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Reconsidering, refashioning, and reconceptualizing research methodology in international business

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ABSTRACT

We introduce this *Journal of World Business* special issue on methodological advances in international business (IB) research. Due to technological advances and the availability of bigger, deeper, and multi-level data, there is a need to reconsider, refashion, and reconceptualize IB research methodology. To do so, we discuss ethnography, multilevel modeling, textual analysis and multimodal data, visual methods, machine learning, accommodating multiplicity in qualitative research, and crowdsourcing. The future is bright for the field of IB because there are almost unlimited contributions that it can make to organizations and societies. But, to continue to do so, we must adapt and rethink our "research business model:" The way we think, conduct research, and report results to make meaningful contributions and impact both IB theory and practice.

1. Introduction

Research in the social sciences faces an unending challenge to progress - from the questions that are asked, through the theories used to conceptualize phenomena, to the empirical techniques used to reveal and describe the values, tendencies, and relationships that exist in the observable world. Recently, there has been additional pressure to cast a critical and discerning eye on the methodologies used in empirical research (e.g., Aguinis et al., 2023; Loken & Gelman, 2017). Standard practices that have been used without question for decades, such as the reporting of *p*-values, the reluctance to publish replication research, and the lack of data archives (Aguinis et al., 2020; Open Science Collaboration, 2015; Schwab et al., 2023), are now being called into question. Increasingly, empirical researchers are being held to higher technical standards as well as higher standards of accountability. At the same time, they are challenged to utilize the potential of methodological innovations made possible by new digital technologies, including Big Data.

Research in international business (IB) is no exception to this trend (Aguinis et al., 2017; Nielsen et al., 2020; Ramani & Aguinis, 2023). The IB scholarly community has become increasingly cognizant of the need to forge a new era of empirical acuity and accountability. Our practices of conducting, reporting, and archiving research are being re-examined to uncover where and how we can improve our practices, relevance, and positive impact. Notably, the IB scholarly community must also consider what opportunities exist to develop research that effectively incorporates cutting-edge methodologies.

Enabling this progression is a challenging task. Like any institutional change, it involves not only raising awareness of the limitations of our current "research business model" but also deploying appropriate incentives to learn and implement such approaches and methods as well as providing a culture that reinforces such behaviors (Aguinis, Archibold & Rice, 2022). As such, we believe it is incumbent on our research community to address three issues that concern how we conduct research in IB: (1) *reconsidering* how we design and empirically implement our research, (2) *refashioning* our considerations of the traditional methods used in terms of data collection and analysis, and (3) *reconceptualizing* what we regard as rigorous practices and standards in our research.

To that end, we present this special issue and our Introduction. We offer several ideas on what opportunities exist to reconsider, refashion, and reconceptualize our research practices. We then link these ideas to the articles that comprise the special issue. As we conclude, we hope to not only reinforce the current momentum but also help accelerate the progression of our research methodologies to a scholarly world that

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wholeheartedly embraces the principles of transparency, rigor, and meaningful and impactful contributions to theory and practice.

2. Background

A broad spectrum of research methods has been used in research in IB (Eden et al., 2020). Yet, an assessment of the diversity of research methodologies in published work in the past 50 years concluded that we are moving to values that reflect less rather than more diversity (Nielsen et al., 2020). This trend is rooted in an ever-greater percentage of published papers that have a high degree of quantification, using standard multivariate analytical methodologies (e.g., based on ordinary least squares and maximum likelihood estimation). Although such techniques, when combined with effective measurement (Chang et al., 2020), can yield meaningful insights, an over-reliance on these forms of modeling has limitations. Indeed, the ensuing narrowing of the methodological bandwidth limits knowledge production and potentially threatens rigor (Nielsen et al., 2020). The possibilities to move beyond this de facto standard set of methods to gain insight into IB phenomena is well-evidenced in this special issue.

The tight linkage between the phenomena we study and the methods we implement illustrates the criticality of ensuring that our methodologies are determined by the questions we seek to answer and emphasizes that, for a wide range of research questions, we expect a commensurate degree of methodological plurality. Plurality is a reasonable goal, but it is not a sufficient condition for advancing the usefulness and accuracy of our application of research methods to contemporary problems. Indeed, we must continue to seek to improve the rigor of our methods to identify better where relationships and patterns exist and, ideally, to move to the identification of how much and under what circumstances a relationship or pattern matters for the achievement of organizational, managerial, and societal objectives (Cuervo-Cazurra et al., 2016).

