S., Ferruz, L., Gargallo, P., & Salvador, M. (2018). Environmental versus economic performance in the EU ETS from the point of view of policy makers: A statistical analysis based on copulas. *Journal of Cleaner Production*, 176, 1111–1132. <https://doi.org/10.1016/j.jclepro.2017.11.218>
11. Ye, L., Xie, N., Boylan, J. E., & Shang, Z. (2024). Forecasting seasonal demand for retail: A Fourier time-varying grey model. *International Journal of Forecasting*, 40(4), 1467–1485. <https://doi.org/10.1016/j.ijforecast.2023.12.006>
12. Ying, S., Sindakis, S., Aggarwal, S., Chen, C., & Su, J. (2021). Managing big data in the retail industry of Singapore: Examining the impact on customer satisfaction and organizational performance. *European Management Journal*, 39(3), 390–400. <https://doi.org/10.1016/j.emj.2020.04.001>