Aside from the examples and achievements demonstrated in the constituent articles of this special issue, we would like to illustrate several other points of methodological advancements that are important to emphasize to the IB community. We would like to stimulate discussions around meeting the challenge of complexity in research designs (Aguinis et al., 2023), exploring the potential of new digital technologies, and revisiting the standards we use to judge each other's work. In doing so, we can benefit from, and contribute to, developments in management and the social sciences. There is substantial scope to drive research in IB to be consistent with the increasing sophistication of technologies and methodological advances in the social sciences (Welch & Piekkari, 2017).

3. Reconsidering how we design and conduct our research

There are considerable methodological challenges in IB due to the inherent multilevel structure of data and the need to implement multidisciplinary approaches (Aguinis & Gabriel, 2022; Eden & Nielsen, 2020). Although IB research faces these challenges as a function of our quest to model real-world complexity adequately, it is simultaneously fighting methodological inertia as the range of commonly accepted, familiar, and utilized methodologies narrows (Nielsen et al., 2020; Ramani & Aguinis, 2023). This requires reconsidering IB research designs, measures, and analysis. Fortunately, as illustrated in this special issue, IB scholars are rising to the challenge by employing increasingly diverse analytical techniques – something we will consider in the next section. Still, more can be done (see also Knight et al., 2022). Greater diversity is not just about adopting cutting-edge methodological innovations but also about turning to existing methodologies the field has long neglected or, at best, under-utilized. We now provide two examples – one qualitative, one quantitative – of established methodologies that IB scholars can employ to address their study's phenomena. These methodologies are more than a set of techniques: we emphasize that they offer research designs well-suited to capture the complexity of IB settings.

3.1. Ethnography

The longstanding dominance of the "Eisenhardt template" (Langley & Abdallah, 2015), which established qualitative case studies as an inductive complement to "mainstream deductive research" (Eisenhardt, 1989), was undoubtedly important in gaining legitimacy for qualitative research (Welch & Piekkari, 2017). But it has perhaps come at a cost – neglecting other qualitative research traditions and approaches – that the field should not continue ignoring.

One of the most serious and enduring missed opportunities for qualitative research in IB remains the need for ethnographic studies. As Miller (2021) documented, anthropology, with its rich tradition of studying different cultures, was one of the original reference disciplines for the emerging field of IB in the 1970s. Ned Hall (1959) work was well known, and its relevance to IB was well understood. However, ethnographic studies failed to appear in one of the field's most visible journals – the *Journal of International Business Studies* – until 2009 (Brannen & Peterson, 2009). There are undoubtedly pragmatic reasons why ethnographic studies remain under-represented in IB journals, given the methodological training, time commitment, and organizational access they require to do well.

But more than that, the potential contribution that ethnographic studies can make and the standards for judging ethnographic work still needs to be better understood in IB. For example, ethnographic studies famously provide "thick descriptions" of settings (e.g., Geertz, 1973), but this term and its implications are poorly understood. Thick description is more than merely descriptive, although based on meticulous and intense study of a social setting. Instead, it is a form of theorizing (Cornelissen, 2017) based on the holistic logic derived from the hermeneutic tradition, that only by placing a social phenomenon or event into its broader context can its meaning be understood. Put more simply, the part cannot be understood detached from the whole.

Thick description, done well, transforms our understanding. However, its theoretical output and value are not expressed in the familiar terms of the "propositional style" (Cornelissen et al., 2021) that dominates most IB journals. Troublingly, all too often, it is mistaken for mere storytelling. It has also been hampered by an unfounded bias against research conducted in single settings (Welch & Piekkari, 2017). Yet ethnography remains central to the core mission of IB as a field of research – to understand the complex ways in which diverse cultural, political, and institutional settings affect cross-border interactions. Its greater acceptance would be a sign that the methodologies IB scholars use are suited to realizing this goal. Making our journals more hospitable to ethnographic studies remains a work in progress, but one to which this special issue contributes (Mahadevan & Moore, 2023).

3.2. Multilevel Modelling (MLM)

Our observation is that there needs to be more research utilizing advanced analytical techniques to capture patterns of interdependencies within and across levels of IB phenomena. In particular, multilevel modeling (MLM) is increasingly employed to allow for conventional theory testing of complex nested IB phenomena (Lindner et al., 2021; Peterson et al., 2012).

The multilevel strategy can be beneficial when dealing with repeated measurements (e.g., when data are collected from the same firms over time) or with unequal sample sizes, and more generally, when handling dependency (nesting) structures in the data (e.g., individuals within teams, teams within organizations, organizations within industries). For example, these nesting structures are frequently found in IB data, where subsidiaries are nested within MNC HQs and host (or home) countries. Essentially, MLM allows for variance decomposition at different levels (e.g., country, industry, firm, team) and analysis of cross-level direct and interaction effects (Aguinis & Molina-Azorín, 2015).

That said, IB phenomena are often not cleanly hierarchically nested as they involve actors and contexts interwoven in complex ways not recognized in IB scholarship (Park et al., 2020). To address this, a different class of MLMs allows for more complex data structures (e.g., cross-classified nesting) to account for multiple, non-nested (overlapping) contextual (group) variations. For instance, firms often belong to (are nested within) two (or more) types of clusters, such as industries and countries, that are not hierarchically nested within one another. Such structures are not hierarchically nested because not all companies from a particular country compete in the same industry, and companies competing in a particular industry do not all originate from the same country. Because industries are not hierarchically nested within countries or vice-versa, the two levels are "crossed," giving rise to data structures that are categorized as cross-nested or cross-classified (Raudenbush & Bryk, 2002; Snijders & Bosker, 2011).

Cross-classified random coefficient modeling (CCRCM) can appropriately handle this non-hierarchical data structure.[1] CCRCM allows for separating the effects of the cross-cutting hierarchies (e.g., country and industry) on the dependent variable (e.g., firm performance) and thus may help IB scholars test complex theoretical models involving multiple contextual levels. Cross-nesting of levels in data structures may occur at any level (e.g., cross-functional teams). Specifying such complexity is pivotal to IB research (see Nielsen, 2021).

Notably, multilevel structural equation modeling (MLM-SEM) can be applied to account for more complex systems of relationships (simultaneous equations) and extended to multilevel latent growth models (MLM-LGM) to account for dynamism. Finally, Bayesian multilevel models (B-MLM) use probability to model uncertainty and allow a priori knowledge to be incorporated in data analysis via prior distribution. Such advanced MLM approaches can help IB scholars develop and test the complex multilevel theory that moves away from the simplistic and often inaccurate assumption of independence of observations towards a more realistic set of nested and interdependent observations across contextual levels.

4. Refashioning methods for data collection and analysis

Digital advances comprise the availability of vast digital data sources and new technologies for automating analysis. These innovations are transforming traditional techniques - such as content analysis, cluster analysis, and latent variable modeling - and providing new opportunities for data collection. As in the previous section, we will discuss the implications for both qualitative and quantitative research. We highlight that these implications go beyond the need to master new software or to learn the fundamentals of software programming. The digital revolution also allows us to go beyond some of the limitations and simplifications traditional techniques impose.

4.1. Textual analysis and multimodal data

In the face of the "Big Data" revolution, a danger arises that the rich "up close and personal" nature of qualitative research will be sidelined. What, then, is the role of qualitative research in the era of Big Data? This question has been posed and debated in other areas of the social sciences (Mills, 2018; Törnberg & Törnberg, 2018), and it certainly warrants consideration by IB researchers. We suggest that the digital era can and should lead to a refashioning of qualitative research in two ways: (1) ensuring that analysis of large textual datasets includes qualitative and quantitative techniques and (2) contributing innovations in qualitative methods and research designs.

Turning to the first point, the ability of qualitative research to address the question of "what is really going on here?" remains one of its core strengths and perhaps even more so in the digital era. Finding patterns in large datasets can lead to potentially misleading results unless accompanied by more intense scrutiny of these patterns and an in-depth understanding of the nature of the data itself. Stated differently, data breadth must be accompanied by data depth. In the digital era, it is more feasible than ever before to combine breadth and depth by utilizing the increasing power of automated textual analysis in conjunction with the in-depth, line-by-line analytical techniques offered by traditional qualitative research (Ramani & Aguinis, 2023). Adding a qualitative component to the analysis allows for greater interpretive richness and data triangulation (for a discussion, see Davidson et al., 2019).

The second point is to explore digitization's opportunities to advance existing qualitative approaches. Again, ethnography provides a useful illustration. Ethnographers were amongst the earliest qualitative researchers to develop approaches to study online behavior and virtual communities, and by now have well-established methods for doing so in the form of "netnography" (e.g., Kozinets, 2019). Netnography does not just inspire IB scholars in the form of new data and settings to explore, but it also sensitizes us to the challenges that online research presents (such as ethical concerns and data quality) – and how they might be overcome. As more and more cross-border interactions are conducted virtually, ethnographic techniques for understanding this type of setting will become more relevant to IB scholarship and are worth adding to the qualitative repertoire. The multimodal nature of much online data and social media highlights a somewhat surprising gap in our methodologies: the failure to use a wider range of sources of evidence. Visual methods such as photographs, films, or videos are not new but have proliferated in the digital age. If "a picture is worth a thousand words," there is now a more significant opportunity to use this potential. Media representations of certain businesses, professions, or countries are readily accessible to all. However fanciful (Hällgren & Buchanan, 2020; Hartman et al., 2011), such representation can structure political attitudes (Bartlett et al., 2021) and have a real-world impact on IB – and these representations are, therefore, a source of evidence about what is happening. Videos and graphic novels (Carollo, 2021) produced by businesses, governments, or independent filmmakers can be deconstructed and analyzed for underlying meaning. Yet, compared to their availability and importance, using social media as a research tool remains limited (Choi et al., 2020). There is much scope here for more imaginative and immediate research methodologies. For example, virtual reality (VR) immerses research participants in a computer-generated environment. VR can allow researchers to create and test theories and study phenomena that are either difficult or impossible to examine using more traditional methodological approaches (Hubbard & Aguinis, 2023). Our journals now have the technology to embed visuals and animations, and we look forward to their greater use.

4.2. Machine Learning (ML)

The application of ML includes a range of techniques to analyze complex data. However, despite ML's common use in other disciplines, these models and algorithms have yet to reach IB research (Messner, 2022; van Tulder et al., 2019). Generally, ML can be subdivided into unsupervised, supervised, and semi-supervised learning models (Sivarajah et al., 2017) with different utilities in relation to IB research.

4.3. Unsupervised ML

The unsupervised ML approach uses algorithms to analyze and

[1] If the probability of a lower level unit (e.g., firm) being nested within any of the crossed higher level factors (e.g., industry or country) is approximately equal across all units, the resulting data structure is considered completely cross-classified. However, if for some reason firms competing in certain industries are more likely to emanate from certain countries and firms from certain countries only compete in certain industries, the resulting data structure is partially cross-nested because units of one crossed factor (e.g., industry) can only affiliate with part (not all) of the other crossed factor (e.g., home country).

cluster unlabeled (raw) data sets. These algorithms discover hidden patterns in data without human intervention, which is why they are called "unsupervised" as the ML explores and determines what is interesting in the dataset (i.e., anomaly detection or semantic clustering). Unsupervised ML methods are particularly useful for description because they aim to find relationships in a data structure without having a measured outcome. The goal of unsupervised learning is to identify patterns in complex data structures (e.g., nonlinear associations, interactions, underlying dimensions, or subgroups) in contrast to "traditional" parametric methods that involve numerous statistical assumptions (e.g., normality of residual scores) and require a priori specification of dimensions or subgroups of interest, the functional form of the relationship between predictors and the outcome, and interactions among predictors.

Refashioning IB methodology to include unsupervised ML approaches has many benefits. For instance, hierarchical clustering of unlabeled data via ML involves the organization of data in such a way that there are high intra-cluster and low inter-cluster similarities, which may help determine appropriate (yet potentially hidden) patterns in international networks (social, organizational, financial). In addition, this technique can help identify and incorporate multiple levels of data that can serve as *inputs* into multilevel analysis, as discussed earlier.

Moreover, IB data are often large, multilevel, messy, and multidimensional. Unsupervised ML can help find the essential pattern of the underlying data by extracting intrinsic dimensions and reducing messiness by detecting outliers due to such issues as noise or measurement error. As IB scholars seek to better capture real-world complexity via big data, such ML approaches will help prepare datasets for meaningful statistical analyses by identifying data-driven dimensions and subgroups that may lead to the formulation of meaningful and interesting hypotheses.

4.4. Supervised ML

The supervised ML approach represents a simple, guided approach to training or "supervising" algorithms to classify labeled input and output training data. Supervised ML involves the search for algorithms that reason from externally supplied instances to produce general hypotheses, which then make predictions about future instances. The most commonly used supervised ML algorithms are conventional regression (logistic and linear), decision trees, and super learning models. Supervised ML may be preferable to traditional statistical methods if the goal is prediction optimization in large data structures because such methods have fewer and less restrictive statistical assumptions than traditional parametric methods. A related prediction goal is identifying the variables that most strongly contribute to prediction accuracy (e.g., identifying the drivers of MNE performance from variables at country, industry, HQ, subsidiary, and team or individual levels). Moreover, supervised ML approaches have recently been linked to causal inference (Blakely et al., 2020), where pre-final estimation steps in causal inference— a prediction that can be aided by machine learning—offer a useful conceptual approach to deploy potential outcomes thinking in IB.

4.5. Semi-supervised ML

Semi-supervised ML aims to understand how combining labeled and unlabeled data may change the learning behavior and design algorithms that use such a combination (Zhu & Goldberg, 2009). An advantage of semi-supervised ML is that it can use readily available unlabeled data to improve supervised learning tasks when the labeled data are scarce or expensive. Furthermore, semi-supervised ML aims to train a classifier from labeled and unlabeled data. It is better than the supervised classifier trained on the labeled data alone. For example, constrained clustering obtains better clustering than the clustering from unlabeled data alone. Hence, as a preliminary step, IB scholars may utilize semi-supervised ML to extract meaning from large databases containing raw, unlabeled firm-level accounting or investment data. Similarly, large databases exist, including variables at other levels of analysis (e.g., country, industry, or individual) that may provide important insights into firm strategic behavior across contexts and time. Semi-supervised ML also has the potential as a quantitative tool to enhance our understanding of multicultural learning flows from individuals via groups to organizations, where most of the input is typically unlabeled.

Large unstructured datasets now exist for variables at various levels about IB phenomena. Machine learning offers an efficient way to explore complex patterns in high-dimensional data inductively and to deductively test complex hypotheses.

5. Reconceptualizing what we regard as high-quality practices and standards for research

Changing how we do our research requires more than mastery of new techniques. New techniques must be accompanied by a reassessment of longstanding beliefs and value systems about what "good" research looks like. Changing norms and standards for doing research – that is, reconceptualizing rigor – is a community-wide effort. The methodological developments we have outlined will not be achieved without everyone – including reviewers and editors – recognizing the need for multiple approaches for research designs, methodologies, and techniques to improve the credibility and trustworthiness of our results (Cuervo-Cazurra et al., 2016). In this section, we propose two ways to emphasize the multiplicity of methodological approaches that could be used to improve the quality of IB research: (a) accommodating multiplicity in qualitative research and (b) crowdsourcing and multiverse analysis.

5.1. Accommodating multiplicity in qualitative research

Qualitative research has become more accepted in IB journals, but the challenge remains that only a narrow range of qualitative designs, methodologies, and techniques is utilized. The standard format of multiple case studies, based on interview data and a cross-sectional research design, still prevails (e.g., Nielsen et al., 2020). This prevalence exists despite qualitative research having a diverse and versatile set of traditions. As we have discussed, we expect the multiplicity of options to grow in our more technologically developed and digital era, with advances leading to new data sources, phenomena, research settings, and analytical techniques.

Diversifying, renewing, and innovating our qualitative repertoire will not be possible without challenging and overcoming assumptions, beliefs, and even "methodological myths and urban legends" (e.g., Lance & Vandenberg, 2014) that are still deeply entrenched in IB. This means openly discussing what constitutes "high-quality" in qualitative research, something that has been addressed in the pages of the *Journal of World Business* and elsewhere (e.g., Welch & Piekkari, 2017) but needs to be an ongoing debate that informs not only qualitative scholars but also the journal editors and reviewers who evaluate qualitative submissions. This is a wide-ranging discussion, but we will focus on key issues that have surfaced from our discussion about future directions for qualitative research.

The first misunderstanding is to associate high-quality research with a particular data collection or analytical technique. For example, semi-structured interviews and thematic analysis loosely based on grounded theory techniques are ubiquitous, leading to an expectation that a qualitative manuscript must contain tables of representative quotes and a "data structure" showing the aggregation of themes into a small number of constructs. This is one way of doing qualitative research, but one which is based on particular assumptions and preferences that qualitative researchers familiar with alternative traditions would contest (Mees-Buss et al., 2022). We introduce this misunderstanding here as we want to emphasize that the role of reviewers is not to impose their preferred qualitative "template" on others but rather to assess whether the work being evaluated is transparent and has justified the choices made about the aims of the research (Aguinis & Solarino, 2019).

The second misunderstanding derives from continuing misgivings about the scientific value of $n = 1$, which has undoubtedly hindered the publication of ethnographic research. Fortunately, using single cases and settings has become more widespread in IB journals. However, it is still worth repeating that in qualitative research, "generalization" refers not to generalizing a population but generalizing conceptual abstractions (Tsoukas, 2009; Yin, 2014). The strength of qualitative research remains its ability to conceptualize the empirical world in ways that challenge, enlighten, and provide pragmatic value. Doing so meaningfully – going beyond initial impressions and questioning "what really is going on" – requires lengthy field engagement and contextualization. Single settings can allow for this, and therefore have an essential contribution to make to the field. For this reason, an $n = 1$ should not be the basis for not publishing a qualitative manuscript because it is not of sufficiently high quality.

The third misunderstanding concerns the theoretical contributions of qualitative research. While they can be expressed in propositional form, providing the basis for testable hypotheses, this is by no means the only possible outcome – and is alien to many qualitative traditions. Diversifying our qualitative repertoire, therefore, requires us to diversify the forms of theorizing that we use in IB – and hence the range of theoretical contributions that we are willing to accept (Welch et al., 2022). A discussion about the variety of theorizing forms or "styles" has been underway for some time in management research (e.g., Cornelissen, 2017). Earlier in our article, we referred to the tradition of thick description, but it is not the only theorizing style with a rich qualitative heritage. For example, in a recent contribution, Cornelissen et al. (2021) identified six alternative "explanatory programmes" distinct from the dominant propositional style and favored by qualitative researchers. The implications are that when we evaluate the theoretical contribution of a qualitative study, the question first needs to be posed: What is the theorizing style in use? Only then will the theoretical contribution of a study be assessed on its merits.

5.2. Crowdsourcing and multiverse analysis

Social scientists have moved from a begrudging acceptance of the need for replication to a broader cognition of its utility to advance substantially our understanding of phenomena and our ability to develop, test, and advance theory (Baker, 2016). Much of the impetus emerged from what has been called the replication crisis in psychology, economics, strategic management, entrepreneurship, and other fields (Bergh et al., 2017; Camerer et al., 2016; Crawford et al., 2022; Hardwicke et al., 2022). As a result, researchers across fields are not only increasingly embracing the practice of replication, but also working to define it better, such as in terms of reproduction, generalization, and other more nuanced terms to indicate the form of replication implemented (Kraimer, 2023; Wang et al., 2022). Several journals, such as the *Journal of Management Scientific Reports, Academy of Management Discoveries*, and *Journal of Business Venturing Insights*, explicitly state that they will entertain manuscript submissions describing replications. Moreover, Schwab et al. (2023) conducted a literature review and found that more than 50 journals in management and related fields have published replications since 2016.

Yet, even within the replication community, there continue to be ongoing advances. Indeed, suppose we adopt some of the new precepts of high quality research – pre-registration, data archiving, and heightened methodological transparency – to facilitate future reproductions and generalization tests. Why do we not incorporate these steps into the research design stage? One way to accomplish this is to use crowdsourcing. Crowdsourcing involves using multiple researchers to simultaneously and independently undertake a specific research task. The specific research task will often involve the same data set and research question. The core idea of crowdsourcing data analysis is to examine the sensitivity of empirical conclusions from the same data set to the choices that similarly trained analysts make independently to construct their analyses.

The wide variance that can be obtained as conditioned on analysts' choices was amply demonstrated by Silberzahn et al. (2018), who found that 61 analyst conclusions regarding the same research question yielded variances in not only effect sizes but also outcomes that varied from a negative to a positive relationship. Also, Bergh et al. (2017) attempted to reproduce the empirical findings of 88 articles published in *Strategic Management Journal* using the correlation matrices reported in the articles. Unfortunately, one-third of the reported statistically significant hypotheses were not replicated. Moreover, these outcomes were not conditioned on how peers evaluated the quality of work done. Put another way, demonstrably equal-quality analyses yielded substantially different outcomes.

The quality of analysis and differential outcome link might seem paradoxical to some scholars, but it becomes less paradoxical when we consider the number of decisions and judgement calls involved to connect a series of independent variables to the outcome variable. Analysts must collect data to investigate the phenomenon. This is an area where there can be substantial variance. Crowdsource experiments that use similar research designs, but vary the sample used for the experiment, explore for generalizability at the research implementation stage by intention as embedded in the research design.

When moving to crowdsourcing analysis for archival data, the data are defined as fixed, hence eliminating sample-based heterogeneity as a potential source of results divergence, should such occur. However, with the same sample, analysts are still charged with making challenging decisions about the data, such as defining independent and dependent variables and handling outliers and missing data. Unfortunately, these seemingly innocuous yet essential decisions are often unreported, hampering replication (Wu et al., 2023).

For example, in an entry mode study, researchers often have access to data on whether a subsidiary is a greenfield or acquired, and the ownership positions. However, decisions remain as to whether to compare all greenfield versus acquired, where to divide entry mode into three categories – acquired, greenfield wholly-owned, and joint venture, and if joint venture, what are the equity levels (5, 10, 20 percent) used to define whether a partner is a portfolio investor or a direct investor in the entity. Hence, even with seemingly definitionally constrained data, researcher subjectivity exists.

Once data issues are settled, the researcher must select the analytical methods to estimate relationships. Continuing with our theme, multiple choices exist, often conditioned by the characteristics of the dependent variable as well as the underlying characteristics of the data. Again, seemingly innocuous choices about model specification can influence outcomes considerably. For example, a shift in model estimation from Poisson to Poisson with robust standard errors (Wooldridge, 2016) can substantially change inferences about independent variables based on non-trivial changes in coefficient estimates. Or, as more closely related to our discussion, MLM that applied grand mean centering of predictor variables versus group mean centering, for instance, yielded great differences in results (Enders & Tofighi, 2007).

These issues about data and modeling pervade the social and physical sciences. For IB scholars, the question should not be about whether they are important to the validity of our empirical work. Instead, it should be about how to contend with such design issues in our research actively. The importance of so doing is illustrated in a large research project that examined the generalizability and replicability of 29 different studies in IB (Delios et al., 2022). Although replicability predicated generalizability, the baseline rate of successful replication was just 40% across these 29 studies.

Results from studies such as the above, alongside emergent findings from recently implemented crowdsourcing studies, indicate the frailty of empirical results. Importantly, this frailty is not a consequence of empirical mis-execution, but instead it connects most tightly to the choices made by analysts along such dimensions as data cleaning, handling missing data, variable definition, empirical modeling, sample choice, sample selection, model specification, and so forth (Aguinis et al., 2021).

If multiple valid choices exist for a study's research design, and these choices can yield substantially different empirical observations and inferences, then we must entertain the premise in our research that a given set of empirical data can yield multiple versions of the same seemingly objective world. Put another way, there are a multiplicity of research strategies that can involve the valid investigation of any research question; which in turn, leads to a potential multiplicity of empirical outcomes (Hutson, 2018; Gelman & Hennig, 2017). The implication is that as long as we know that researcher subjectivity exists and it can influence research outcomes, we must be clearer on how such choices influence outcomes. Only by embracing the limitations of our research approaches can we improve our research designs and heighten the confidence that other researchers, managers, and policymakers have in our empirical work.

This realization is captured in what can be called multiverse analysis, where the baseline premise is that we expect multiple empirical realities to exist across teams of analysts working with the same research questions and even the same set of empirical data. This alteration in premise from similarity to plurality necessitates a fundamental reconceptualization of how we address the uncertainty in our empirical techniques. The consequent reconceptualization in multiverse analysis moves researchers away from trying to combat and reduce uncertainty to embracing uncertainty as an inevitability of the research process. Moreover, suppose uncertainty is a given, not a methodological anomaly, and researchers accept that multiple empirical realities can (and will) emerge from any data set. In that case, multiverse analysis emphasizes the importance of developing cumulative evidence within a study instead of across studies. The advantage of the within-study approach is that it allows for a distinct focus on critical choice points and their connection to empirical outcomes, which will provide clear feedback on the implications of these choices for future empirical work.

Both crowdsourcing and multiverse analysis are still in their infancy. That said, they have great potential in IB research for three connected reasons. First, IB phenomena demand not only sophistication in empirical techniques but also a recognition that researchers' choices matter for the results obtained. Second, crowdsourcing and multiverse analysis brings the issue of analyst choice to the design stage of the research instead of to the post-publication stage, where published research is subjected to reproductions and generalizations.

Second, we must recognize that the IB research community is necessarily a diverse one. This diversity can be harnessed to leverage the many available analysts distributed across various geographies, many of whom are embedded in different research cultures. At the same time, the pursuit of large multi-analyst projects will contribute to harmonizing research standards via a better understanding of the critical choice points (variable operationalization, model choices, sample choices) in a given area of IB research.

Third, we need to expand our consideration of acceptable research approaches in IB. Indeed, this reconsideration was core to our motivation for this special issue. It is also important for the general advancement of the social sciences. We need to understand better the implications of our research choices, not only to undertake better research but also to keep pace with the fascinating developments occurring in the rest of the physical and social sciences. For example, among these developments are the use of large research teams to overcome resource constraints found in traditional small-team research. We hence need to balance consideration of what level of investment is appropriate; that is, the solution is not about asking researchers to do more work; it is a better identification of what is rigorous and appropriate given our explicit recognition of some of the weaknesses in our decades-old research models in IB.

The practical implications of these ideas are reflected in the articles for this special issue, to which we now turn. Importantly, we note that special issues such as this allow us to stretch the systemic boundaries of reviewer and editorial constraints that limit opportunities for researchers to explore and implement novel methodologies. We wholeheartedly acknowledge that many challenges to novelty in research commonly articulated are systemic in scope (Aguinis, Archibold & Rice, 2022). Although we do not directly question that herein, we fully embrace the view that aside from the technicalities covered in this special issue, there is substantial opportunity to balance technical solutions with systemic solutions.

Concerning the technical, the six papers cover a wide range of methodological concerns. Still, the commonality across the papers is that they provide alternatives to the traditional approaches favored by IB scholars and expand possibilities for the future. In the following section, we provide an overview of the six papers with particular attention to how they address the three elements set out above: (1) reconsidering how we design and empirically implement our research; (2) refashioning our considerations of the traditional methods used in terms of data collection and analysis; and (3) reconceptualizing what we regard as high-quality practices and standards in our research.

6. Overview of papers

Richter and Hauff (2022) reconsider approaches used to establish what they identify as additive, configurational, and necessity causal logics. Through this reconsideration, Richter and Hauff (2022) propose refashioning analytical techniques as grounded in the necessity logic to introduce necessary condition analysis (NCA). Although NCA has been utilized in other fields, its implementation has been rare in IB studies, even though a necessity logic is frequently used. As such, a greater implementation of NCA will bring greater alignment between theorizing and methods in IB.

Sanchez et al. (2023) reconsider the traditional possibilities for research designs by demonstrating how to conduct multi-paradigm research. They illustrate how combining phenomenological interpretivist and positivist approaches can lead to a questioning of past findings and assumptions in a research area. In doing so, they also challenge us to reconsider established views about the incommensurability of research paradigms while reconceptualizing how we consider the quality of assumptions and the associated interpretation of results.

Hoorani, Plakoyiannaki and Gibbert (2023) refashion qualitative research via an explicit reconsideration of how time fits with qualitative studies. The authors identify four temporal styles of theorizing: temporal variation, temporal accumulation, temporal evolution, and temporal story. This refashioning of time helps researchers to engage actively with time in parallel importance to context and theory. It likewise helps to promote a pluralization of temporal theorizing styles, while also better understanding linear and non-linear time.

Mahadevan and Moore (2023) refashion the use of ethnography in IB research. The motivation for this refashioning emerges from the authors' observation that the under-representation of ethnographic work in IB relates to the simple but powerful point that ethnographic research is poorly understood in terms of implementation but also its ability to inform context and build theory. This limitation can be overcome by reflexive engagement which involves the ethnographer, the research subjects, and the readers of the consequent paper to be more tightly engaged as the three sides in the ethnographic triangle.

Nguyen and Tull (2022) reconceptualize qualitative research by looking critically at the extended case method (ECM). Their work shows how the ECM can reinforce the contextual relevance of the case method. The addition and emphasis of context in the ECM is particularly important in International Business research where as much as in any sphere of research context matters in the identification and interpretation of the focal phenomenon. Given challenges to generalization that exist within the case method, the reconceptualization of qualitative research to ECM provides valuable opportunities for theory development via a methodological innovation.

Finally, Lukoianove et al. (2022) reconceptualize the measurement of the political environment, one of the most elusive business environment dimensions to define both conceptually and empirically in IB research. Although several well-respected measures exist to measure both political risk and policy uncertainty, the dynamic factor analysis approach advanced in Lukoianove et al. (2022) creates a multi-dimensionality in the measurement of the political environment that has largely been absent in previous measurement.

7. Conclusions

There is little question that we are in an era where we need to reconsider, refashion, and reconceptualize IB research methodology given higher technical standards, higher standards of accountability, as well as new technological developments such as Big Data. Further, IB research is not isolated: Trends in the social sciences have alerted scholars to the need to devise empirical strategies to address multilevel data structures from a multidisciplinary perspective. Part of the increase in effectiveness can come from adopting Open Science Standards and embracing the need for pre-registration. Yet, as contended here, there are opportunities for further gains to be made by expanding the increasingly narrow focus that permeated much IB research through the first two decades of the 21st century. To that end, we introduced several ideas to reconsider, refashion, and reconceptualize methodologies in IB research, including ethnography, multilevel modeling, textual analysis and multimodal data, machine learning, accommodating multiplicity in qualitative research, and crowdsourcing and multiverse analysis.

Yet, we also want to emphasize that we are initiating, not ending, a conversation. The *Journal of World Business* is open to papers that illustrate methodological innovations to further develop the agenda that we have established here. With such progress, we believe the field of IB can remain relevant in the future and deliver on the promise that we all know the field has. But, to do so, we must adapt and rethink our "research business model:" the way we design and implement research with the goal of making meaningful and impactful contributions to theory and practice.

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